Uncertainty-Based Mine Planning Framework for Oil Sands Production Scheduling and Waste Management

by

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ACCESSIBILITY CLAUSE AND PERMISSION TO USE

This work is dedicated to the memory of my beloved parents,

Ramadan and Arosia,

who have meant and continue to mean so much to me.

Although they are no longer of this world, their memories continue to guide my life. They taught me the value of hard work, and they always believed in my ability to be successful.

Mom and Dad:

You left a void that can never be filled in my life. I love you and miss you beyond words.

May Allah (SWT) grant you Jannat Al-Firdaws.

Amen

ABSTRACT

In open pit mining, the most significant challenge is determining the optimum long-term production schedules that maximize the project value by providing ore to the processing plant at full capacity while satisfying all required constraints. For oil sands strategic mine planning and waste management, as mining advances in a specified direction, in-pit tailings-cells' dyke footprints are released for dyke construction. The dykes are constructed from overburden, interburden and tailings coarse sands dyke materials which come from the mining operation. The construction of in-pit (and ex-pit) tailings impoundment dykes therefore needs to be well integrated with the waste management strategy to ensure regulatory compliance and sustainable mining.

In this research, an uncertainty-based mathematical programming framework is developed based on mixed integer linear goal programming (MILGP) model for oil sands production scheduling and waste management. The effect of grade uncertainty on production schedules is investigated. The grade uncertainty financial risk associated with a production schedule is minimized using kriged estimates with a variance penalty scheme. This investigation is based on the concept of mean-variance analysis, which is the process of weighing variance (risk) against the expected net present value (NPV). Subsequently, the impact of organic rich solids (ORS) content on bitumen recovery during processing is also studied. ORS content is used to predict ore processability in addition to the traditional use of bitumen and fines contents, and its impact on NPV quantified. The developed MILGP model is implemented using new robust automated production targeting (APT) constraints that optimize the annual capacities for material mined and processed over the mine life. In addition, mining-cells are deployed for the generation of in-pit tailings-cells designs used as dedicated disposal areas for backfilling.

Two main waste management approaches are used to implement the developed model. Implementation A; where the ultimate pit is divided into predetermined pushbacks as tailings-cells within the ultimate pit limit (UPL), and Implementation B; where the ultimate pit is divided into mining-cells that are used to generate in-pit tailings-cells designs. To verify the research models, three oil sands case studies were carried out.

The first case study investigates the effect of grade uncertainty on production schedules. The technique applied is based on the concept of mean-variance analysis, which is the process of weighing risk (variance) against expected NPV. The model generates a range of NPV which represents the mining investment risk profile associated with grade uncertainty. The second case study explores the impact of ORS content on oil sands ore processability. The results showed a 3.46% overestimation of NPV arising from not taking into account the effect of ORS content on bitumen recovery during mine planning. The final case study examines the implementation of waste management strategies based on different size and number of unit mining-cells used in creating tailings-cells for backfilling. The results showed that, decreasing the volume of unit mining-cells used in creating the in-pit tailings-cells increases the NPV of the operation due to increased operational flexibility. Additionally, as the percentage of in-pit volume to be backfilled increases, more savings is generated from not sending tailings to external facilities at a higher cost. These results proved that the uncertainty-based MILGP model is a robust tool for optimizing oil sands long-term production schedules whilst taking into account grade uncertainty, ore processability and tailings-cells designs.

Keywords

Oil sands mine planning, waste management, mixed integer linear goal programming, grade uncertainty, kriged estimates, organic rich solids, mathematical programming, backfilling schedule, tailings-cells, automated production targeting.

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Ahlam Maremi, June 2020

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LIST OF ABBREVIATIONS

AER	Alberta Energy Regulator
APT	Automated Production Targeting
CHWEP	Clark Hot Water Extraction Process
CPTF	Cumulative Production Tonnage Fluctuation
DP	Dynamic Programming
EBV	Economic Block Value
EPGAP	Relative mixed integer programming gap tolerance
GP	Goal Programming
IB	Interburden
IP	Integer Programming
LP	Linear Programming
LTPP	Long-Term Production Planning
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Programming
MPMs	Mathematical Programming Models
MILGP	Mixed Integer Linear Goal Programming
MMF	McMurray Formation
MPT	Modern Portfolio Theory
NPV	Net Present Value
OB	Overburden
OI	Overburden and Interburden
OK	Ordinary Kriging
ORS	Organic Rich Solids
RM	Reclamation Material
TCS	Tailings Coarse Sands
UPL	Ultimate Pit Limit

CHAPTER 1

INTRODUCTION

1.1 Background

In open pit mining, the goal is usually to maximize the net present value (NPV) of the project by providing the plant with ore at full capacity while satisfying physical, operational and economic constraints. The very first and a highly important step in the mine planning process is modeling the ore body appropriately. All other activities throughout the mine life starting from evaluating the economic viability of the entire mining operation to undertaking all the processes of mine planning will be based on the ore body model (Hustrulid and Kuchta, 2006). The different phases of the mine planning process include: 1) Block model determination that consists of drilling in different locations and depths of the mine, obtaining samples of material for grade and density interpolation, dividing the orebody into blocks of equal sizes, and assigning estimated tonnage, density and mineral grades to each block. As a result, the estimated extraction profit or loss for each block in the model needs to be computed. This generates what is referred to as an economic block model. 2) Definition of the ultimate pit limit (UPL), which is the area in which extraction will take place. Before any block can be extracted, all blocks immediately above and at certain angles must be extracted. To determine the UPL, it is necessary to determine the slope angles. This depends on the structural composition of the rocks and the location and depth of each block. 3) Production planning, which involves the decision of which blocks should be extracted and when and how this should be done (Chicoisne et al., 2012). Extracting mining blocks from an open pit mine in a specific sequence to give the highest NPV is known as open pit mine planning optimization. This is subject to a variety of production, grade blending and pit slope constraints (Whittle, 1989).

The focus of this research is long-term production planning (LTPP) optimization with integrated waste management. LTPP is the cornerstone of the entire mining operation, and any deviations from this plan might result in significant financial losses, delayed reclamation, resource sterilization and early mine closure.

Oil sands mining of the McMurray Formation (MMF) was studied and used as a case study. Researchers have tried to integrate oil sands waste disposal planning into the mine planning optimization problem. However, three main challenges have to be taken into consideration. First is the size of the optimization problem due to scheduling multiple material types, multiple elements, different destinations and mining locations. Second is environmental issues and limited lease areas that require the in-pit disposal areas with dyke construction planning to be integrated into the optimization problem. These in-pit disposal areas must be available on a continual basis through the life of mine to support the tailings storage plan. Third is the competing challenge between production scheduling that drives NPV and waste disposal planning that drives sustainability, and which targets must be traded off and at what cost.

An uncertainty-based mixed integer linear goal programming (MILGP) model has been developed for an oil sands mining scheme. The implementation of the uncertainty-based MILGP model for oil sands production scheduling and waste disposal planning as outlined in this thesis has been set up in an optimization framework. The developed model is capable of considering multiple material types, multiple elements, multiple destinations and mining locations. In addition to the integration of mine production planning and waste management, the model features the concept of directional mining with the optimization of mining and processing production targets, tailings-cells design for waste management, grade uncertainty, ore processability and limited duration stockpiling options. The thesis also highlights the practical implementation of the uncertainty-based MILGP model and the generated production schedules.

Most open pits are mined in a sequence of phases (or pushbacks). An initial pushback is established within the outline of the UPL, and then expanded in pushbacks. The direction in which the first pushback expands is the mining direction. Based on this concept and for integrating waste management planning, two main approaches are used to implement the developed model for this research: Implementation A; where the ultimate pit is divided into predetermined pushbacks as tailings-cells within the UPL, and Implementation B; where the ultimate pit is divided into mining-cells that are used to generate in-pit tailings-cells designs.

1.2 Overview of oil sands mining, problem definition and assumptions

Oil sands mining operations result in different material types: ore (O), overburden (OB), interburden (IB), reclamation material (RM) and waste. Material with a bitumen grade of 7 wt% or more is classified as ore as stated by Directive 082 (Alberta Energy Regulator, 2016). Processing ore results in huge amounts of tailings. Based on the fines content, the tailings are divided into tailings coarse sands (TCS) and tailings slurry. TCS is used for dyke construction, and tailings slurry is deposited in the disposal areas created with dykes. Tailings slurry needs to be contained in tailings facilities because of their wide range of environmental impacts such as large scarred areas, seepage and potential water contamination, trapping of birds, devastation of aquatic life, fugitive emissions, risk of a tailings dam failure and lack of progressive reclamation (Devenny, 2009). Any ore material that has a bitumen grade less than 7 wt%, known as interburden, is reclassified based on the fines content. Material with fines content less than 50 wt% is used for dyke construction; otherwise, it will be classified as waste. Fines content (<45 µm) is used to predict the processability of ore; however, this is not always effective. It has been found that certain solid fractions known as organic rich solids (ORS) still exist, even after the treatment of oil sands by multiple extraction toluene. The total ore comprises about 5 wt% of the ORS that potentially affect the processability of oil sands ore. Typically, oil sands with bitumen grade less than 12 wt% have a higher fines content compared to high-grade oil sands. As the fines content increases, the bitumen recovery using the Clark hot water extraction process (CHWEP) decreases (O'Carroll, 2002; Sparks et al., 2003). Overburden (OB) is comprised of the Pleistocene unit and Clearwater Formation. OB is used either for road or dyke construction if it meets the fines requirement. Muskeg reclamation material (RM), the topmost layer of overburden, is extracted, stockpiled and used to reclaim the mined-out areas during or at the end of the mine life. Any material that does not meet the requirements of ore, dyke materials or reclamation material is classified as waste and sent to a waste dump.

The focus of this research includes the generation of in-pit tailings containment areas in a timely manner to minimize environmental challenges. Figure 1-1 shows a schematic representation of two research implementations toward the generation of in-pit tailings containment areas for waste management. For both implementations, material intersecting a pushback and a bench (or a mining-cell and a bench) is known as a mining-panel (Figure 1-1). Each mining-panel contains corresponding set of mining-cuts. Mining-panels are used to control the mine production operation sequencing. Mining-cuts are clusters of mining blocks within the same level or mining bench that are grouped based on a similarity index defined using attributes such as the location, grade, rock type and the shape of mining-cuts that are created on the lower bench (Tabesh and Askari-Nasab, 2011).

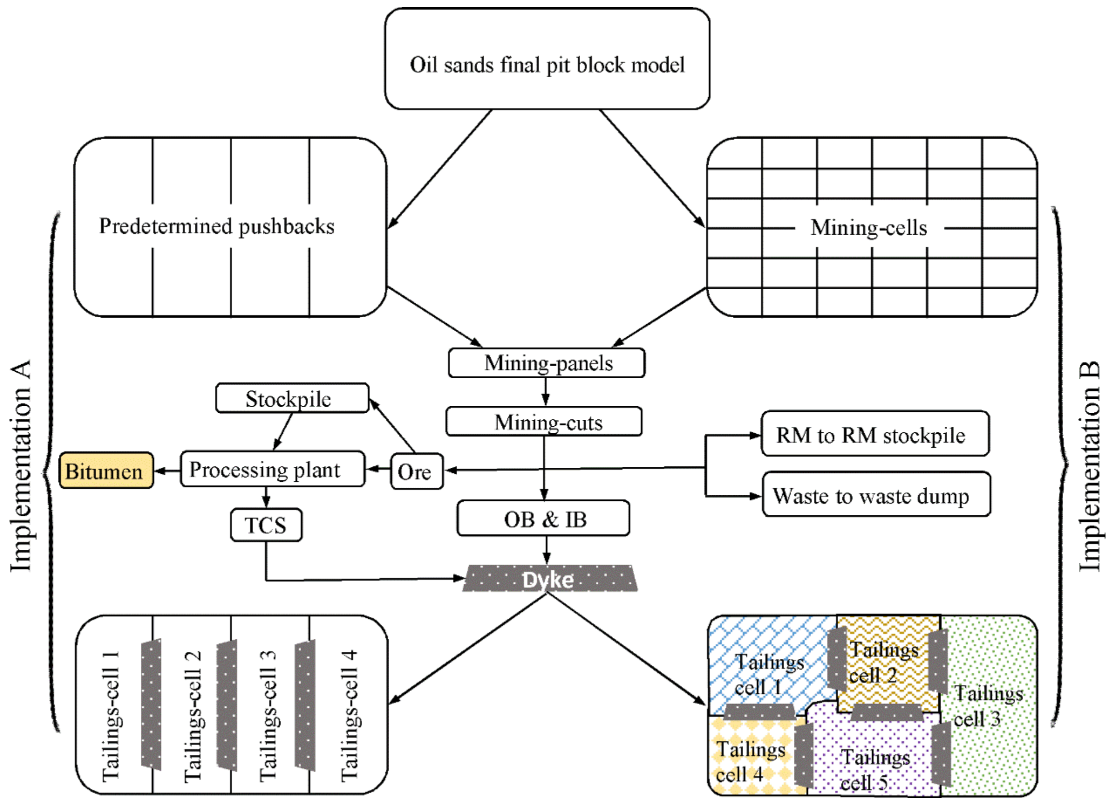


Figure 1-1: Schematic representation of the two research implementations

Each mining-cut is made up of one or more of ore, interburden and overburden dyke materials, reclamation material or waste. The mining-cuts provide control for ore selectivity for the processing plant. The material in each mining-cut is to be scheduled over T periods based on the goals and constraints associated with the mining operation. The extracted ore from mining-cut k within mining-panel p at any period will be sent to the processing destination a. Any material that exceeds the plant capacity in period t will be sent to the stockpile sp and reclaimed in period $t+ts$, where ts is the stockpiling duration limit controlled by the planner to minimize oxidation of the stockpiled ore that reduces the processing recovery factor. The ore extracted in the current period t and the ore that has been sent to the stockpile in period $t-ts$ together will be sent to the processing destination for bitumen extraction. The generated TCS material together with the OB and IB dyke materials will be used for constructing tailings cell dykes. Muskeg reclamation material, RM, is sent to the reclamation material stockpile area to be used for land reclamation during or at the end of life of mine, and waste will be sent to the waste dump area. The ore processing recovery is calculated using two different techniques: 1) based on bitumen and fines content, referred to in this thesis as AER recovery and 2) based on ORS content in addition to the bitumen and fines content, referred to in this thesis as ORS recovery (Maremi et al., 2020).

1.2.1 Problem definition: Implementation A

In this approach, the ultimate pit is divided into predetermined pushbacks that coincide with the areas required by tailings dyke engineers to set up in-pit tailings facility cells. Pushbacks will be used as dedicated disposal areas for tailings deposition. Pushbacks define where the pit extraction process begins and where it stops. Pushbacks ensure safe pit walls, assist in meeting ore production requirements and provide a minimum mining width for mining equipment (Jélvez et al., 2018). Figure 1-2 depicts the scheduling of an oil sands ultimate pit block model containing K mining-cuts within P mining-panels within J pushbacks. Ore is sent to the processing plant or to the stockpiling area. TCS, OB and IB dyke materials are used in the construction of dykes for tailings facilities in the predetermined pushbacks. Any excess dyke material can be used for other purposes such as shelling dumps, road construction, sand capping, and fines trapping as in non-segregating tailings.

The strategic and operational schedules to be developed are subject to a variety of economic, technical and physical constraints. The constraints control the material extraction sequencing and ore and dyke material blending requirements. The constraints also control mining, processing, reclamation and dyke materials goals that specify the quantities of allowable material for the mining operation, processing plant, reclamation works and dyke construction. Taking into consideration uncertain input variables in mine planning will minimize the difference between the theoretical and actual NPV and will result in a high-degree of confidence for the mining project. Based on this, the production schedule financial risk arising from grade uncertainty is investigated as well.

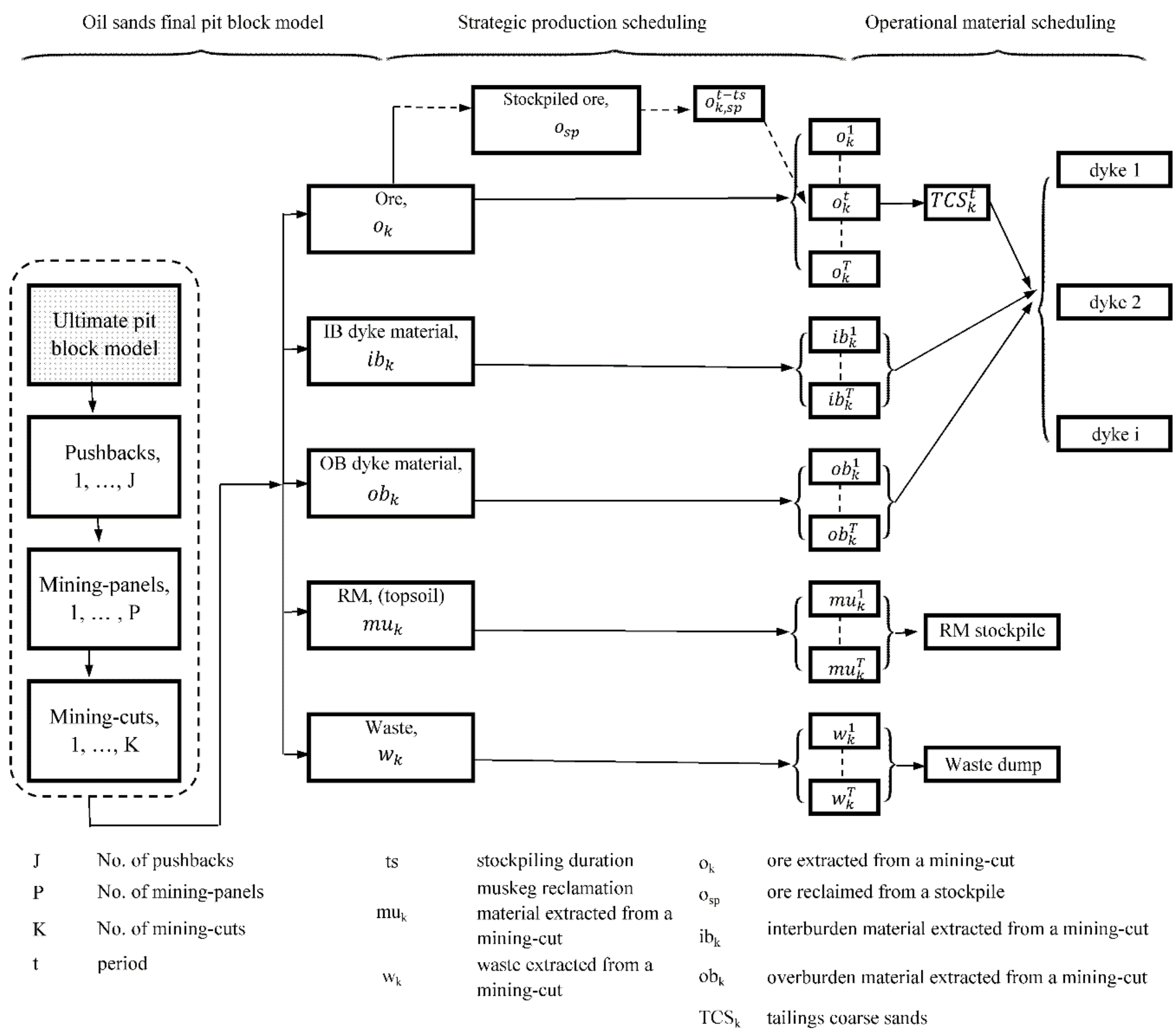


Figure 1-2: Schematic representation of the problem definition showing strategic production and operational material scheduling, modified after Ben-Awuah et al. (2015)

1.2.2 Problem definition: Implementation B

In this approach, the final pit is divided into a pattern of regularly spaced areas. Each area represents a vertical unit that spans from the topography to the bottom of the pit and is referred to as a mining-cell, m. Mining-cells are used to define the design of in-pit tailings-cells. Tailings-cells are consequently used as dedicated disposal areas for tailings deposition. The material intersecting a mining-cell and a bench is known as a mining-panel. The scheduling of an oil sands ultimate pit block model containing K mining-cuts within P mining-panels within M mining-cells is depicted in Figure 1-3. The extracted ore will be sent to the processing destination to extract the bitumen. The generated TCS material together with OB and IB dyke materials will be used for constructing dykes for tailings-cells. Reclamation material will be sent to the reclamation material stockpile area.

For this approach, the strategic schedules and tailings-cells to be developed are subject to a variety of financial, technical and physical constraints. The strategic schedules and tailings-cells optimization determine the profitability and sustainability of the mining project. In addition to the schedules, the size, shape and location of tailings-cells control the NPV of the operation and enable a robust waste management planning strategy.

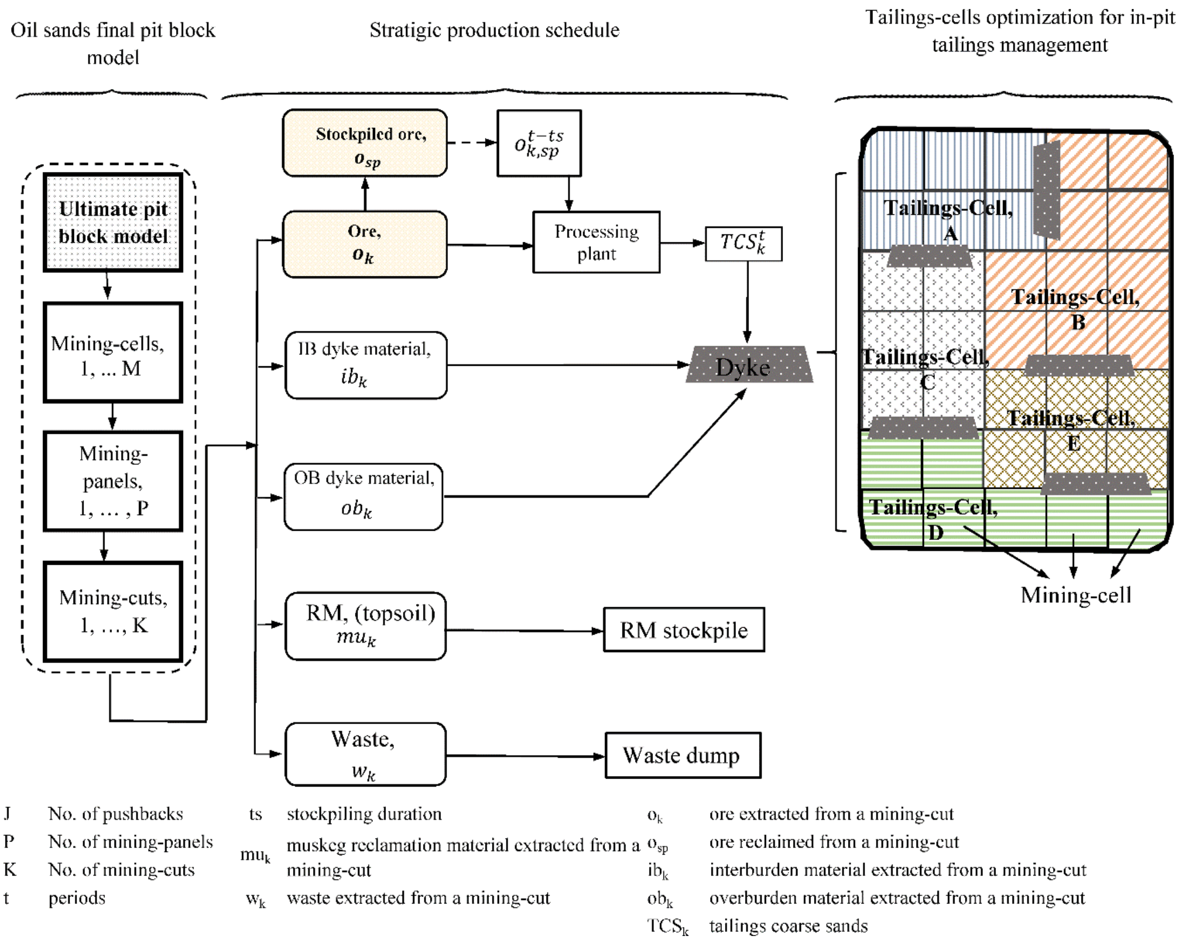


Figure 1-3: Schematic representation of the problem definition showing strategic production and tailings-cells optimization

An effective and efficient waste disposal plan ensures that appropriate dyke materials and tailings storage areas are provided at the right time. This enables the maximum use of ex-pit and in-pit tailings facilities, resulting in low-footprint tailings-containment. Improper waste management planning can lead to environmental issues, resulting in immediate mine closure by regulatory agencies.

1.2.3 Assumptions

It is assumed that:

- When a mining-panel is scheduled, all the mining-cuts, blocks or parcels within this mining-panel are extracted uniformly;
- When modeling the relationship between the mining-panels and mining-cuts, the planner has access to all the mining-cuts within each mining-panel;
- When modeling the relationship between the mining-cells and mining-panels, the planner has access to all the mining-panels within each mining-cell;
- The stockpiling strategy is considered in the optimization problem for extra ore that exceeds the mill capacity, and there are stockpile pads available for each period;
- The exact amount of ore sent to the stockpile in each period will be reclaimed after a stockpiling duration controlled by the planner;
- There is no change in processing recovery factor during limited duration stockpiling.

1.3 Summary of literature review

Since the 1960s, researchers have studied and applied mathematical programming models (MPMs) for mine production scheduling (Osanloo et al., 2007; Newman et al., 2010). MPMs for production scheduling in the literature can be divided into two main research areas: 1) deterministic solution methods and 2) uncertainty-based methods for optimization. A variety of deterministic optimization methods including linear programming (LP), integer programming (IP), mixed integer linear programming (MILP) and dynamic programming (DP) are commonly used in addition to goal programming (GP) (Osanloo et al., 2008). Researchers have solved the LTPP problem using MPMs that have been developed using LP and MILP (Johnson, 1969; Gershon, 1983; Dagdelen, 1985; Dagdelen and Johnson, 1986; Akaike and Dagdelen, 1999; Caccetta and Hill, 2003; Ramazan and Dimitrakopoulos, 2004a; Ramazan and Johnson, 2005; Osanloo et al., 2007; Ramazan, 2007; Boland et al., 2009; Newman et al., 2010).

GP is one of the deterministic approaches used in solving multi-objective LTPP optimization problems. Using GP, the optimizer provides solutions as close as feasible to the required objectives. It minimizes the deviations between the target values of the objectives and the satisfying solution (Orumie and Ebong, 2014). GP allows for some level of interaction between the planner and the optimization process (Zeleny, 1980; Hannan, 1985). GP was used by Chanda and Dagdelen (1995) for the mine planning of a coal deposit. Due to goal functions interactions involved in solving the problem, the optimal solution could not always be achieved. Ben-Awuah and Askari-Nasab (2013) combined GP and MILP into mixed integer linear goal programming (MILGP) models to solve oil sands production scheduling and waste disposal planning problems. The authors stated that the use of MILGP is appropriate for their application because based on the importance of the goals, the MILGP structure will allow the planner to achieve some goals, while others are traded off. The optimal solution, however, might be affected by some uncertain input variables. Current practices in open pit mine planning and scheduling tends toward incorporating uncertainties in MPMs. Results have shown that significant differences might exist between actual production and theoretical expectations due to geological and economic uncertainties which are stated as the most important sources of risk in mining operations, especially in the first years of production. Uncertainty can be reduced only by getting more data over time.

MPMs have the capability of considering multiple material types, multiple elements, and different destinations and mining locations. As the solution gets closer to optimality, MPMs result in production schedules that generate higher NPV than those obtained from heuristic optimization methods. Applying MPMs to the LTPP problem, however, results in large-scale optimization problems with many binary decision variables used to control the mining sequence. These optimization problems are difficult to solve with the available software and hardware, and might need lengthy solution times. Efforts have been made to reduce the solution time and the size of the LTPP problem prior to optimization using MILP with block clustering techniques. Using this technique, large data are classified based on similarities into relatively smaller clusters to decrease the number of binary decision variables and to maintain the minimum mining width required for large mining equipment (Askari-Nasab and Awuah-Offei, 2009). Clustering has been successfully implemented for some LTPP problems in isolation from other mine production systems such as waste management planning. Waste management is an important part of the mining operation and should be well managed to avoid inappropriate considerations of the mining cost, suboptimal schedules that reduce the project value, and the incorrect classification of ore and waste in addition to environmental and economic challenges (McFadyen, 2008; Askari-Nasab and Ben-Awuah, 2011; Fu et al., 2019).

Waste management for the oil sands industry is related closely to production scheduling as required by Directive 085 issued by the Alberta Energy Regulator (AER) (2017). Directive 085 requires oil sands operators to periodically publish their integrated waste disposal and tailings plans publically (McFadyen, 2008; Ben-Awuah and Askari-Nasab, 2013). Tailings dykes are constructed to store large amounts of tailings one section at a time as mining advances (Azam and Scott, 2005). However, one of the most significant aspects in dealing with tailings is space limitations, which increase the need for in-pit tailings-containment in addition to dedicated ex-pit storage space (Devenny, 2009). To support the tailings storage plan, the incorporation of the availability of in-pit disposal areas with dyke construction planning on a continual basis throughout the mine life is needed to ensure the maximum use of the mined-out areas (Ben-Awuah and Askari-Nasab, 2013; Ben-Awuah et al., 2015). Previous research efforts in oil sands mine planning and waste management proceeded by dividing the final pit area into pushbacks based on the footprint required by tailings dam engineers to set up in-pit tailings facility cells (Ben-Awuah et al., 2012; Ben-Awuah and Askari-Nasab, 2013; Seyed Hosseini and Ben-Awuah, 2018). Pushback selection is time consuming and subject to requirements of mine planning engineers. Efforts have been made to optimize the selection of intermediate pushbacks; however, the main purpose was not for waste management planning. Also, some efforts have been made to optimize mining and processing capacities, as they affect the selection of UPL and the pushbacks, production scheduling, and cut-off grade that will ultimately influence the NPV and capital cost of the project (Elkington and Durham, 2011).

There are some limitations in the current production scheduling optimization models for oil sands open pit mining including: (i) limitations in integrating mine planning and waste management; (ii) limitations in solving large-scale problems, as they require large computer memory and speed; (iii) treatment of uncertain variables such as grade as deterministic parameters that might generate suboptimal results; (iv) a trial-and-error process to finding the optimal annual mining and processing capacities; (v) limited criteria used in calculating the oil sands ore recovery; and (vi) limitations in the selection of pushbacks and tailings-containment cells for waste management. These limitations impact the profitability, practicality and sustainability of oil sands mining projects, emphasizing the need for optimization tools that take into consideration these deficiencies. Consequently, it is important that robust models are developed to address these challenges.

This research will introduce a MILGP framework for integrated production scheduling and waste management for open pit mines, specifically oil sands mining. The problem presented in this research involves simultaneous ore, reclamation and dyke materials production scheduling that maximizes the project value and supports the sustainable development of oil sands deposits in the presence of grade uncertainty. The MILGP framework also features the application of ORS recovery, generation of sophisticated annual mining and processing capacities, as well as the optimal size, shape and location of tailings-cell design for tailings containment.

1.4 Objectives of the study

The primary objective of this research is to develop an uncertainty-based mine planning framework based on MILGP for oil sands production scheduling and waste management. The model is implemented and verified with Matlab programming platform and a branch and cut optimization algorithm using IBM/CPLEX solver (ILOG, 2017). To achieve the primary objective, the research includes the development of an incremental theoretical and conceptual framework that focuses on the following objectives:

1. A strategic schedule that determines the sequence of extracting ore, reclamation material, overburden and interburden dyke material from a predefined UPL over the life of mine to maximize the NPV of the project;
2. An operational schedule that determines the destination of reclamation material to minimize rehandling costs and the destination of dyke materials to minimize dyke construction costs;
3. A reclamation strategy for the oil sands ore that is stockpiled for a limited duration to reduce oxidation;
4. An uncertainty-based production schedule that maximizes NPV and minimizes the financial risk (risk) associated with grade uncertainty through a variance penalty scheme;
5. A production planning strategy that uses ORS content during optimization to adjust oil sands ore recovery;
6. Optimizing the size, shape and location of in-pit tailings-containment areas in relation to integrated mine planning and waste management; and

7. Optimizing the annual mining and processing production targets.

1.5 Context and scope of work

An uncertainty-based MILGP model for oil sands mine planning and waste management optimization has been developed. The developed MILGP model generates optimal long-term open pit production schedules for multiple material types, multiple elements, different destinations and mining locations for oil sands mining. The model minimizes the risk associated with grade uncertainty. The conceptual mining process supports in-pit and ex-pit waste management strategies in oil sands mining. Clustering techniques are used to maintain the minimum mining width for the large mining equipment used in oil sands mining and to decrease the number of binary integer decision variables that increase the size of the optimization problem. A limited duration stockpile strategy is used for ore that exceeds the plant capacity. Automated Production Targeting (APT) constraints are introduced in the model to control the periodic deviation of material mined and processed for optimum life of mine scheduling. The topmost layer of the overburden is used to reclaim disturbed landscape during or at the end of mine life. Organic Rich Solids (ORS) content is included in the production scheduling strategy to enhance bitumen recovery. Finally, the model optimizes the capacity, shape and location of tailings-cells used as dedicated disposal areas for tailings containment. It should be mentioned that in developing the uncertainty-based MILGP framework, the following were not considered:

- The geotechnical properties of the dyke construction material;
- The technical details of the dyke design;
- Rock type uncertainty; and
- Future cost and price uncertainties.

1.6 Research methodology

The main scope of this thesis relates to oil sands long-term production scheduling and waste disposal planning using an uncertainty-based MILGP mine planning framework. Literature on deterministic and uncertainty-based open pit optimization and production scheduling models, clustering algorithms, stockpiling, oil sands mining and waste management, pushback and production capacities optimization has been reviewed. Subsequently, an oil sands dataset from a mine in Alberta, Canada was analyzed for experimental studies. A conceptual mining and mathematical model was formulated to define the inputs and outputs of the uncertainty-based MILGP mine planning framework. This research focuses on the development, analysis and implementation of four main components of the formulated MILGP model: (i) maximize the NPV of the mining project, (ii) minimize the waste management and reclamation costs, (iii) minimize the financial risk from grade uncertainty associated with production schedules, and (iv) maximize the pseudo revenue generated from backfilling the mined-out areas with tailings; consistent with the savings made from not sending the tailings to the external facility. This research deploys appropriate numerical modeling and solution techniques to convert the formulations into accomplishing the research objectives. Figure 1-4 illustrates a summary of the research methodology.

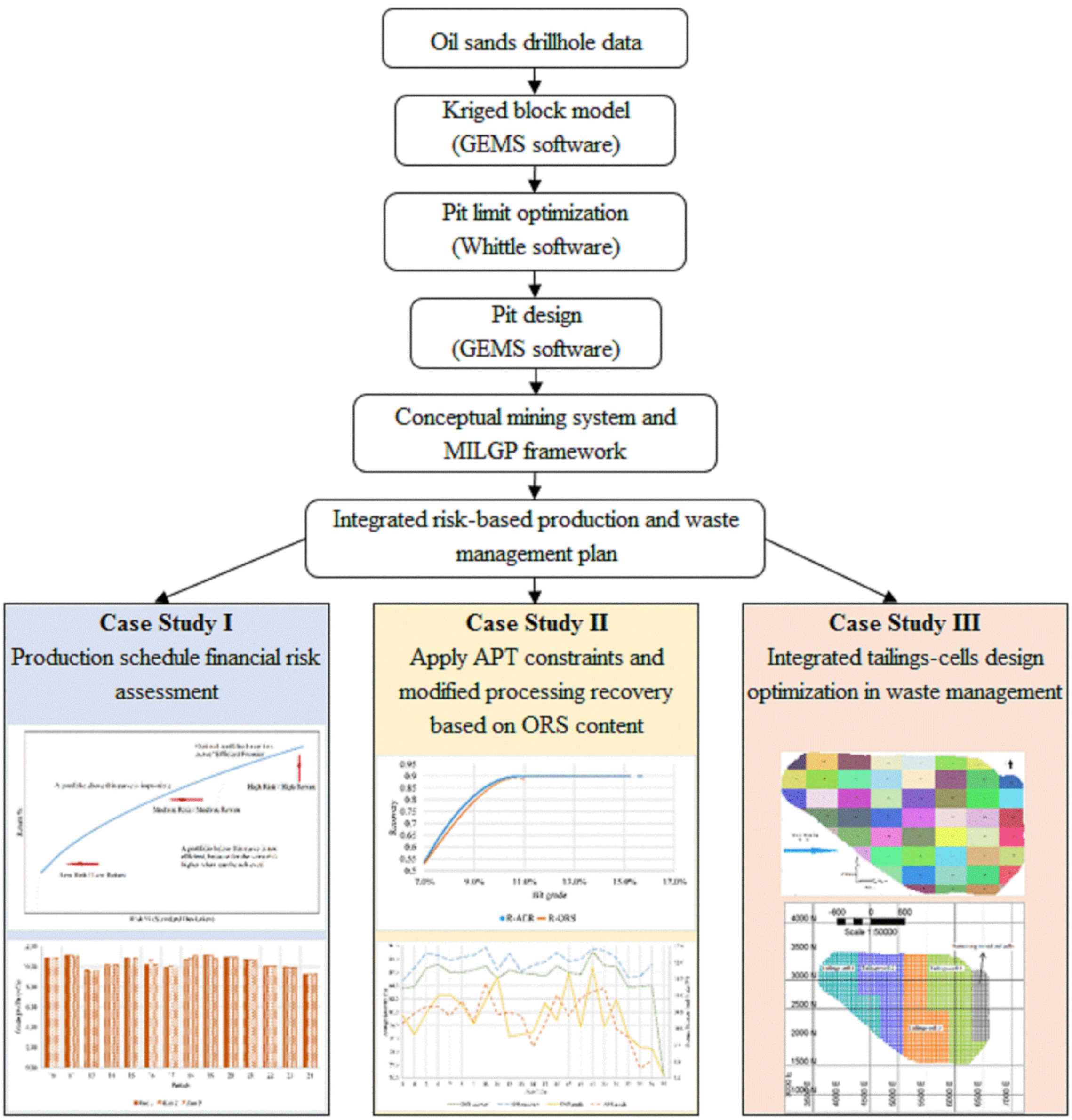


Figure 1-4: Summary of research methodology

A kriged block model is developed using Geovia GEMS Software (Geovia Dassault Systems, 2018). The UPL is generated using Geovia Whittle Software (Geovia Dassault Systems, 2017), and the mining blocks within the pit limit are used as input data for the MILGP model. A MATLAB (Mathworks, 2017) application is used as the programming platform to define the uncertainty-based MILGP framework, and an IBM/CPLEX (ILOG, 2017) solver that uses a branch and cut optimization algorithm is employed to solve the optimization problem.

The user sets a measure of optimality or a gap tolerance (EPGAP), which is an optimization termination criterion in CPLEX. EPGAP 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 forces CPLEX to dismiss once a feasible integer solution within the set EPGAP has been found. The developed model is implemented and verified with three different experimental case studies on a large oil sands dataset. The results are analyzed to draw relevant conclusions with appropriate recommendations.

Details of the research tasks that have been completed in three incremental stages to achieve the objectives of this study are as follows:

1. Develop a mathematical model based on kriged estimates to classify the oil sands block model into different materials according to the regulatory and technical requirements controlling oil sands mining operations;
2. Propose and develop a theoretical framework for an uncertainty-based MILGP model for optimizing the oil sands long-term production plan for ore, dyke and reclamation material;
3. Introduce two sophisticated automated production targeting constraints to optimize the annual mining and processing capacities with a limited duration stockpiling option;
4. Extend the MILGP model to minimize the financial risk associated with production scheduling;
5. Extend the MILGP framework to include a production planning strategy using geochemical indicators that facilitate modified processing recovery;

6. Extend the MILGP framework to optimize the size, shape and location of in-pit tailings-containment areas in relation to integrated mine planning and waste management;
7. Test, calibrate and verify the formulations with small oil sands dataset and analyze the results in relation to the expected and inherent behavior of the theoretical and practical aspects of the formulations;
8. Implement the framework with real-size oil sands mine case studies to validate the developed formulations in generating the life of mine ore, dyke and reclamation material production schedules;
9. Quantify the effect of using the uncertainty-based MILGP formulation and workflow for integrated oil sands mine planning based on the NPV and practicality of the generated production schedules; and
10. Document the workflow and parameter calibration for the formulations and deployments.

In general, the incremental development and implementation of the uncertainty-based MILGP optimization framework was undertaken with three main case studies. The main goal of the first case study was to quantify the financial risk from grade uncertainty associated with the production schedule using kriged estimates with a variance penalty scheme. The first case study also investigates the capability of the developed MILGP model to integrate production scheduling and waste management for oil sands ore, reclamation and dyke materials with a limited duration stockpiling option in an optimization framework. For this case study, the processing plant bitumen recovery was assumed to be 90% to facilitate the fundamental MILGP framework development. The second case study is conducted to investigate the effect of ORS content on oil sands ore recovery and processability and, consequently, the NPV of the project. Mining and processing annual capacities are optimized using sophisticated APT constraints. In the last case study, the MILGP model was deployed to optimize the tailings-cells capacity, shape and location to improve waste management for practical and sustainable mining.

1.7 Scientific contributions and industrial significance of the research

The main contributions of this research are the development of an uncertainty-based MILGP framework that schedules for multiple material types, multiple elements, different destinations and mining locations for integrated oil sands mine planning and waste management. The research added to the current literature on open pit production scheduling and waste management by:

1. Developing a robust uncertainty-based MILGP model and workflow to simultaneously schedule for the processing plant, dyke construction and reclamation, thereby expanding the boundaries of integrated mine planning and waste management.
2. Providing a model that integrates limited duration stockpiling for oil sands ore while using ORS content to modify processing recovery.
3. Providing new insights on the effect of grade uncertainty on production scheduling. The uncertainty-based model is employed to evaluate and quantify the financial risk associated with production scheduling.
4. Formulating new mining and processing capacities constraints to control annual tonnage fluctuations for sophisticated life of mine schedules.
5. Promoting sustainable oil sands mining by optimizing tailings-cells capacity, shape and location for integrated waste management.

The industrial significance of this research is the introduction of an uncertainty-based MILGP framework and workflow that seeks to enable the oil sands mining industry to generate a strategic production schedule for ore, dyke and reclamation materials and waste. This is in accordance with the requirements of Directive 085 issued by the Alberta Energy Regulator (AER) (2017) on tailings performance and criteria for oil sands mining schemes (McFadyen, 2008). The formulation and workflow seek to optimize the oil sands mining operation by maximizing the NPV of the operation, maximizing the pseudo revenue generated from backfilling the mined-out areas with tailings, minimizing the financial risk associated with grade uncertainty, and minimizing reclamation and dyke construction costs. The formulation and workflow also seek to optimize the annual mining and processing capacities, as well as tailings-cells design for waste management, and adjust ore processability for more practical and realistic results. 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 the thesis

This manuscript is composed of five chapters. The first chapter provides a general overview of the research. It includes the background of the research, followed by the problem definition and a summary of the literature review, the objectives of the study, the context and scope of the study, the applied methodology and the contributions of this research.

Chapter 2 documents the literature review, which provides an overview of open pit long-term mine planning and design including historical and recent perspectives on deterministic and uncertainty-based production scheduling algorithms. It also provides a literature review on mining and waste disposal planning in oil sands. Clustering and stockpiling algorithms and their applications in mine planning are also highlighted. The effect of ORS on oil sands ore processability is discussed in addition to pushback optimization algorithms. The chapter concludes with the rationale for this PhD research.

Chapter 3 contains the uncertainty-based MILGP model theoretical formulation. The chapter focuses on formulating, modeling and developing the objective function, goal functions and constraints of the MILGP model and their interrelationships.

Chapter 4 includes the implementation and verification of the proposed MILGP framework. Three oil sands mining case studies are discussed to elucidate the robustness and flexibility of the uncertainty-based MILGP framework in integrating production scheduling and waste disposal planning. Also, the case studies highlight the versatility of the model in quantifying the financial risk associated with grade uncertainty, and optimizing annual production schedules and tailings-cells designs. Relevant discussions, conclusions and recommendations are given for each case study based on its objectives.

Finally, Chapter 5 contains the thesis summary and concluding statements. The benefits and contributions of this research, and suggestions for future work on integrated mine planning and waste management are summarized.

CHAPTER 2

LITERATURE REVIEW

2.1 Background

This chapter provides an overview of the literature on open pit oil sands mining and waste disposal planning. This includes a review on past and recent improvements in deterministic and uncertainty-based mathematical programming algorithms used to solve production planning problems for open pit mines. The chapter also presents literature on optimizing tailings-cells and production capacities. Factors affecting oil sands ore processability and related regulations are reviewed as well. Clustering and paneling techniques and their applications in mine planning are highlighted as well as stockpiling algorithms for production scheduling. The chapter concludes with the rationale for this PhD research and a summary of the literature review.

2.2 Open pit long-term production planning and scheduling

Open pit long-term production planning (LTPP) and scheduling is the cornerstone of open pit mining operations. It is defined as finding the extraction sequence of the blocks and their corresponding destinations to maximize revenue while satisfying all required constraints. Effective LTPP is critical to the profitability of surface mining projects and can considerably increase the mine life. Researchers have extensively studied mine optimization mathematical models and divided them into deterministic and uncertainty-based approaches. Deterministic approaches assume all inputs are certain and fixed values, while uncertainty-based approaches assume some inputs are variables. Solving mathematical models with deterministic approaches result in solutions with known limits of optimality (Ben-Awuah and Askari-Nasab, 2013). As the solution gets closer to optimality, it leads to production schedules that generate a better NPV than heuristic approaches. On the other hand, solving these mathematical programming models (MPMs) through uncertainty-based approaches result in risk-based solutions (Sabour and Dimitrakopoulos, 2011).

2.2.1 Deterministic algorithms

Since the 1960s, researchers have studied and applied MPMs for mine production scheduling. A variety of deterministic optimization methods including linear programming

(LP), integer programming (IP), mixed integer linear programming (MILP), dynamic programming (DP) and goal programming (GP) are commonly used for LTPP problems (Osanloo et al., 2007; Newman et al., 2010). These MPMs have proved to be robust in solving LTPP and scheduling problems. They are capable of considering multiple material types, multiple elements and different mining locations and destinations during optimization.

2.2.1.1 Linear programming

Linear programming (LP) was introduced by Johnson (1969) for mine planning research and applied it to a long-term multi-destination open pit production planning problem. The proposed model considered different processing types and dynamic cut-off grade. The author broke the large problem down into a master and a set of sub-problems that are solved separately. Johnson’s (1969) approach did not generate optimum results for the LTPP problem. It resulted in fractional block extraction due to the use of continuous variables. In addition, the size of the optimization problem was computationally intractable at the time, as it had too many constraints.

2.2.1.2 Integer programming

Lagrangian relaxation, clustering and branch-and-cut approaches are used to solve integer programming (IP) models. Dagdelen and Johnson (1986) used a Lagrangian relaxation approach to solve IP models for LTPP problems. To make the problem tractable, the authors decomposed the problem into smaller sub-problems. They relaxed the mining and processing constraints by adjusting Lagrangian multipliers until the optimum solution was obtained. However, for some cases, when there are no multipliers, a feasible solution cannot be guaranteed (Osanloo et al., 2007). Akaike and Dagdelen (1999) tried to solve IP mine planning problems using a 4D-network relaxation method. Their model considers the concept of dynamic cut-off grade with a stockpiling option using binary variables for the scheduling process. This improved the NPV of the mining operation. However, the optimal solution could not be guaranteed for complex problems, and the implementation of the model with cut-off grade was a challenge. Ramazan and Johnson (2005) solved their IP model using a clustering approach. Clustering is used to classify large data into relatively few classes of similar objects. The authors were able to reduce the size of the model by reducing the number of binary variables and improving the NPV. However, this may not guarantee a global optimum solution to the problem. The branch-and-cut approach is an exact optimization algorithm used to solve a sequence of linear programming relaxations of IP problems (Horst and Hoang, 1996). It is a combination of cutting planes and branch-and-bound techniques. Caccetta and Hill (2003) used the branch-and-cut approach to solve IP models of LTPP problems. Their model could generate optimal solutions for medium-sized mine production planning problems but not for large problems.

2.2.1.3 Mixed integer programming

To avoid getting an infeasible solution, the IP formulations could be converted to a mixed integer programming (MIP) model by defining some variables as continuous variables. That results in reducing the number of binary variables and, consequently, the solution time significantly. The initial LP model developed by Johnson (1969) was modified by Gershon (1983) to a MIP model by adding continuous decision variables. The modified model allows for partial mining of mining blocks only if all precedent blocks are already mined. The model requires nine precedence constraints per block and results in a practical extraction sequence. The model, however, is unable to solve real-size mine planning problems due to the increase in binary constraints.

2.2.1.4 Dynamic programming

Dynamic programming (DP) approach is used to solve LTPP problems by dividing the primary problem into smaller sub-problems and, for each, an optimal solution can be generated. Osanloo et al. (2008) presented a DP model that maximizes the NPV, subject to mining and processing constraints. The model considers both the time value of money and block sequencing to determine the ultimate pit limit in addition to the production schedule. However, it cannot be applied to large-scale problems, and there is no guarantee that mining and processing constraints will be satisfied.

2.2.1.5 Goal programming

One of the mathematical programming approaches that has been explored in dealing with LTPP and scheduling problems is goal programming (GP). This is a popular deterministic approach for solving multi-objective optimization problems by minimizing the deviation for each objective from the required target and the satisfying solution (Orumie and Ebong, 2014). Using GP, the optimizer provides results close to the desired multiple, sometimes conflicting, goals. GP allows for some level of interaction between the mine planner and the optimization process (Zeleny, 1980; Hannan, 1985). GP and LP models have similar formulation architecture; however, GP provides solution and information to the planners, even if complete goal achievement is not possible. On the other hand, LP maximizes or minimizes a single objective function (Orumie and Ebong, 2014). Rosenthal (1983) classified GP models into three categories: (1) Weighted GP, where the planner assigns weights to the goals based on their importance and determines a solution that minimizes the weighted sum of the deviations from the required goals; (2) Preemptive GP, which gives a high rank to the most important goal, and the rank decreases as the importance of the goal decreases; and (3) prioritized GP, which is the combination of weighted goal programming and preemptive goal programming.

Charnes and Cooper (1957) developed a single objective priority GP model. The model could not use the concept of linear programming because it incorporated contradictory goals as constraints. Arthur and Ravindran (1978) developed an efficient linear GP model based on the concepts of a hierarchical structure of preemptive models using partitioning and elimination techniques. The algorithm first controls the constraints with the first priority goals. If multiple optimal solutions exist to this first priority model, the planner will add constraints affecting the next higher priority and the resulting model solved. This procedure continues until a single optimal solution is generated. The model was used to solve problems with different sizes and complexities. The results showed that the algorithm could solve the problems in a shorter time.

Comparisons for various linear goal programming techniques with existing optimization algorithms have been done in terms of accuracy and solution time. Results have shown that some GP formulations have better computational times in all the problems solved (Orumie and Ebong, 2014). In the optimization of multiple goals, some authors believe that achieving ideal goals always come at the expense of other goals. In this sense, Orumie and Ebong (2014) state that there are no problems in the rationale of GP theories. The efficiency of GP models depend mainly on the efficiency of the mine planner or modeler in general. Moreover, the major advantage of GP is the use of deviational variables that always provide a solution to the optimization problem (Orumie and Ebong, 2014).

2.2.1.6 Mixed integer linear goal programming

Ben-Awuah and Askari-Nasab (2013) formulated the oil sands LTPP and waste disposal problem using a combination of MILP and GP formulations. They called the hybrid a

MILGP model. The MILGP model has an objective function, goal functions and constraints. The goals are prioritized according to the impact of a deviation from their targets on the entire mining operation. The authors stated that their MILGP formulation was appropriate for oil sands mine planning and waste management because based on the importance of the mining operation goals, the MILGP structure will allow the planner to achieve some goals, while others are traded off. For the resulting production schedule, a higher NPV is achieved as the solution gets closer to optimality.

Upadhyay and Askari-Nasab (2016) presented a mixed integer linear goal programming model to optimize the mining operations of a company. The authors set four desired goals of the company, which were maximizing production, minimizing deviations in head grade, minimizing deviations in tonnage feed to the processing plant, and minimizing operating cost. The authors implemented the proposed MILGP model with an iron ore mine case study. The authors stated that the operational objectives of minimizing the deviations in feed tonnage and grade to processing plants compared to the desired feed tonnage and grade were satisfactorily met.

A fuzzy mixed integer linear goal programming model with a flexible goal hierarchy scheme was suggested by Rahimi et al. (2013). The model aims to achieve the optimized compromise solution from a given number of design requirement options. The goal was to maximize an aggregate function of the achievement degrees of three conflicting objectives including cost, customer satisfaction and development time. The authors stated that after several experiments, they were able to demonstrate the efficiency of the proposed approach, which can easily and efficiently be matched with quality function deployment problems. Also, they stated that using this model, decision makers may take into account hierarchical levels of goals and quantify their importance at the same time.

A mixed integer linear goal programming model was proposed by Rajesh (2014) to deal with product-mix problems when multiple constrained assets exist. The proposed MILGP model put emphasis on the use of all bottlenecks as the main goal and maximization of throughput as the secondary goal. The author experimented the proposed model on problems cited in literature as well as arbitrarily generated problems. The author stated that the proposed model reported optimum results.

In general, all the above-mentioned mathematical programming frameworks are based on deterministic formulations. However, in practice, the optimum solution is usually affected by uncertainties in the input parameters. Section 2.2.2 will review formulations that integrate geological and economic uncertainties in solving LTPP problems.

2.2.2 Uncertainty-based algorithms

LTPP problems determine the extraction sequence of ore and waste blocks that maximize the NPV of the project, taking into consideration the required constraints such as grade constraints, ore tonnage requirements, pit slope restrictions, and equipment specifications (Gholamnejad and Moosavi, 2012). Traditionally, the orebody is modeled based on the drillhole data and geological information. The deposit is divided into equal-sized blocks, and the economic value for each block is calculated based on deterministic parameters such as operating and capital costs in addition to the commodity price, which depends on the metal content. Optimization algorithms are then used to determine the optimum production plan. In practice, however, mining projects are considered risky due to the instability of future metal prices, foreign exchange rates and geological parameters. Unfortunately, significant decisions related to production scheduling must be made by mine planners based on limited key inputs and analysis during early conceptual and prefeasibility studies. The key inputs include the exact values of the quantity and quality of ore in the ground. These decisions are often accepted as certain and not reassessed for suitability as mine planning advances and more information becomes available.

2.2.2.1 Uncertainties in typical mining projects

In open pit production planning, the most recent trend is to integrate the uncertainties in the optimization process. Uncertainties involved in mine planning can be classified as: 1) orebody model and in-situ grade uncertainty, and material type distribution; 2) technical mining specification uncertainties, for example, mining and processing capacities and slope consideration; and 3) financial uncertainties including prices and costs (Dimitrakopoulos, 1998). Results have shown that significant differences might exist between actual production and theoretical expectations due to geological and economic uncertainties, which represent the most important sources of risk in mining operations, especially during the early years of production. Geological uncertainties might lead to significant deviation from production targets during the extraction process (Osanloo et al., 2007; Groeneveld and Topal, 2011;

Gholamnejad and Moosavi, 2012). The Canadian mining industry lost about $1.4 billion in early 1991 due to geological and economic uncertainties (Sabour and Dimitrakopoulos, 2011). A survey of mining operations in their early production years showed that 60% of mines had 70% less production than the designed capacity (Osanloo et al., 2008). Risk in a mining operation should be minimized, as it is a major challenge to eliminate. Uncertainty can be minimized by getting more data over time. In this sense, projects have to be developed in a way that increases flexibility to respond to uncertainties. Also, as hardware, software, and solution techniques evolve, more accurate models are expected (Osanloo et al., 2008; Groeneveld and Topal, 2011; Gholamnejad and Moosavi, 2012).

2.2.2.2 Economic uncertainties

Many researchers have incorporated economic uncertainty into the optimization process during production scheduling. Abdel Sabour and Dimitrakopoulos (2011) integrated metal price and exchange rate uncertainties, and operational flexibility into open pit mine design selection. They proposed a multi-criteria design ranking system using Monte Carlo simulation and real options. They applied the proposed model to a copper deposit. The authors stated that the uncertainty-based solution showed a significant difference in the design ranking, which indicates the importance of integrating uncertainties into mine design selection. The developed mine planning and scheduling system instantly reacts to new information. Lemelin et al. (2007) proposed a stochastic model based on price uncertainty. The authors reported significant differences between the deterministic and uncertainty-based approaches.

2.2.2.3 Geological and technical mining specifications uncertainties

Dimitrakopoulos and Ramazan (2004) presented a risk-based production scheduling formulation for complex, multiple-element deposits. The model was based on expected block grades and probabilities of grades that are above required cut-offs. The model also considers processing and mining capacities and performs multi-period optimization. The proposed model was applied on a nickel-cobalt laterite orebody. The authors stated that, the proposed model generated better results in meeting planned production targets, as more certain areas of the deposit are mined in earlier production periods. However, the model does not generate the maximum NPV. A stochastic integer programming model using multiple realizations to optimize mine production scheduling considering grade uncertainty was developed by Dimitrakopoulos and Ramazan (2008). The model controls the production targets through a penalty scheme. The penalty function was calculated from a geological discount rate (GDR). The authors tested their proposed model with two different deposits. The results showed a significant increase in the NPV using the proposed model compared to the traditional approach. However, they did not provide details on how to define the GDR parameter.

Gholamnejad and Moosavi (2012) introduced a binary integer programming model for open pit long-term production scheduling that considers geological uncertainty. They used indicator kriging method to quantify geological uncertainty. The authors applied the proposed model as well as the traditional model to an iron ore deposit. They stated that the uncertainty-based approach generates more practical schedules than the traditional approach by decreasing the risk of not meeting production targets during early production periods. Ramazan and Dimitrakopoulos (2004b) developed a model that considers grade uncertainty in open-pit mines. They modified the objective function to consider a penalty for production capacity constraint deviations in addition to maximizing the NPV. The proposed model produced a practical schedule that is more capable of meeting production constraints.

A stochastic optimization model to investigate the effect of resource uncertainties on mine planning is presented by Rahmanpour and Osanloo (2016). The authors defined three performance indicators, and an optimized mining schedule was used to simulate the performance of these indicators throughout the life of mine. The model aims to minimize the deviation of expected quality and quantity from the required values. The model was applied to a surface gold mine, and the results demonstrated resilient decisions and better quality control. Dowd (1995) explored the effect of grade and tonnage uncertainties of mining blocks on feasibility studies. The author concluded that geostatistical methods are a good approach for introducing uncertainties for risk analysis.

A stochastic integer programming model to manage the risk of not achieving the required ore tonnes, grade and quality is presented by Leite and Dimitrakopoulos (2007). The model was applied to a copper deposit. The authors reported that the model maximizes the economic value of a project and minimizes the risk that comes from deviations from production targets. Leite and Dimitrakopoulos (2014) used a set of multiple simulated orebody models as input into a stochastic integer programming model to manage the risk of not meeting production targets. The proposed model allows the planner to define a risk profile based on the existing uncertainty quantified by simulated orebody models. The model was applied on a hypothetical dataset. The authors claimed that the stochastic model is demonstrated to have significant economic benefits, be efficient in terms of solution time, and be applicable to large open pit mines.

An uncertainty-based model for production scheduling was presented in Gholamnejad and Osanloo (2007). The authors considered grade uncertainty through a probability distribution function obtained using geostatistical simulation; however, they did not give details or examples to assess the model performance. Koushavand et al. (2009) presented two different methodologies based on grade uncertainty for open pit mine production schedules. The authors evaluated the output parameters such as the NPV, ore tonnage, head grade, stripping ratio, amount of final production and annual target production. They reported a significant uncertainty in the long-term production schedules and stated that a long-term schedule generated based on one particular simulated ore body model is not optimal for other simulated geological models.

Godoy and Dimitrakopoulos (2004) developed a new uncertainty-based optimization approach to LTPP based on the effective management of waste mining and grade uncertainty. The authors applied the developed model to a case study from a large gold mine. They stated that the utilization of grade uncertainty and optimal mining rates leads to production schedules that meet targets whilst being risk-robust and generates considerable improvements in project value. Bley et al. (2010) introduced a model for open pit production scheduling that accounts for grade uncertainty with a stockpile option. The authors incorporated ore reserve uncertainty, waste management, and economic and mining considerations to generate a production schedule that maximizes the NPV of the project. The proposed model could achieve the required targets while being risk-robust and considerably improving the NPV.

Applying uncertainty-based approaches have some limitations including: the approach does not generate the optimal solution every time; the approach cannot be implemented on large scale deposits; and the approach uses complex techniques. To conclude, solving open pit LTPP problems using deterministic or uncertainty-based mathematical programming approaches is a challenge in terms of the size of the optimization problem with many integer and continuous variables. The problem becomes more challenging and may require lengthy solution times as the size of the optimization problem increases by integrating additional objectives such as effective waste management.

2.3 Oil sands mining and waste management

Oil sands mining is one of the most rapidly developing industries in North America. This industry started in the 1960s with surface mining operations that used the Clark hot water extraction process (CHWEP) to recover bitumen from oil sands and an upgrading complex to upgrade the extracted bitumen to a light synthetic crude (Sanford, 1983; Morgan, 2001; Masliyah, 2010). A truck-shovel system is used to extract oil sands from the Athabasca Wabiskaw McMurray deposit, which is located in the northeastern part of the province of Alberta and used as a case study for this research. It is the largest deposit in the world and is mostly located near the surface (Sanford, 1983; Masliyah, 2010). Muskeg is the topmost layer of the formation, which is comprised mainly of organic matter that is used for reclamation works (Figure 2-1). The Pleistocene unit is the next rock profile and is considered as waste. The Clearwater Formation overlying the McMurray Formation (MMF) is comprised of marine clay, fine sands and siltstone. Both the Pleistocene unit and Clearwater Formation are defined as overburden and are used for road and dyke construction in the mine based on the soil properties and their mineral content. The MMF contains bitumen, the element of interest, and ranges between zero and 130.0 m thick. The MMF is informally subdivided into upper, middle and lower formations based on the environment of sediments deposition. Devonian carbonates mark the end of the oil sands deposit (Sanford, 1983; Morgan, 2001; Masliyah, 2010). Figure 2-1 shows a schematic view of the vertical soil profile for an oil sands formation.

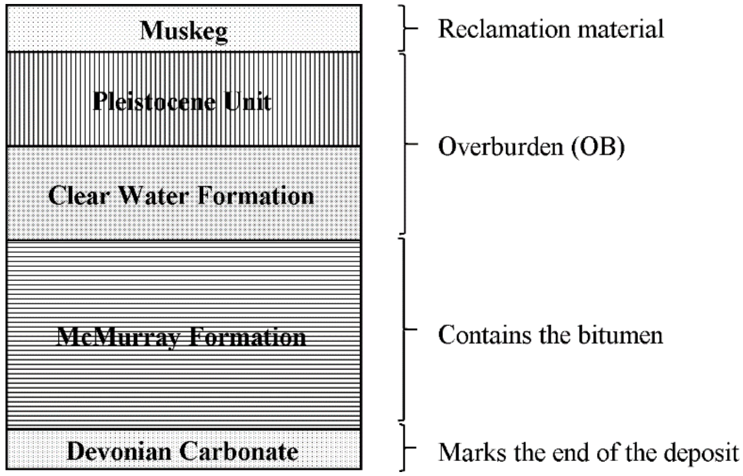


Figure 2-1: Schematic view of the vertical soil profile for an oil sands formation

The physical characteristics of oil sands in the MMF are used to separate the ore into its well-defined components. Oil sands are comprised mainly of bitumen (0.2 – 17.0 wt%), water (0.5 – 12.0 wt%), solids (80.2 – 94.4 wt%), fines (1.2 – 85.0 wt%), clay (0.2 – 20.8 wt%), ORS (0.5 – 5.2 wt%) and ultra-fines (0.2 – 22.5 wt%) (O'Carroll, 2002; Masliyah, 2010). The recovered volume of bitumen from the mining and processing operations is specified by Directive 082 issued by the AER (2016). The four required operating criteria for oil sands mining based on Directive 082 are:

1. The minimum in-situ oil sands cut-off grade is defined at 7 wt% bitumen;
2. The minimum mining thickness of ore is 3 meters;
3. The ratio of total volume to bitumen in place (TV/BIP) is set at 12 and should be used to determine the UPL; and
4. The recovery of the processing plant changes based on the average bitumen grade.

The extraction of bitumen starts with sending bituminous sands to the processing plant. Processing the ore results in huge amounts of a mixture of water, fine materials, sands and residual bitumen known as tailings. Using a hydro-cyclone, tailings is classified into tailings coarse sands (TCS) and fine sands that are sent to tailings-containments areas. Suncor's processing plant flow sheet is used to find the mass-balance-relation between ore feed and TCS tonnage (Kalantari et al., 2013). Based on Suncor's operational factors, it is assumed that there is no uncertainty with the TCS production process and the operational factors would not change during the mine life. The ore, waste and TCS tonnage produced in each period is investigated in order to find the relationship between TCS tonnage and the ore tonnage processed in each period. Sand and water are the main components of TCS while fines are the smallest constituent. It has been found that when fines content of the feed increases, the total mass of TCS produced decreases and vice versa. Also, the sand content increases with reducing the fines content. This results in a mass-balance-relation between TCS tonnage and average sand content of the feed. The other waste material mined from the pits are sent to waste dump areas or used for dyke construction. The open pit oil sands industry has complicated and unique waste handling needs, including tailings disposal that requires unconventional planning considerations. Inefficient waste management plans for tailings and general mine waste result in environmental and economic issues for oil sands mining projects such as (1) greenhouse gas emissions resulting from the CHWEP (Devenny, 2009); (2) environmental challenges due to the toxicity of the tailings, resulting in the pollution of the fresh water table by polluted tailings water leaks; (3) ex-pit tailings-containment which increases the volume of disturbed landscape difficult to reclaim; and (4) mine closures or financial liabilities (Ben-Awuah and Askari-Nasab, 2011).

To manage these environmental and economic concerns, tailings should be stored in tailings dams that are built in-pit and ex-pit one section at a time as mining advances. Tailings dam dykes should be ready on time, and within budget and design specifications throughout the mine life. Material used for dyke construction is derived from the overburden and interburden layers of the deposit in addition to tailings coarse sand from the processing plant (Fauquier et al., 2009). The geologic block model is used to predict the dyke construction materials. In this sense, waste management must be an integrated part of oil sands mine planning to drive sustainability. Schedules for ore and dyke material should be generated concurrently to enable consistent material supply to the plant and for dyke construction. It is also required by Directive 085 issued by the AER (2017) that oil sands operators must periodically publish their waste disposal and tailings plans publicly (McFadyen, 2008; Ben-Awuah and Askari-Nasab, 2013). Managing oil sands mining using MPMs can be challenging when it comes to the size of the optimization problem due to the planning and scheduling of multiple material types, multiple elements and different destinations and mining locations.

2.4 Integrated oil sands waste disposal planning and optimization problems

The literature on LTPP and scheduling is extensive. However, the literature on integrated waste disposal planning optimization is very limited, as production plans and waste disposal schedules are usually managed separately. Modeling integrated mine planning systems adds more complexity to the LTPP problem. Managing oil sands waste disposal planning as a post-production scheduling optimization activity leads to inappropriate consideration of material cost, suboptimal schedules that reduce project value, and incorrect classification of ore and waste (Fu et al., 2019). Some researchers have partially incorporated waste management into production plans.

Ben-Awuah and Askari-Nasab (2011) developed an MILGP theoretical framework for oil sands open pit production scheduling with multiple material types. Their formulation uses binary integer variables to control mining precedence and continuous variables to control the mining of ore and dyke material. The optimization model generated a uniform schedule for ore and dyke material using block clustering techniques. This is in line with recent regulatory requirements from the Energy Resources Conservation Board (Directive 074) (Alberta Energy Regulator, 2017) that requires oil sands mining companies to develop life of mine plans, which ties into their in-pit tailings disposal strategy. The schedule gives the planner good control over dyke material and provides a robust platform for effective dyke construction planning.

An integration of MILP and GP in solving large scale mine planning optimization problems using clustering and pushback techniques was presented by Ben-Awuah et al. (2012). Using an oil sands mining case, the MILGP model generated a smooth and uniform mining schedule that generates value and a sustainable operation through effective waste disposal planning. The schedule ensures that the main drivers for oil sands profitability and sustainability, which are maximizing profits and concurrently creating timely tailings storage areas, are satisfied within an optimization framework.

To develop a link between oil sands long-term mine plans and tailings management plans, mathematical formulations and simulation models were developed by Kalantari et al. (2013). The models assist in predicting the quality and quantity of composite tailings, the byproduct of processing oil sands ore. The authors stated that the stochastic simulation approach can be used to overcome some of the environmental challenges caused by under-estimating the composite tailings tonnages produced during or at the end of mine life.

Ben-Awuah and Askari-Nasab (2013) introduced a MILGP mine planning model to determine the extraction sequence of ore, dyke material and waste over the mine life. The model maximizes the operation's value and minimizes dyke construction costs by determining the dyke material destinations. The authors stated that 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 mining engineer 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 profits while creating timely tailings storage areas.

Badiozamani and Askari-Nasab (2014) included material requirements for reclamation works as part of the mine planning process. The authors developed a long-term MILP model that integrates tailings capacity and reclamation material requirements into the mine plan. To generate a practical schedule and reduce the solution time, the authors aggregated the mining blocks into mining-cuts. The developed model aims to maximize the value of the project and minimize the material handling costs associated with reclamation operations. The model was implemented and verified using an oil sands dataset, and resulted in an integer solution with a 2% optimality gap. The authors stated that the generated production schedule guarantees the production of the required reclamation material and meets the capacity constraint of the tailings facility.

An integrated long-term mine planning model based on the CHWEP was introduced by Badiozamani and Askari-Nasab (2016). The model integrates composite tailings production and deposition planning into the long-term mine planning optimization framework. An oil sands dataset was used to verify the model. The authors used block aggregation techniques to reduce the problem size. The developed model generated an integer solution with 1% optimality gap in seconds. The resulting directional mining production schedule creates enough space for an in-pit tailings facility in later periods.

Seyed Hosseini and Ben-Awuah (2018) developed a heuristic optimization model that generates an optimum cut-off grade policy incorporating waste management cost and limited duration stockpiling for oil sands long-term production scheduling. The developed model was implemented and verified using a real dataset of an oil sands deposit. The authors stated that, the model generates an optimum cut-off grade policy and a uniform production schedule for ore, overburden, interburden, TCS and waste material over the mine life.

Ben-Awuah et al. (2018) formulated and implemented an MILGP model to integrate waste management strategies with production scheduling for oil sands mining operations. The proposed model aims to maximize the NPV of the operation and minimize the cost of dyke construction and deviations from set goals. The proposed MILGP model generated a uniform ore schedule that is compared to a schedule generated by Whittle software (Geovia Dassault Systems, 2017). The model generated a higher NPV compared to Whittle Milawa NPV algorithm, which is widely used in the mining industry.

For improved sustainability and to support waste management planning, the incorporation of the availability of in-pit disposal areas with dyke construction planning on a continual basis throughout the mine life was needed to ensure the maximum use of the mined-out areas (Ben-Awuah and Askari-Nasab, 2013; Ben-Awuah et al., 2015). Currently, for tailings disposal planning, the oil sands deposit area is divided into pushbacks and used as tailings deposition cells. Pushbacks are generated for different reasons such as: (i) to control the sequence of extraction of an orebody, where it begins and where it stops; (ii) to be used as a guide for the subsequent production scheduling stage; (iii) to ensure safe pit walls; (iv) to assist in meeting ore production requirements; (v) to provide a minimum operational mining width for large mining equipment; (vi) to provide different accesses to the mine (Consuegra and Dimitrakopoulos, 2010; Elkington and Durham, 2011; Jélvez et al., 2018); and (vii) to support the tailings storage plan in reducing the environmental footprint of external tailings facilities, which subsequently affects the NPV of the mining project. Ben-Awuah and Askari-Nasab (2013); Ben-Awuah et al. (2015) developed a MILP formulation that integrates waste management into mine planning optimization problems using predetermined pushbacks. The author investigated the effect of having different numbers of predetermined pushbacks used as in-pit tailings-cells on the NPV. The research concludes that increasing the number of pushbacks used for tailings cells improves operational flexibility, increases proportion of in-pit area backfilled and increases NPV.

2.5 Application of clustering and paneling in mine planning

It is clear that optimizing activities separately is not likely to generate a globally optimum solution, and local optimization may result in suboptimal solutions that affects the overall value of a project. Clustering techniques (Ramazan and Johnson, 2005) are introduced in MPMs to reduce the size of the optimization problem. A wide range of clustering algorithms has been developed in the literature that work based on defining a measure of similarity or dissimilarity between the objects. Clustering algorithms can be generally categorized into hierarchical and partitional or overlapping clustering (Tabesh and Askari-Nasab, 2011). Hierarchical clustering is implemented by creating a hierarchy of clusters, while partitional clustering is implemented by partitioning data objects into groups. Hierarchical clustering results in better clusters compared to partitional clustering at the expense of solution time (Feng et al., 2010). In mine planning, hierarchical and partitional clustering are used because all blocks must belong to a single cluster.

In the literature, various MPMs based on clustering techniques are introduced. A binary mathematical model is used by Busnach et al. (1985) to cluster all the blocks on the same level into horizontal layers to solve the LTPP problem. Klingman and Phillips (1988) used binary variables to determine whether a layer should be considered as ore or waste. Based on the same idea, Gershon (1983) labeled the layers as ore and waste before formulating the mathematical model. Using binary integer variables makes the problem extremely hard to solve for large-scale problems. Therefore, researchers have tried to find different approaches including clustering to formulate the problem and generate near-optimal solutions.

An iterative aggregation and disaggregation approach was developed by Boland et al. (2009) towards minimizing the size of the problem. The authors aggregated blocks as mining units to control the mining operation and blocks to control the processing operation. Weintraub et al. (2008) grouped the blocks into larger units using K-means clustering. The authors introduced a dissimilarity measure based on tonnage, metal content and speed of extraction to determine the clusters. The model was applied to an underground copper mine. The authors reported that the aggregation technique reduced the solution time significantly, and the result was very close to the non-aggregated objective value.

A customized clustering approach more suitable to the mining industry was developed by Tabesh and Askari-Nasab (2011). In their clustering research, mining blocks are clustered based on their location, rock type, grade, destination, size and shape of the generated clusters. These clusters are referred to as mining-cuts. Paneling is another technique that has been introduced in production scheduling to maintain practical mining widths and reduce the size of the optimization problem. The intersections of pushbacks and mining benches generate mining-panels (Ben-Awuah and Askari-Nasab, 2013). Each mining-panel contains a set of mining-cuts and is used to control the mine production operation sequencing. Tabesh and Askari-Nasab (2011) used hierarchical clustering to create mining units based on grade and rock type. The authors modified the cluster shapes to decrease the number of precedence constraints using Tabu search (Glover and Laguna, 1999). The clustered blocks were used as mining units for open pit production planning. Ben-Awuah et al. (2012) used hierarchical clustering and commented on the quality of the generated solutions. Clustering is used in mine planning to minimize the number of integer decision variables as well as to maintain the minimum mining width required for large mining equipment (Askari-Nasab and Awuah-Offei, 2009).

Epstein et al. (2003) aggregated mining blocks vertically to create economic columns for their proposed model. To reduce the size of the mine planning mathematical model, Pourrahimian et al. (2012) used clustering to group draw points in block caving operations. An aggregation-disaggregation technique to solve the open pit mine production scheduling problem was proposed by Jélvez et al. (2016). The technique aggregates the model into larger units then solves the clustered block model using a sliding time window heuristic. The model is implemented on “MineLib” datasets. The authors stated that their technique can solve all the cases to near-optimality in a reasonable solution time. Tabesh and Askari-Nasab (2019) presented four agglomerative hierarchical clustering algorithms: one based on deterministic estimates and three based on geological uncertainties. The authors reported that uncertainty-based algorithms created clusters that are within a controlled size, have minable shapes and resulted in clusters that are most likely not influenced by uncertainties. Tabesh and Askari-Nasab (2013) introduced a clustering algorithm with shape control parameters. The model was implemented and evaluated based on the homogeneity of grade and rock types, determined destinations, and run times on two small datasets and a real gold deposit. For this study, the hierarchical clustering algorithm developed by Tabesh and Askari-Nasab (2011) was used.

2.6 Application of stockpiling in mine planning

It is required for open pit LTPP to determine the destination of the mined blocks, either to the processing plant, waste dump or stockpile (Moreno et al., 2016). Stockpiling can be used in mine operations for many reasons such as managing processing plant capacity, blending material, or storing overproduced or low-grade ore for future processing. It can also be used to store waste material for reclamation purposes (Moreno et al., 2016). In general, stockpiles are only used if they improve the NPV of the project (Whittle, 1988). Some researchers have tried to mathematically model stockpiling used to manage processing plant capacity. They studied the interplay of material flows from the mine to a stockpile, from the mine to a processing plant, and from a stockpile to a plant and evaluated the revenue generated from using it. Other researchers used stockpiling without providing the mathematical framework or did not consider a stockpile as part of the global optimization problem (Lamghari and Dimitrakopoulos, 2016; Moreno et al., 2016).

Some mine planning software packages such as Mintec (Minesight, 2014), MineMax (MineMax planner, 2018) and Whittle (Geovia Dassault Systems, 2017) have stockpiling options. These software packages are used by industry, but they have limited benefit due to the nature of their modeling and solution techniques. Mintec and MineMax software do not guarantee global optimal solutions (Moreno et al., 2016). Whittle accumulates the tonnage and metal information in the stockpile and calculates the average grade. Therefore, ore withdrawal from the stockpile will be at the average grade. Using Whittle, the optimal solution is not guaranteed, as it does not use optimization techniques to model the stockpile (Moreno et al., 2016).

Montiel and Dimitrakopoulos (2015) proposed a risk-based model with a stockpiling option to optimize mining operations. They stated that the proposed model met the production targets and generated a higher NPV than using conventional deterministic approaches. An uncertainty-based model with a stockpile option for low-grade ore was proposed by Lamghari and Dimitrakopoulos (2016). They used four different heuristics to solve the model and stated that the proposed solution methods are effective and able to solve instances in a reasonable solution time. Smith (1999) used mixed integer programming to solve a short-term production scheduling problem considering a stockpile option. He noticed that linear formulations are required to correctly calculate the grade in the stockpile and the quantity retrieved from the stockpile at any time. Caccetta and Hill (2003) proposed a deterministic approach to solve a monolithic mine production scheduling problem. The authors discussed the possibility of considering a stockpile in their model but without providing any mathematical formulation. A simple optimization model was proposed by Asad (2005) to evaluate the tradeoffs between cut-off grades and stockpile levels for a two-element mineral deposit. However, the static model ignores production scheduling decisions.

Tabesh and Askari-Nasab (2019) stated that most of the work in literature is limited to production planning problems in the absence of grade blending and stockpiling constraints, as they change the structure of the model. Ramazan and Dimitrakopoulos (2013) implemented a stochastic framework with a stockpiling option. The authors used the block grades in the orebody model to determine the amount of material to be stockpiled. They ignored the mixing of material in the stockpile. Koushavand et al. (2014) presented an uncertainty-based model that quantifies ore grade uncertainty with a stockpile option. The authors assumed that the stockpile has its grade set in advance and that it is used to minimize uncertainty, that is, overproduction can be carried over until the next time. Moreno et al. (2016) explained that the characteristics of the material retrieved from the stockpile must be treated as variables since the amount of ore is not known in advance. Based on that, the model will have some non-convex, nonlinear constraints. Solving this problem results in local optimal solutions or consists of linearizing the model. That might lead to unrealistic assumptions. Tabesh et al. (2015) also stated that stockpiling should theoretically be modeled nonlinearly. They suggested to linearize the formulation by using a "sufficient number" of stockpiles, each with a lower and upper bound of grades.

Asad (2005) cautioned that long-term stockpiling could result in problems such as leaching, the deterioration of material and oxidation, which might result in poor recovery at the treatment plant. For oil sands mining, the stockpiled material must be processed within a limited duration due to oxidation that affects the efficiency of the processing plant.

2.7 Organic rich solids and bitumen recovery

As mentioned before in regard to oil sands mining, the Clark Hot Water Extraction Process (CHWEP) is used to separate bitumen from the watery froth (slurries) that contain significant amounts of solid fractions and emulsified salty water (Masliyah, 2010). The CHWEP depends on the surface characterization of solid particles in the ore matrix. Oil sands particles are primarily water-wet. The water forms a film around the particles, which prevents the oil from sticking to the surface of mineral solids (Clark, 1944). The tailings slurry is classified into coarse and fine sands. It is collected in tailings ponds, where it settles to intractable mature fine tailings (MFT) with a maximum solids content of about 30 wt%. The froth from the extraction process is diluted with recycled naphtha before upgrading, then it is filtered and centrifuged. This results in a diluted bitumen with about 0.5 wt% solids, which are believed to impact bitumen processability and should be removed prior to upgrading (Sparks et al., 2003). Measurements of fines (<45 μm) are used to predict the processability of ore; however, this is not always effective. It has been found that certain solid fractions known as organic rich solids (ORS) still exist even after the treatment of oil sands by multiple extraction toluene. The total ore comprises about 5 wt% of ORS, which potentially affects the processability of oil sands ore (O'Carroll, 2002; Sparks et al., 2003). During the bitumen separation process, ORS carry any associated bitumen into the aqueous tailings, thus reducing overall bitumen recovery. In this sense, these solids are considered active, and their associated quantity per tonne of ore can be estimated and used as an additional predictor of ore processability, augmenting the traditional use of ore fines content (O'Carroll, 2002). O'Carroll (2002) noted that losses in bitumen recovery are associated with higher ORS content in the ore. Oil sands ore sample analysis shows that the bitumen to ORS ratio increases with higher bitumen content and hence has the potential for use as an index in the characterization of oil sands ore processability. Overall, it should be noted that these efforts are performed experimentally, and the results can be numerically modelled and included in the production scheduling optimization problem as it directly affects revenue.

2.8 Mining and processing capacities optimization

Determination of the UPL will provide a resource estimation, and consequently, a preliminary production rate can be calculated. Uncertainty in the grade may cause a change in the resource estimate and lead to re-examining of the mining capacity decision and its impact on the NPV of the project. Taylor’s Rule (Taylor, 1986) is used to calculate the life of mine and the production rate based on the estimated reserve. Taylor’s Rule is an experimental relationship and does not provide an optimized production rate for a given orebody; however, it is a good starting point for further analysis (Long, 2009). Typical constraints on an open pit schedule include mining and processing capacities, ore quality and precedence constraints. Mining and processing capacities are usually predetermined prior to scheduling to reduce the problem size. Very little work has been done to simultaneously optimize mining and processing capacities. Elkington and Durham (2011) explained that mining and processing capacities affect the selection of final pit outlines and pushbacks, scheduling, and cut-off grade that will ultimately impact the NPV and the capital cost of the project. The authors stated that a large upfront cost is needed for overproduction, which might take many years to pay back, or underproduction, which might not result in a significant recovery of the sunk cost or, in some cases, never paid back.

2.9 Rationale for PhD research

Currently, oil sands waste disposal planning is handled as a post-production scheduling optimization activity. Sustainable oil sands mining requires effective and efficient planning considerations because of its unique waste handling needs, including tailings disposal. Also, it is required by Directive 085 issued by the AER (2017) that oil sands mining companies have to publish their waste management plans publically. That makes it significant to incorporate waste management into long-term mine planning optimization problems. Modeling such an integrated mine planning system adds more complexity to the LTPP problem.

The strategic scheduling of an open pit mine is a matter of finding which block should be extracted, when and to which destination to maximize the value of the project. The scheduling process is subject to economic, operational, and physical constraints. Heuristic optimization methods are used for scheduling procedures; however, they cannot guarantee the optimal solution. Applying MPMs with deterministic solution methods such as LP, IP, MILP, DP and GP for optimization have proved to be robust and result in solutions with known limits of optimality. As the solution gets closer to optimality, the production schedule generates higher NPV compared to results from heuristics. However, it is still difficult to apply MPMs to large-scale LTPP problems due to the number of binary integer and continuous decision variables. The size of the optimization problem increases significantly, which is beyond the capacity of current computing software and hardware and may have lengthy solution times. The current application of MPMs with block clustering and paneling techniques were successfully undertaken to minimize the size of the optimization problem and maintain a minimum mining width.

The literature review showed that in open pit mining projects, production scheduling methodologies based on deterministic approaches will lead to optimistic production schedules. Practically, mining projects are considered uncertain due to the variability of economic and geological parameters. Substantial decisions related to production planning are made based on limited key inputs during early prefeasibility studies. These decisions should not be accepted as certain to avoid deviation from production targets during the extraction process. The production schedule should be revisited as mine planning advances and more information becomes available.

Oil sands mine planning seeks to provide ore to the processing plant at the required grade and tonnages and to provide sufficient in-pit tailings-containment at the right time. Tailings-cells are used as dedicated disposal areas for tailings backfilling. Dyke construction and backfilling activities require well-managed techniques to support progressive reclamation at the earliest opportunity, which directly affects the profitability and sustainability of oil sands mining operations. Conventionally, bitumen and fines contents are used to predict oil sands ore processability. However, it is evident that certain solid fractions known as ORS still exist, even after the treatment of oil sands ore by multiple extraction with toluene. Ore processability results show that ORS have the ability to carry any associated bitumen into the aqueous tailings, thereby reducing the overall bitumen recovery. The amount of ORS in oil sands ore can be estimated and used as an additional parameter for predicting ore processability in conjunction with the traditional use of bitumen and fines content.

The lack of an uncertainty-based mathematical programming model that integrates waste management with open pit production scheduling, taking a large number of detailed constraints into account with the ability to maximize the project value is worrisome. This research will introduce an MILGP mine planning framework for an integrated oil sands production scheduling and waste disposal planning system. The developed model takes into account multiple material types, multiple elements, different destinations and mining locations. The model also considers grade uncertainty, directional mining, and sustainable practical mining strategies. Bitumen recovery is adjusted based on the ORS content. A stockpiling option with limited duration is introduced in the model for mined ore that exceeds plant capacity. The model has the capability to simultaneously optimize the shape, size and location of tailings-cells for tailings backfilling. The model also features automated production targeting constraints that optimize the annual capacities for material mined and processed over the mine life. An oil sands dataset is used for three case studies in this research. The implementation of the proposed model generates near-optimal production schedules for ore, dyke and reclamation materials as well as practical tailings-cells designs for backfilling activities with a measure of the financial risk associated with the production schedule.

2.10 Summary and conclusions

In this chapter, the literature relevant to the research was reviewed. In mining projects, the mine economics depend mainly on the long-term production plan. Deviations from the optimal mine plan might result in significant economic losses, future financial liabilities, delayed reclamation, or early mine closure. In recent decades, researchers have studied mathematical models used to solve production scheduling optimization problems and divided them into deterministic and uncertainty-based approaches. Deterministic approaches assume all inputs are known and fixed values, while uncertainty-based approaches assume some inputs are variables.

In the literature, maximizing the NPV of mining projects and achieving uniform and practical production schedules is the main focus. Researchers have used the grade of mining blocks to control material sent to the plant, consequently optimizing the processing plant feed. Minimizing the differences between actual production and theoretical expectations is another focus, which will be achieved using uncertainty-based algorithms. Uncertainty-based algorithms result in a high-degree of confidence in the NPV of the mining operations.

There are some limitations in production scheduling optimization methods for oil sands open pit mining including: (i) shortcomings in integrating waste management and reclamation planning directly into the production scheduling optimization process; (ii) shortcomings in integrating geological uncertainty into oil sands production scheduling optimization problems; (iii) shortcomings in modeling limited duration stockpiling required by the processing plant; (iv) shortcomings in optimizing mining and processing targets as part of the optimization problem and not through a trial and error process; (v) limitations in optimizing tailings-cells designs for waste management; and, (vi) not incorporating functional metallurgical variables that impact ore processing and waste management. These limitations affect the practicality of mining projects and could be minimized using robust optimization tools. Therefore, it is important that versatile models are developed to address these challenges. This research will introduce an uncertainty-based MILGP mine planning framework for LTPP problems with a novel waste management strategy, which will improve how mining operations are engineered and managed.

CHAPTER 3

MILGP THEORETICAL MODEL FORMULATION

3.1 Background

Chapter 3 contains the uncertainty-based MILGP theoretical model formulation as applied to integrating oil sands mine planning and waste management. Generally, the conceptual theoretical framework, the mathematical models and how they relate to each other in an optimization environment are developed for achieving the objectives of the research. The primary objective of this research is to develop an uncertainty-based theoretical framework that maximizes the NPV of an oil sands mining operation, maximizes the pseudo revenue generated from backfilling the mined-out areas with tailings, minimizes the grade uncertainty risk, and minimizes the reclamation and dyke materials cost using a MILGP model. Recent regulatory requirements in Directive 085 issued by the AER (2017) require that oil sands mining companies develop life of mine plans that tie into their in-pit tailings disposal strategy (McFadyen, 2008). This requires a new fundamental approach for the planning of oil sands resources.

The strategic and operational production schedules consider the time and sequence of extracting the ore, RM, OB, IB and waste blocks as well as determining their destinations from a predefined UPL over the mine life. The proposed uncertainty-based MILGP model is capable of considering multiple mining locations, multiple destinations and different material types. Geological uncertainty is usually present because of an absence of geological information that dramatically affects the optimality of the production scheduling problem. The financial risk associated with the production schedule as a result of grade uncertainty is estimated through a grade uncertainty cost calculated by applying a grade-variance penalty scheme. Stockpiling is deployed for the mined ore that exceeds the plant capacity in any given year. For oil sands mining, to avoid the risk of oxidation, the ore needs to be reclaimed within a predetermined maximum duration controlled by the planner. Clustering and paneling techniques are used to manage the size of the mathematical programming model, to maintain a minimum mining width, and to generate a robust, practical, and near-optimal schedule. The bitumen recovery is adjusted based on ORS content in addition to fines content and bitumen grades. The proposed oil sands production scheduling model integrates waste management through directional mining, dyke construction and tailings backfilling activities in the mined-out areas. The MILGP model is subject to economic, technical and physical constraints that control the mining operation and enforce the mining block extraction sequence, dyke construction capacities, and blending and backfilling requirements.

The workflow that was followed to schedule an oil sands open pit mine using the developed MILGP model in this research includes:

1. Importing drillholes data to GEMS software (Geovia Dassault Systems, 2018) including coordinates, length, dip, azimuth, assay, rock type and rock code;
2. Creating a block model using GEMS software (Geovia Dassault Systems, 2018) and assigning estimated tonnage and kriged mineral grades to each block;
3. Exporting the block model to Whittle software (Geovia Dassault Systems, 2017) to generate the UPL using the LG algorithm;
4. Importing the ultimate pit to GEMS software for pit design (including ramps) that should be within the 10% acceptable error based on industry standards;
5. Exporting blocks within the pit design for subsequent processing including material segregation, calculating economic block values, clustering and paneling, determining mining-cuts, mining-panels, mining-cells and pushback precedence, and preparing relevant Matlab matrices;
6. Defining the input scheduling parameters for the MILGP model;
7. Creating the objective function, goal functions and constraints at mining-cuts, mining-panels, and mining-cells resolution levels; and
8. Solving the problem with different scenarios and discussing the results.

3.2 Conceptual mining system

The key drivers for oil sands mine planning are to provide the plant with a processable blend of ore at the required grade and to provide tailings containment at the right time. Waste management is a significant part of oil sands mining operations. It requires well-managed tailings disposal techniques to avoid economic liabilities and delayed reclamation (Boratynec, 2003; Azam and Scott, 2005; Ben-Awuah and Askari-Nasab, 2013). Figure 3-1 and Figure 3-2 are used to illustrate how the MILGP framework is deployed for the mining system in Implementations A and B. The mining system is made up of an oil sands deposit area that is to be mined and simultaneously used as an in-pit tailings storage facility. For this research, two different implementations are used to deploy the developed model. Implementation A is based on using predetermined pushbacks for tailings-cells, while Implementation B is based on vertical units defined as mining-cells to create tailings-cells. Details on the conceptual mining system for each implementation are given in the following sections.

3.2.1 Implementation A

Implementation A presented in Figure 3-1 shows a conceptual mining system that is consistent with practical oil sands mining and waste management. In this implementation, the final pit block model is divided into pushbacks that coincide with the areas required by tailings dam engineers to set up in-pit tailings facility cells. Figure 3-1 shows that the deposit under study is divided into four pushbacks (in-pit cells) with approximate dimensions of 2.0 km × 4.0 km × 75.0 m based on the literature on oil sands mining operations regarding the standard sizes of ex-pit and in-pit tailings facility cells (Fort Hills Energy Corporation, 2009; Kearl Oil Sands Project, 2009; Suncor Energy Incorporated Oil Sands, 2009; Syncrude Aurora North, 2009). It was assumed that mining starts in Pushback 1 and progresses south. During the mining of Pushback 1, all OB, IB and TCS dyke materials are sent to construct the external tailings facility (ETF) dyke. Fine tailings (slurry) generated from Pushback 1 will be sent to the ETF after the dyke construction is progressively completed. Once mining of Pushback 1 is completed, Dyke ‘A’ is constructed to create Cell 1 using OB, IB and TCS dyke materials from Pushback 2. Slurry generated from Pushback 2 will be sent to Cell 1 after the dyke construction is progressively completed. As mining advances to Pushbacks 3 and 4, the OB, IB and TCS dyke materials produced can be used to progressively construct Dykes ‘B’ and ‘C’ to create Cells 2 and 3 for tailings storage. Cell 4 is available for tailings storage at the end of mine life.

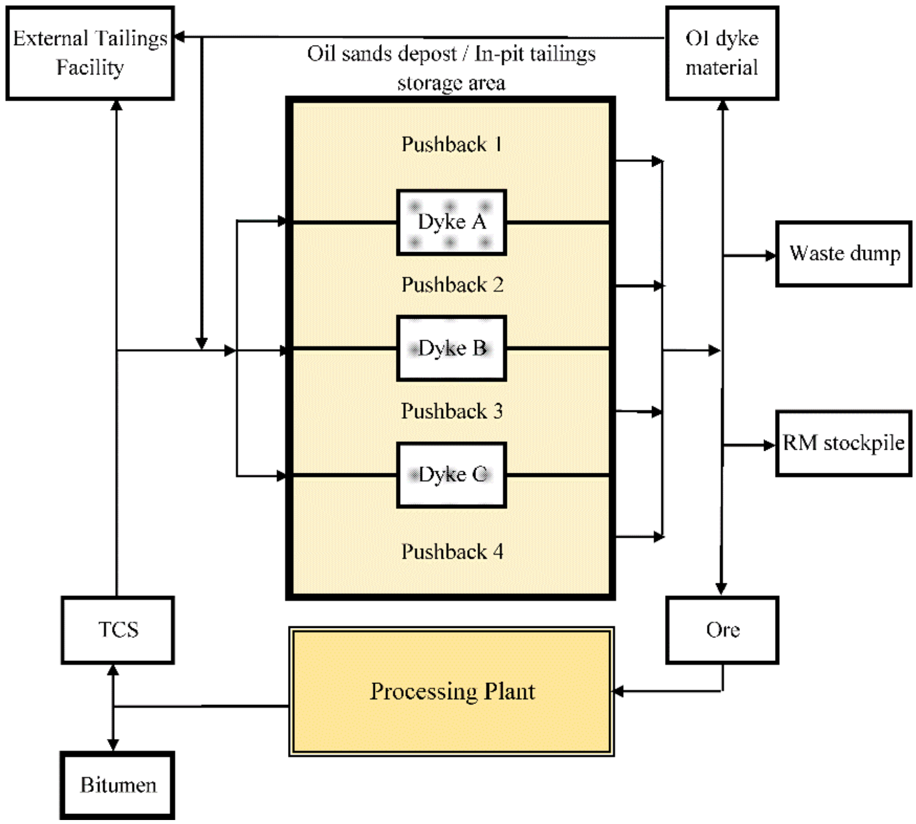


Figure 3-1: Conceptual system for the mining and waste management strategy for Implementation A modified after Maremi et al. (2020)

3.2.2 Implementation B

Implementation B presented in Figure 3-2 shows a conceptual mining system consistent with practical oil sands mining and waste management. In this approach, the oil sands deposit area is divided into vertical units known as mining-cells. Mining-cells will be accumulated when solving the optimization problem to create tailings-cells based on the required capacity, shape and location. For this illustration, it is assumed that mining will start at the northern section and progress southwards (directional mining). During the extraction of mining-cells to create the first tailings-cell, all IB, OB and TCS dyke material will be sent to the external tailings facility (ETF) for the construction of the ETF dyke. The slurry produced from Tailings-cell “A” will be sent to the ETF after the dyke construction is progressively completed. Once the required volume with the appropriate shape and location for Tailings-cell “A” is reached, the first in-pit dyke footprint required to construct Tailings-cell “A” becomes available. OB, IB and TCS dyke material generated from Tailings-cell “B” will be used for the construction of the first dyke to enable in-pit tailings storage to start in Tailings-cell “A”. As mining progresses to Tailings-cell “B”, “C”, and “D”, the OB, IB and TCS dyke material produced is used to construct the second, third and fourth dykes to make available Tailings-cells “B”, “C” and “D”, respectively, for tailings storage. For this study, it is assumed that all the tailings-cells should be ready four years earlier than the end of mine life. There will be a remaining mined-out area that could be used for tailings deposition for any additional pits, or could be used as a waste dump area.

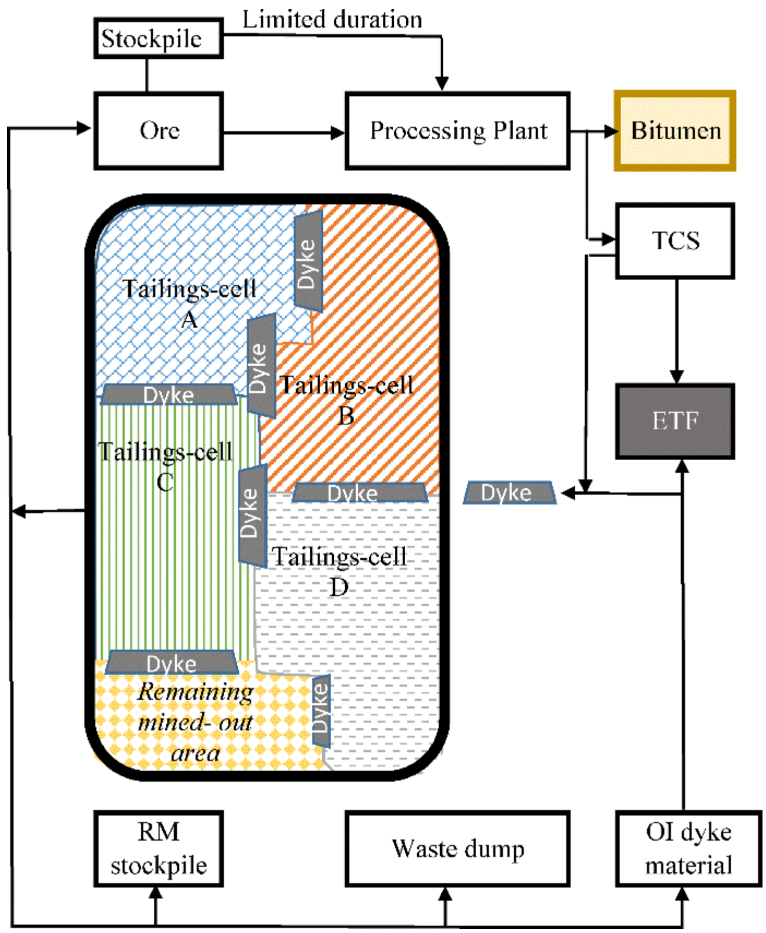


Figure 3-2: Conceptual system for the mining and waste management strategy for Implementation B modified after Maremi et al. (2020)

3.3 Uncertainty-based MILGP model for LTPP and waste management

The strategic and operational production schedules consider the time and sequence of extracting ore, reclamation material, overburden, interburden and waste blocks as well as determining their destinations from predefined UPL. The proposed MILGP model is capable of considering multiple mining locations and processing destinations, multiple pushbacks and different types of materials. The stockpiled ore can be reclaimed after pit mining is completed or simultaneously during active pit mining with a pre-determined stockpiling duration limit. Long-term stockpiling could result in problems such as leaching and deterioration of material and oxidation, which can affect the processing recovery efficiency. For oil sands mining, to avoid the risk of oxidation, the ore needs to be reclaimed within a pre-determined period controlled by the planner. Stockpiling is for the mined ore that exceeds the plant capacity in any given year. The proposed oil sands production scheduling model integrates waste management through directional mining and dyke construction in the mined-out areas for tailings-containment. The MILGP model is subject to economic, technical and physical constraints that control the mining operation. The notations used in the formulation of the oil sands long-term production planning and waste management framework have been classified as indices, sets, parameters and decision variables.

3.3.1 Indices

$a \in A, A = \{1,...,A\}$	index and set for all possible processing destinations in the model.
$d \in D, D = \{1,...,D\}$	index and set for all possible destinations for materials in the model.
$e \in E, E = \{1,...,E\}$	index and set for all elements of interest in each mining-cut.
$j \in J, J = \{1,......,J\}$	index and set for all pushbacks in the model.
$k \in K, K = \{1,...,K\}$	index and set for all mining-cuts in the model.
$l \in L, L = \{1,...,L\}$	index and set for all possible mining locations (pits) in the model.
$m \in M, M = \{1,...,M\}$	index and set for all mining-cells in the model.
$p \in P, P = \{1,...,P\}$	index and set for all mining-panels in the model.
$sp \in SP, SP = \{1,...,SP\}$	index and set for all possible stockpiles in the model.
$t \in T, T = \{1,...,T\}$	index and set for all the scheduling periods, years.
$ts \in TS, TS = \{1,....,TS\}$	index and set for all possible stockpiling durations, years.

3.3.2 Sets

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

be extracted prior to the extraction of mining-panel p, where Z'' is the total number of mining-panels in the set $IP_p(Z'')$.

$MK_p(H')$ — For each mining-panel p, there is a set $MK_p(H') \subset K$ defining the mining-cuts that belong to the mining-panel p, where H' is the total number of mining-cuts in the set $MK_p(H')$.

$MP_j(H'')$ — For each phase j, there is a set $MP_j(H'') \subset P$ 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 $MP_j(H'')$.

$NP_m(S)$ — For each mining-cell, there is a set $NP_p(S) \subset P$ defining the mining-panels within this specific mining-cell. All the mining-panels must be extracted to make this mining-cells ready to be used to create a tailings-cell, where S is the total number of mining-panels in the set $NP_p(S) \subset P$.

$NC_p(C)$ — To create each tailings-cell, there is a set $NC_p(C) \subset M$, where C is the number of active mining-cells that can be used to create a tailings-cell.

3.3.3 Decision variables

$b_p^t \in [0,1]$ — 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.

$bv_m^t \in [0,1]$ — Binary integer variable controlling the precedence of extraction of mining-cells. bv_m^t is equal to one if the extraction of mining-cell m has started by or in period t; otherwise, it is zero.

$c_{k,sp}^{a,t+ts} \in [0,1]$ — Continuous variable representing the ore portion of mining-cut k to be reclaimed from stockpile sp and processed at destination a in period $t+ts$.

$dv_1^{-,l,t}$ — Negative deviation from the mining goal (tonnes) in period t at location l.

$dv_2^{-,a,t}$ — Negative deviation from the processing goal (tonnes) in period t at processing destination a (tonnes).

$dv_3^{-,d,t}$ — Negative deviation from the reclamation material goal (tonnes) in period t at destination d (tonnes).

$dv_4^{-,d,t},...,dv_6^{-,d,t}$	Negative deviation from the *OB*, *IB* and *TCS* dyke material goals in (tonnes) respectively in period t at destination d (tonnes).
$q_k^{d,t} \in [0,1]$	Continuous variable representing the tailings coarse sands dyke material portion of mining-cut k to be extracted and used for dyke construction at destination d in period t.
$s_k^{sp,t} \in [0,1]$	Continuous variable representing the ore portion of mining-cut k to be extracted and sent to the stockpile sp in period t.
$tv_m^{l,t} \in [0,1]$	Continuous variable representing the volume of mining-cell m that is available for backfilling at location l in period t.
$u_k^{d,t} \in [0,1]$	Continuous variable representing the interburden dyke material portion of mining-cut k to be extracted and used for dyke construction at destination d in period t.
$v_k^{d,t} \in [0,1]$	Continuous variable representing the muskeg reclamation material portion of mining-cut k to be extracted and stockpiled at destination d in period t.
$x_k^{a,t} \in [0,1]$	Continuous variable representing the ore portion of mining-cut k to be extracted and processed at destination a in period t.
$y_p^{l,t} \in [0,1]$	Continuous variable representing the portion of mining-panel p to be mined in period t from location l, which includes ore, overburden and interburden dyke material, muskeg reclamation material and waste from the associated mining-panel.
$z_k^{d,t} \in [0,1]$	Continuous variable representing the overburden dyke material portion of mining-cut k to be extracted and used for dyke construction at destination d in period t.

3.3.4 Modeling of economic mining-cut value and pseudo backfilling revenue

The notion of economic mining-cut value is based on ore parcels within mining-cuts, which could be mined selectively. The profit from extracting a mining-cut is a function of the value of the mining-cut based on the processing destination and the costs incurred in mining, processing, dyke construction and reclamation work at a specified destination. The dyke construction cost is a function of the location of the tailings facility being constructed and the type and quantity of dyke material required. Similarly, the reclamation work cost is a function of the location of the stockpiling area, the quantity of the stockpiled material and the rehandling cost. Based on the value of a mining-cut and the costs incurred during mining, processing, dyke construction and reclamation work operations, the discounted profit from each mining-cut equals the discounted revenue obtained by selling the final product contained in mining-cut k minus the discounted costs. Equations (3.1) and (3.2) define the discounted economic value for a mining-cut if it is sent from the mine to the processing plant $dm_k^{d,t}$ or from the stockpile to the processing plant $ds_{k,sp}^{d,t}$, respectively. Equation (3.3) defines the discounted revenue $rm_k^{a,t}$ generated from selling the final product within each mining-cut minus the discounted processing cost for mining-cuts sent directly from the mine to the processing plant. Equation (3.4) defines the discounted revenue $rs_{k,sp}^{a,t}$ generated from selling the final product within each stockpiled mining-cut minus the discounted processing cost and the extra discounted rehandling cost for mining-cuts sent from the stockpile to the processing plant. As mentioned before, the processing recovery used for case studies II and III is adjusted based on the ORS content to reflect practical ore processability conditions.

There is a discounted cost for extracting a mining-cut as waste as well as extra discounted costs of mining reclamation and dyke materials. Equation (3.5) defines the base discounted cost for extracting mining-cut k as waste. Equation (3.6) shows the extra discounted cost of mining reclamation material (muskeg unit). Equations (3.7) to (3.9) show the extra discounted cost of mining the OB, IB and TCS dyke materials from mining-cut k, respectively. The extra discounted cost mentioned in Equations (3.6) to (3.9) includes any additional costs resulting from mining different rock types as well as any extra haulage costs. From Equation (3.10) a discounted pseudo backfilling revenue per cubic meter of mining-cut $rt_k^{l,t}$ is defined to facilitate the backfilling operation. The concepts presented in Ben-Awuah et al. (2018) and Maremi and Ben-Awuah (2018) were used as the starting point for this development.

$$dm_k^{d,t} = rm_k^{a,t} - dw_k^{l,t} - dmu_k^{d,t} - dob_k^{d,t} - dib_k^{d,t} - dt_k^{d,t} \tag{3.1}$$

$$ds_{k,sp}^{d,t} = rs_{k,sp}^{a,t} - dw_k^{l,t-ts} - dmu_k^{d,t-ts} - dob_k^{d,t-ts} - dib_k^{d,t-ts} - dt_k^{d,t-ts} \tag{3.2}$$

$$rm_k^{a,t} = \sum_{e=1}^{E} o_k \times g_k^e \times rp_{avg}^{a,e} \times \left(p^{e,t} - sc^{e,t} \right) - \sum_{e=1}^{E} o_k \times pc^{a,e,t} \tag{3.3}$$

$$rs_{k,sp}^{a,t} = \sum_{e=1}^{E} o_k \times g_k^e \times rp_{avg,sp}^{a,e} \times \left(p^{e,t} - sc^{e,t} \right) - \sum_{e=1}^{E} o_k \times pc^{a,e,t} - \sum_{e=1}^{E} o_k \times pc_{sp}^{a,e,t} \tag{3.4}$$

$$dw_k^{l,t} = (o_k + mu_k + ob_k + ib_k + w_k) \times mc^{l,t} \tag{3.5}$$

$$dmu_k^{d,t} = mu_k \times muc^{d,t} \tag{3.6}$$

$$dob_k^{d,t} = ob_k \times obc^{d,t} \tag{3.7}$$

$$dib_k^{d,t} = ib_k \times ibc^{d,t} \tag{3.8}$$

$$dt_k^{d,t} = t_k \times tc^{d,t} \tag{3.9}$$

$$rt_k^{l,t} = vc_k \times p_v^{\ l,t} \tag{3.10}$$

Where:

$rm_k^{a,t}$	Discounted revenue obtained by selling the final products within mining-cut k in period t if it is sent to processing destination a, minus the extra discounted cost of mining all the material in mining-cut k as ore and processing at destination a.
$rs_{k,sp}^{a,t}$	Discounted revenue obtained by selling the final products within mining-cut k from stockpile sp in period t if it is sent to processing destination a, minus the extra discounted cost of re-handling all the material in mining-cut k as ore and processing at destination a.
$rt_k^{l,t}$	Discounted pseudo revenue obtained per cubic meter of mining-cut k to be backfilled in period t from location l to facilitate the backfilling operation.
$rt_p^{l,t}$	Discounted pseudo revenue obtained per cubic meter of mining-panel p to be extracted in period t from location l to facilitate the backfilling operation. Each mining-panel p contains its corresponding set of mining-cuts.
$rt_m^{l,t}$	Discounted pseudo revenue obtained per cubic meter of mining-cell m to be extracted in period t from location l to facilitate the backfilling operation. Each mining-cell contains its corresponding set of mining-panels.
$dm_k^{d,t}$	Discounted economic mining-cut value obtained by extracting mining-cut k and sending it to destination d in period t.
$ds_{k,sp}^{d,t}$	Discounted economic mining-cut value obtained by extracting mining-cut k and sending it to stockpile sp and reclaiming it to destination d in period t.
$dw_k^{l,t}$	Discounted cost of mining all the material in mining-cut k in period t as waste from location l.
$dw_p^{l,t}$	Discounted cost of mining all the material in mining-panel p in period t as waste from location l. Each mining-panel p contains its corresponding set of mining-cuts.

$pc^{a,e,t}$	Extra cost in present value terms per tonne of ore for mining and processing at processing destination a for element e in period t.
$pc_{sp}^{a,e,t}$	Extra cost in present value terms per tonne of ore for stockpiling at stockpile sp and processing at destination a for element e in period t.
$dmu_k^{d,t}$	Extra discounted cost of mining all the material in mining-cut k in period t as muskeg reclamation material at destination d.
$dob_k^{d,t}$	Extra discounted cost of mining all the material in mining-cut k in period t as overburden dyke material for dyke construction at destination d.
$dib_k^{d,t}$	Extra discounted cost of mining all the material in mining-cut k in period t as interburden dyke material for dyke construction at destination d.
$dt_k^{d,t}$	Extra discounted cost of mining all the material in mining-cut k in period t as tailings coarse sand dyke material for dyke construction at destination d.
$rp_{avg}^{a,e}$	Proportion of element e recovered (processing recovery) taking into consideration ORS if it is sent from the mine to processing destination a.
$rp_{avg,sp}^{a,e}$	Proportion of element e recovered (processing recovery) taking into consideration ORS if it is sent from the stockpile sp to processing destination a.
g_k^e	Required average head grade of element e in the ore portion of mining-cut k.
$muc^{d,t}$	Cost in present value terms per tonne of reclamation material at destination d in period t.
$obc^{d,t}$	Cost in present value terms per tonne of overburden dyke material for dyke construction at destination d in period t.
$ibc^{d,t}$	Cost in present value terms per tonne of interburden dyke material for dyke construction at destination d in period t.
$tc^{d,t}$	Cost in present value terms per tonne of tailings coarse sand dyke material for dyke construction at destination d in period t.
$mc^{l,t}$	Cost in present value terms of mining a tonne of waste in period t from location l.
$p^{e,t}$	Selling price of element e in present value terms per unit of product in period t.
$sc^{e,t}$	Selling cost of element e in present value terms per unit of product in period t.
$p_v^{l,t}$	Pseudo revenue in present value terms per cubic volume v available for backfilling at location l in period t.

o_k, o_p	Ore tonnage in mining-cut k and mining-panel p, respectively.
mu_k, mu_p	Reclamation material tonnage in mining-cut k and mining-panel p, respectively.
ob_k, ob_p	Overburden dyke material tonnage in mining-cut k and mining-panel p, respectively.
ib_k, ib_p	Interburden dyke material tonnage in mining-cut k and mining-panel p, respectively.
cs_k	Tailings coarse sand dyke material tonnage in mining-cut k.
w_k, w_p	Waste tonnage in mining-cut k and mining-panel p, respectively.
$vc_m^{l,t}$	Mining-cell m volume that is available for backfilling at mining location l in period t. Each mining-cell m contains its corresponding set of mining-cuts k.
$vc_k^{l,t}$	Mining-cut k volume that is available for backfilling at mining location l in period t.
i	Discount rate.

3.3.5 Uncertainty-based MILGP objective function

The MILGP model multi-objective function for oil sands long-term production planning and waste management is developed based on deterministic and uncertainty-based approaches. The objective function seeks to:

- Maximize the NPV of the mining project using Equation (3.11);
- Maximize the pseudo backfilling revenue through backfilling the in-pit mined areas using Equation (3.12);
- Minimize the financial risk associated with the production schedule using Equation (3.13);
- Minimize reclamation material mining and rehandling costs using Equation (3.14);
- Minimize dyke materials mining costs using Equation (3.15); and
- Minimize deviations from the production goals using Equation (3.16).

$$Max\sum_{l=1}^{L}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{sp=1}^{SP}\sum_{a=1}^{A}\sum_{e=1}^{E}\sum_{t=1}^{T}\left(\sum_{\substack{k\in MK_p\\ p\in MP_j}}\left[rm_k^{a,t}\times x_k^{a,t}+rs_{k,sp}^{a,t}\times c_{k,sp}^{a,t+ts}-dw_p^{l,t}\times y_p^{l,t}\right]\right) \tag{3.11}$$

$$Max\sum_{l=1}^{L}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{sp=1}^{SP}\sum_{a=1}^{A}\sum_{e=1}^{E}\sum_{t=1}^{T}\left(\sum_{\substack{k\in MK_p\\ p\in MP_j}}\left[rt_m^{l,t}\times tv_m^{l,t}\right]\right) \tag{3.12}$$

$$Min\sum_{l=1}^{L}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{sp=1}^{SP}\sum_{a=1}^{A}\sum_{e=1}^{E}\sum_{t=1}^{T}\left(\sum_{\substack{k\in MK_p\\ p\in MP_j}}\left[PN_u\times y_p^{l,t}\right]\right) \tag{3.13}$$

$$Min\sum_{l=1}^{L}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{sp=1}^{SP}\sum_{a=1}^{A}\sum_{e=1}^{E}\sum_{t=1}^{T}\left(\sum_{\substack{k\in MK_p\\ p\in MP_j}}\left[dmu_k^{d,t}\times v_k^{d,t}\right]\right) \tag{3.14}$$

$$Min\sum_{l=1}^{L}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{sp=1}^{SP}\sum_{a=1}^{A}\sum_{e=1}^{E}\sum_{t=1}^{T}\left(\sum_{\substack{k\in MK_p\\ p\in MP_j}}\left[dob_k^{d,t}\times z_k^{d,t}+dib_k^{d,t}\times u_k^{d,t}+dt_k^{d,t}\times q_k^{d,t}\right]\right) \tag{3.15}$$

$$Min\sum_{l=1}^{L}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{sp=1}^{SP}\sum_{a=1}^{A}\sum_{e=1}^{E}\sum_{t=1}^{T}\left(\sum_{\substack{k\in MK_p\\ p\in MP_j}}\begin{bmatrix}P_1\times PN_1\times dv_1^{-,l,t}+P_2\times PN_2\times dv_2^{-,a,t}\\ +P_3\times PN_3\times dv_3^{-,d,t}+P_4\times PN_4\times dv_4^{-,d,t}\\ +P_5\times PN_5\times dv_5^{-,d,t}+P_6\times PN_6\times dv_6^{-,d,t}\end{bmatrix}\right) \tag{3.16}$$

Where:

P_1	Priority level associated with minimizing the deviations from the mining goal.
P_2	Priority level associated with minimizing the deviations from the processing goal.
P_3	Priority level associated with minimizing the deviations from the reclamation material goal.
P_4	Priority level associated with minimizing the deviations from the overburden dyke material goal.
P_5	Priority level associated with minimizing the deviations from the interburden dyke material goal.
P_6	Priority level associated with minimizing the deviations from the tailings coarse sand dyke material goal.
PN_1	Penalty paid per tonne for deviating from the mining goal.
PN_2	Penalty paid per tonne for deviating from the processing goal.
PN_3	Penalty paid per tonne for deviating from the reclamation material goal.

PN_4	Penalty paid per tonne for deviating from the overburden dyke material goal.
PN_5	Penalty paid per tonne for deviating from the interburden dyke material goal.
PN_6	Penalty paid per tonne for deviating from the tailings coarse sand dyke material goal.
PN_u	Grade uncertainty cost, a pseudo cost for each mining-panel calculated as a product of a penalty value and the mining-panel kriged variance.

Equations (3.11) to (3.16) can be combined as a single objective function formulated as in Equation (3.17);

$$Max\sum_{l=1}^{L}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{sp=1}^{SP}\sum_{a=1}^{A}\sum_{e=1}^{E}\sum_{t=1}^{T}\left(\sum_{\substack{k\in MK_p\\ p\in MP_j}}\begin{bmatrix} rm_k^{a,t}\times x_k^{a,t}+rs_{k,sp}^{a,t}\times c_{k,sp}^{a,t+ts}+rt_m^{l,t}\times tv_m^{l,t} \\ -dw_p^{l,t}\times y_p^{l,t}-PN_u\times y_p^{l,t}-dmu_k^{d,t}\times v_k^{d,t} \\ -dob_k^{d,t}\times z_k^{d,t}-dib_k^{d,t}\times u_k^{d,t}-dt_k^{d,t}\times q_k^{d,t} \\ -P_1\times PN_1\times dv_1^{-,l,t}-P_2\times PN_2\times dv_2^{-,a,t} \\ -P_3\times PN_3\times dv_3^{-,d,t}-P_4\times PN_4\times dv_4^{-,d,t} \\ -P_5\times PN_5\times dv_5^{-,d,t}-P_6\times PN_6\times dv_6^{-,d,t}\end{bmatrix}\right) \quad (3.17)$$

The MILGP formulation uses continuous decision variables to allow for fractional extraction of mining-cuts, mining-panels and mining-cells in different periods for different locations and destinations. To model mining, processing from the mine, processing from the stockpile, reclamation and dyke materials requirements, $y_p^{l,t}$, $x_k^{a,t}$, $c_{k,sp}^{a,t}$, $v_k^{d,t}$, $z_k^{d,t}$, $u_k^{d,t}$, and $q_k^{d,t}$ are used, respectively, for all mining locations, processing destinations, and reclamation and dyke construction destinations. Another continuous decision variable $tv_m^{l,t}$ is used to model the volume of a mining-cell available for backfilling in each period. The continuous deviational variables $dv_1^{-,l,t}$, $dv_2^{-,a,t}$, $dv_3^{-,d,t}$, $dv_4^{-,d,t}$, $dv_5^{-,d,t}$, and $dv_6^{-,d,t}$ are defined to support the goal functions that control mining, processing, RM, OB, IB and TCS dyke materials, for all mining locations, processing destinations, and reclamation and dyke construction destinations. They provide a continuous range of units (tonnes) that is used by the optimizer to satisfy the set goals. In the objective function, these deviational variables are minimized. There are deviational penalty cost and priority parameters in the objective function used to model the focus of mine management in the presence of multiple conflicting goals. The deviational penalty cost parameters PN_1, PN_2, PN_3, PN_4, PN_5, and PN_6 penalize the NPV for any deviation from the set goals. The priority parameters P_1, P_2, P_3, P_4, P_5, and

P_6 are used to add weights to the most important goals. In general, the deviational penalty cost and priority parameters are set up to penalize the NPV if the set goals and the most important goals are not met. When setting up these parameters, the planner has to monitor how continuous mining proceeds period by period, the uniformity of tonnages mined per period, and the corresponding NPV generated to keep track of how these parameter changes affect the key performance indicators. More weight should be assigned to a goal that has a higher priority for mine management. The model again features the parameter "grade uncertainty cost", PN_u, which is a pseudo cost used to enforce preferential mining of low-variance mining-panels. This is used to estimate the risk associated with the generated production schedule. Additionally, the objective function uses a pseudo revenue generated from backfilling the mined-out areas and the savings from not sending the tailings to the external facility to drive the waste management strategy. Also, the MILGP model optimizes the in-pit tailings-cells capacity, shape and location as part of the waste disposal strategy.

In summary, the uncertainty-based objective function presented in Equation (3.17) aims to maximize the NPV of the project, maximize the pseudo backfilling revenue, minimize grade uncertainty costs, minimize reclamation and dyke material mining costs, and minimize deviations from the production goals. The production schedule risk is estimated through the grade uncertainty cost calculated by applying mining-panel grade-variance with an arbitrary penalty scheme. The penalty is increased or decreased in order to generate varying production schedules with different NPVs.

For this research, the MILGP model was formulated incrementally and applied to three different case studies during the development. It should be stated that the objective function has to be modified based on the focus of the case study by setting some parameters in the objective function to zero.

In Case Study I, the goal was to investigate the effect of grade uncertainty on the production schedule using the goal functions for mining and processing capacities; so the following modifications apply:

- No stockpile option was considered, which means no revenue is generated from reclaiming the stockpiled ore;
- No in-pit tailings-cells designs were implemented;

- No reclamation and dyke materials were scheduled; and
- A fixed processing plant bitumen recovery of 90% is assumed.

In Case Study II, the aim of the objective function was to investigate the effect of ORS content on the ore processability using the robust APT constraints Equations (3.24) and (3.25); so the following modifications apply:

- No in-pit tailings-cells designs were implemented;
- No production schedule risk assessment;
- No mining and processing goals constraints were deployed;
- A 2-year pre-stripping production requirement was enforced.

Finally, for Case Study III, the aim was to investigate optimal tailings-cells designs for tailings backfilling using the APT constraints with the modified processing recovery based on ORS content, so the following modifications apply:

- No production schedule risk assessment;
- No mining and processing goals constraints were deployed; and
- No pre-stripping is enforced.

3.3.6 MILGP model goal functions

There are tonnage targets for all mining locations and processing destinations as well as tonnage targets for reclamation and dyke construction destinations. Equations (3.18) to (3.23) represent all developed goal functions. Equation (3.18) defines the mining goal function that controls the total amount of material mined from mining-panel p within pushback j or mining-cell m in each period. The negative allowable deviation from the set mining goal is controlled by the planner using the $dv_1^{-,l,t}$ decision variable. Equation (3.19) defines the processing goal function that controls the total amount of ore from mining-cut k within mining-panel p sent from both the mine and/or stockpile in each period to the processing destination. It should be mentioned that the amount of ore sent to the processing destination from the stockpile in period t and the amount of ore sent to the stockpile from the mine in an earlier period $t-ts$ must be equal. The negative allowable deviation from the set processing goal is controlled by the planner using the $dv_2^{-,a,t}$ decision variable. Equation (3.20) defines the RM tonnage goals that control the amount of reclamation material to be mined from mining-cut k within mining-panel p in each period. The negative allowable deviation from the set RM goal is controlled by the planner using the $dv_3^{-,d,t}$ decision variable. OB, IB and TCS dyke materials goal functions control the dyke materials production targets for different dyke construction destinations. These are defined by Equations (3.21) to (3.23), respectively. These functions provide a feasible schedule for dyke construction. The negative allowable deviation from the set OB, IB and TCS dyke material goals are controlled by the planner using $dv_4^{-,d,t}$, $dv_5^{-,d,t}$ and $dv_6^{-,d,t}$ decision variables, respectively.

$$\sum_{j=1}^{J}\left(\sum_{p\in MP_j}\left(o_p + mu_p + ob_p + ib_p + w_p\right)\times y_p^{l,t}\right) + dv_1^{-,l,t} = Mg^{l,t} \tag{3.18}$$

$$\sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p \\ p\in MP_j}}\left(o_k \times x_k^{a,t}\right) + \sum_{sp=1}^{SP}\sum_{\substack{k\in MK_p \\ p\in MP_j}}\left(o_k \times c_{k,sp}^{a,t}\right)\right) + dv_2^{-,a,t} = Pg^{a,t} \tag{3.19}$$

$$\sum_{p=1}^{P}\left(\sum_{k\in MK_p}\left(mu_k \times v_k^{d,t}\right)\right) + dv_3^{-,d,t} = MUg^{d,t} \tag{3.20}$$

$$\sum_{p=1}^{P}\left(\sum_{k\in MK_p}\left(ob_k \times z_k^{d,t}\right)\right) + dv_4^{-,d,t} = OBg^{d,t} \tag{3.21}$$

$$\sum_{p=1}^{P}\left(\sum_{k\in MK_p}\left(ib_k \times u_k^{d,t}\right)\right) + dv_5^{-,d,t} = IBg^{d,t} \tag{3.22}$$

$$\sum_{p=1}^{P}\left(\sum_{k\in MK_p}\left(cs_k \times q_k^{d,t}\right)\right) + dv_6^{-,d,t} = CSg^{d,t} \tag{3.23}$$

Where;

$Mg^{l,t}$	Mining goal (tonnes) in period t at location l.
$Pg^{a,t}$	processing goal (tonnes) in period t at destination a.
$MUg^{d,t}$	Muskeg goal (tonnes) in period t at destination d.
$OBg^{d,t}$	Overburden dyke material goal (tonnes) in period t at destination d.
$IBg^{d,t}$	Interburden dyke material goal (tonnes) in period t at destination d.
$CSg^{d,t}$	Tailings coarse sand dyke material goal (tonnes) in period t at destination d.

3.3.7 MILGP model constraints

3.3.7.1 Production targeting constraints

Equations (3.24) and (3.25) define the APT constraints that automatically determine the maximum allowable annual capacities for material mined and processed depending on the deposit configuration. Equations (3.24) and (3.25) control the cumulative periodic tonnage fluctuation ($CPTF_m$, $CPTF_p$) for material mined and processed ensuring that uniform schedules are generated. The APT constraints have the capability to determine the maximum achievable production level in each period throughout the mine life, enabling the deployment of sophisticated mining and plant capacity estimates for the mining operation. Equations (3.24) and (3.25) are similar to Equation (3.18) and (3.19) as they both control mining and processing targets. However, Equation (3.18) and (3.19) require the inputs of annual targets while Equation (3.24) and (3.25) require cumulative periodic tonnage fluctuation. Either of these sets of equations are used at any one time as implemented in Case Studies I and II.

$$\sum_{t=1}^{T}\left(\sum_{\substack{p\in MP_j\\ p\in NP_m}}\left(o_p+mu_p+ob_p+ib_p+w_p\right)\times\left(y_p^{l,t+1}-y_p^{l,t}\right)\right)\leq CPTF_m \tag{3.24}$$

$$\sum_{t=1}^{T}\left(\left(\sum_{\substack{k\in MK_p\\ p\in NP_m}}\left(x_k^{a,t+1}+\sum_{sp=1}^{SP}c_{k,sp}^{a,(t-ts)+1}\right)-\left(x_k^{a,t}+\sum_{sp=1}^{SP}c_{k,sp}^{a,t-ts}\right)\right)\times o_k\right)\leq CPTF_p \tag{3.25}$$

Where:

$CPTF_m$	Cumulative periodic mining tonnage fluctuation (tonnes).
$CPTF_p$	Cumulative periodic processing tonnage fluctuation (tonnes).

3.3.7.2 Stockpiling capacity constraints

Constraints that control the upper and lower capacity limits for stockpile pads are presented in Equations (3.26) and (3.27). These equations control the amount of ore sent to stockpile sp in period t. The material sent to the stockpile in period t is reclaimed in period $t+ts$. The planner controls the upper and lower capacity limits for stockpile bins and the stockpiling duration, ts.

$$\sum_{sp=1}^{SP}\sum_{k=1}^{K}\left(o_k \times s_k^{sp,t}\right) \le \overline{os}^{sp,t} \tag{3.26}$$

$$\sum_{sp=1}^{SP}\sum_{k=1}^{K}\left(o_k \times s_k^{sp,t}\right) \ge \underline{os}^{sp,t} \tag{3.27}$$

Where:

$\overline{os}^{sp,t}$ Upper bounds of ore tonnage sent to stockpile sp from mining-cut k in period t

$\underline{os}^{sp,t}$ Lower bounds of ore tonnage sent to stockpile sp from mining-cut k in period t

3.3.7.3 Bitumen and fines grade blending constraints

The MILGP bitumen and fines grade blending constraints ensure that the quality requirements of the processing plant, stockpile and dyke construction destinations are achieved. These constraints are formulated using Equations (3.28) to (3.37). Ore bitumen grade blending constraints ensure the extracted ore from mining-cut k within mining-panel p sent to either processing destination a or to stockpile sp in period t meets the grade quality requirements. Ore bitumen grade blending constraints are formulated using Equations (3.28) to (3.31). Equations (3.28) and (3.29) control the limiting upper and lower bounds ore bitumen grade sent from the mine and stockpile to the processing plant. Equations (3.30) and (3.31) control the limiting upper and lower bounds ore bitumen grade sent from the mine to the stockpile.

$$\sum_{p=1}^{P}\left(\sum_{k\in MK_p} g_k^e \times o_k \times \left(x_k^{a,t} + c_{k,sp}^{a,t-ts}\right)\right) - \overline{g}^{a,e,t}\sum_{p=1}^{P}\left(\sum_{k\in MK_p} o_k \times \left(x_k^{a,t} + c_{k,sp}^{a,t-ts}\right)\right) \le 0 \tag{3.28}$$

$$\underline{g}^{a,e,t}\sum_{p=1}^{P}\left(\sum_{k\in MK_p} o_k \times \left(x_k^{a,t} + c_{k,sp}^{a,t-ts}\right)\right) - \sum_{p=1}^{P}\left(\sum_{k\in MK_p} g_k^e \times o_k \times \left(x_k^{a,t} + c_{k,sp}^{a,t-ts}\right)\right) \le 0 \tag{3.29}$$

$$\sum_{p=1}^{P}\left(\sum_{k\in MK_p} g_k^e \times o_k \times s_k^{sp,t}\right) - \overline{g}^{a,e,t}\sum_{p=1}^{P}\left(\sum_{k\in MK_p} o_k \times s_k^{sp,t}\right) \le 0 \tag{3.30}$$

$$\underline{g}^{a,e,t}\sum_{p=1}^{P}\left(\sum_{k\in MK_p} o_k \times s_k^{sp,t}\right) - \sum_{p=1}^{P}\left(\sum_{k\in MK_p} g_k^e \times o_k \times s_k^{sp,t}\right) \le 0 \tag{3.31}$$

Ore fines grade blending constraints ensure that the extracted ore from mining-cut k within mining-panel p sent to either processing destination a or to stockpile sp in period t meets the fines requirements. Interburden fines grade blending constraints also ensure that the interburden fines for dyke construction are within the upper and lower limits required. Fines grade blending constraints are formulated using Equations (3.32) to (3.37). Equations (3.32) and (3.33) represent inequality constraints used to control the limiting upper and lower bounds grade of ore fines sent from the mine and stockpile to the processing plant. Equations (3.34) and (3.35) represent inequality constraints used to control the limiting upper and lower bounds grade of ore fines sent from the mine to the stockpile. Equations (3.36) and (3.37) represent inequality constraints used to control the limiting upper and lower bounds grade of interburden dyke material fines sent from the mine to dyke construction destinations.

$$\sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p\\ p\in NP_m}} fn_k^e \times o_k \times \left(x_k^{a,t}+c_{k,sp}^{a,t-ts}\right)\right) - \overline{fn}^{a,t,e}\sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p\\ p\in NPm}} o_k \times \left(x_k^{a,t}+c_{k,sp}^{a,t-ts}\right)\right)\le 0 \tag{3.32}$$

$$\underline{fn}^{a,t,e}\sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p\\ p\in MPj}} o_k \times \left(x_k^{a,t}+c_{k,sp}^{a,t-ts}\right)\right) - \sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p\\ p\in MP_j}} fn_k^e \times o_k \times \left(x_k^{a,t}+c_{k,sp}^{a,t-ts}\right)\right)\le 0 \tag{3.33}$$

$$\sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p\\ p\in MP_j}} fn_k^e \times o_k \times s_k^{sp,t}\right) - \overline{fn}^{a,t,e}\sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p\\ p\in MPj}} o_k \times s_k^{sp,t}\right)\le 0 \tag{3.34}$$

$$\underline{fn}^{a,t,e}\sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p\\ p\in MPj}} o_k \times s_k^{sp,t}\right) - \sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p\\ p\in MP_j}} fn_k^e \times o_k \times s_k^{sp,t}\right)\le 0 \tag{3.35}$$

$$\sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p\\ p\in MP_j}} fn_k^{ib} \times ib_k \times u_k^{d,t}\right) - \overline{fn}^{d,t,ib}\sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p\\ p\in MPj}} ib_k \times u_k^{d,t}\right)\le 0 \tag{3.36}$$

$$\underline{fn}^{d,t,ib}\sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p\\ p\in MPj}} ib_k \times u_k^{d,t}\right) - \sum_{p=1}^{P}\left(\sum_{\substack{k\in MK_p\\ p\in MP_j}} fn_k^{ib} \times ib_k \times u_k^{d,t}\right)\le 0 \tag{3.37}$$

Where:

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

$\overline{g}^{a,t,e}$	Upper bound on the required average head grade of element e in period t at processing destination a.
fn_k^e	The average percent of fines in the ore portion of mining-cut k.
$\overline{fn}^{a,t,e}$	Upper bound on the required average fines percent of ore in period t at processing destination a.
$\underline{fn}^{a,t,e}$	Lower bound on the required average fines percent of ore in period t at processing destination a.
fn_k^{ib}	The average percent of fines in interburden dyke material portion of mining-cut k.
$\overline{fn}^{d,t,ib}$	Upper bound on the required average fines percent of interburden dyke material in period t at dyke construction destination d.
$\underline{fn}^{d,t,ib}$	Lower bound on the required average fines percent of interburden dyke material in period t at dyke construction destination d.

3.3.7.4 Variables control constraints

In the MILGP model, all decision variables used to control mining, processing, stockpiling, reclamation material, dyke materials and goal deviations are continuous variables. Inequality Equation (3.38) ensures that all material mined as ore (sent to either processing destination a or stockpile sp) and all reclamation and dyke materials extracted from the mining-cuts belonging to mining-panel p in period t are less than or equal to the total material extracted from mining-panel p in period t from any mining location.

Equation (3.39) ensures that the total fractions of ore mined from a mining-cut (sent to either processing destination a or stockpile sp) is less than or equal to one. Equation (3.40) ensures that the fraction of ore extracted from mining-cut k and sent to the stockpile sp in period $t-ts$ must be equal to the fraction of ore reclaimed from the stockpile sp and sent to the processing destination a in period t, where ts is the stockpiling duration. It has been assumed that there is a stockpile bin for extra mined ore per each period to ensure that the exact amount and quality of material sent previously is reclaimed.

Equation (3.41) ensures that the fraction of TCS dyke material produced from processed ore is less than or equal to the fraction of ore sent from the mine and stockpile to the processing plant in each period. Equation (3.42) ensures that the total fractions of mining-panel p

extracted from the mine and sent to different destinations in different periods is less than or equal to one. Equations (3.43) ensures that the fractions of reclamation material from mining-panel p extracted from the mine and sent to different destinations in different periods is less than or equal to one. Equations (3.44) to (3.46) ensure that the fractions of dyke materials from mining-panel p extracted from the mine (OB and IB) or generated from the processing plant (TCS) and sent to different destinations in different periods is less than or equal to one.

$$\left[\sum_{d=1}^{D}\sum_{sp=1}^{SP}\sum_{a=1}^{A}\sum_{\substack{k\in MK_p\\ p\in MP_j}}\left(o_k\times x_k^{a,t}+o_k\times s_{k,sp}^{a,t}+mu_k\times v_k^{d,t}+ob_k\times z_k^{d,t}+ib_k\times u_k^{d,t}\right)\right]\leq \left[\sum_{l=1}^{L}\sum_{p\in MP_j}\left[y_p^{l,t}\left(o_p+mu_p+ob_p+ib_p+w_p\right)\right]\right] \tag{3.38}$$

$$\sum_{a=1}^{A}\sum_{sp=1}^{SP}\sum_{t=1}^{T}\left(x_k^{a,t}+s_{k,sp}^{a,t}\right)\leq 1 \tag{3.39}$$

$$\sum_{a=1}^{A}\sum_{sp=1}^{SP}\sum_{t=1}^{T}\left(c_{k,sp}^{a,t}-s_{k,sp}^{a,t-ts}\right)=0,\quad t-ts\geq 0 \tag{3.40}$$

$$\sum_{d=1}^{D}\sum_{t=1}^{T}q_k^{d,t}\leq\sum_{a=1}^{A}\sum_{t=1}^{T}x_k^{a,t}+\sum_{sp=1}^{SP}\sum_{t=1}^{T}c_{k,sp}^{a,t} \tag{3.41}$$

$$\sum_{d=1}^{D}\sum_{t=1}^{T}y_p^{d,t}\leq 1 \tag{3.42}$$

$$\sum_{d=1}^{D}\sum_{t=1}^{T}v_p^{d,t}\leq 1 \tag{3.43}$$

$$\sum_{d=1}^{D}\sum_{t=1}^{T}z_p^{d,t}\leq 1 \tag{3.44}$$

$$\sum_{d=1}^{D}\sum_{t=1}^{T}u_p^{d,t}\leq 1 \tag{3.45}$$

$$\sum_{d=1}^{D}\sum_{t=1}^{T}q_p^{d,t}\leq 1 \tag{3.46}$$

3.3.7.5 Mining-panels extraction precedence constraints

The five precedence constraints presented in Equations (3.47) to (3.51) are used to define the precedence of extraction sequence for each mining panel p based on its spatial location. These equations use the binary integer decision variable b_p^t. This variable is equal to one if the extraction of mining-panel p has started by or in period t; otherwise, it is zero. Specifically:

- Equation (3.47) defines the vertical mining precedence. Prior to the extraction of a specific mining-panel, all the mining-panels above it must be extracted so that the mining-panel is accessible. The set $IP_p\left(Z''\right)$ represents the set of immediate mining-panels that are above mining-panel p.
- Equation (3.48) defines the horizontal mining precedence. Prior to the extraction of a specific mining-panel, all the mining-panels in a specified horizontal mining direction on a level must be extracted. The set $IH_p\left(Z'\right)$ represents the set of immediate mining-panels in the specified horizontal mining direction.
- Equation (3.49) defines the pushback mining precedence. Equation (3.49) checks all the mining-panels within the immediate predecessor pushback that must be extracted prior to the extraction of mining-panels in pushback j. The set $MP_j\left(H''\right)$ represents the set of mining-panels in the predecessor pushback.
- Equation (3.50) ensures that mining-panel p can only be extracted if it has not been extracted before.
- Equation (3.51) ensures that once the extraction of a mining-panel starts in period t, this mining-panel is available for extraction during the subsequent periods.

$$b_p^t - \sum_{l=1}^{L}\sum_{m=1}^{t} y_{u_1}^{l,m} \le 0, \quad u_1 \in IP_p\left(Z''\right) \tag{3.47}$$

$$b_p^t - \sum_{l=1}^{L}\sum_{m=1}^{t} y_{u_2}^{l,m} \le 0, \quad u_2 \in IH_p\left(Z'\right) \tag{3.48}$$

$$b_p^t - \sum_{l=1}^{L}\sum_{m=1}^{t} y_{u_3}^{l,m} \le 0, \quad u_3 \in MP_j\left(H''\right) \tag{3.49}$$

$$\sum_{l=1}^{L}\sum_{m=1}^{t} y_p^{l,m} - b_p^t \le 0 \tag{3.50}$$

$$b_p^t - b_p^{t+1} \le 0 \tag{3.51}$$

3.3.7.6 In-pit tailings-cells optimization constraints

The six constraints presented in Equations (3.52) to (3.57) are used to optimize the capacity, shape and location of the tailings-cells. The process depends on the mining-cells size and spatial location. These equations use a continuous decision variable $tv_m^{l,t}$ to allow fractional extraction and backfilling of the mining-cells and a binary integer decision variable $bv_m^{l,t}$ to monitor the mining-cells extraction sequence.

Equation (3.52) connects the production schedule with the mining-cells extraction. The mining operation needs to stay ahead of the creation of tailings-cells and subsequently dyke construction. The mining-cell to be mined in period t from location l is controlled using the integer variable $bv_m^{l,t}$. For each mining-cell, there is a set $NP_p(S) \subset P$ defining the mining-panels within this specific mining-cell. All the mining-panels must be extracted to make this mining-cell ready to be a part of a tailings-cell. S is the total number of mining-panels in a mining-cell. Equations (3.53) and (3.54) control the upper and lower bounds of the tailings-cells capacity. The mining-cells volume that is available for backfilling in period t is represented using the continuous variable $tv_m^{l,t}$.

The shape of the tailings-cells is controlled using Equation (3.55). Equation (3.55) defines the set $NC_p(C) \subset M$ of active mining-cells that can be used to create a tailings-cell. Prior to the creation of a tailings-cell, the mining-cells, C, will be active for the optimizer to choose from to create the tailings-cell. Equation (3.56) ensures that a mining-cell can only be extracted if it has not been extracted before. Equation (3.57) ensures that once the extraction of a mining-cell starts in any period, this mining-cell is available for extraction during the subsequent periods.

$$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T} s \times y_p^{l,t} - bv_m^{l,t} \ge 0 \tag{3.52}$$

$$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T} vc_m^{l,t} \times tv_m^{l,t} \le VU \tag{3.53}$$

$$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T} vc_m^{l,t} \times tv_m^{l,t} \geq VL \tag{3.54}$$

$$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T} bv_m^{l,t} \leq C \tag{3.55}$$

$$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T} tv_m^{l,t} - bv_m^{l,t} \leq 0 \tag{3.56}$$

$$bv_m^{l,t} - bv_m^{l,t+1} \leq 0 \tag{3.57}$$

Where:

VL Lower bound of the tailings-cells capacity in cubic meters.

VU Upper bound of the tailings-cells capacity in cubic meters.

3.3.7.7 Non-negativity constraints

Equation (3.58) ensures that the decision variables for mining, processing, stockpiling (ore sent and reclaimed), RM, OB, IB and TCS dyke materials are non-negative in addition to the decision variables that control the tailings-cells designs optimization process. Equation (3.59) ensures that the deviational decision variables that support the goal functions are non-negative as well.

$$\mathrm{y}_p^{l,t},\ x_k^{a,t},\ \mathrm{s}_{k,sp}^{d,t},\ \mathrm{c}_{k,sp}^{a,t},\ v_k^{d,t},\ z_k^{d,t},\ u_k^{d,t},\ q_k^{d,t}\ ,tv_m^{l,t}\ ,bv_m^{l,t} \quad \geq 0 \tag{3.58}$$

$$dv_1^{-,l,t},\ dv_2^{-,a,t},\ dv_3^{-,d,t},\ dv_4^{-,d,t},\ dv_5^{-,d,t},\ dv_6^{-,d,t} \quad \geq 0 \tag{3.59}$$

3.4 MILGP formulation implementation

The formulation and implementation of the uncertainty-based MILGP model begins with defining its objective function, goal functions and the constraints. These components interact together based on the conceptual mining model and the economic block model in an optimization framework to achieve the set objectives. The conceptual mining model is used to manage the production and waste disposal requirements. This results in an integrated oil sands mine and waste management plan that creates profitability and sustainability.

MATLAB (Mathworks, 2017) is used as the numerical modeling platform to setup the problem and IBM/CPLEX (ILOG, 2017) is used as the optimization solver. The MILGP model input interface enables the setting up of the block model data, production, reclamation and dyke material requirements, as well as parameters defining the waste management strategy. Matlab is used to create the numerical model of the objective function, goal functions and constraints of the MILGP formulation in the form of matrices to be passed on to IBM/CPLEX for solution.

3.4.1 Numerical modeling

IBM/CPLEX solver (ILOG, 2017) that uses branch and cut algorithm is capable of solving large-scale mine planning optimization problems based on mathematical programming models. 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; Mitchell, 2009). A gap tolerance known as EPGAP is an optimization termination criterion in CPLEX. The planner sets the EPGAP as 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. EPGAP is a measure of optimality that terminates CPLEX once a feasible integer solution within the set EPGAP is found.

3.4.2 General formulation

Equations (3.60) to (3.62) are the general structure for MILP problems as required by IBM CPLEX (ILOG, 2017).

$$\min_{dv} f(dv) = cf^{T}.dv \tag{3.60}$$

Subject to:

$$dv_L \le dv \le dv_U \tag{3.61}$$

$$b_L \le A.dv \le b_U \tag{3.62}$$

Where

- cf is the coefficient factors vector ($i \times 1$) of the linear objective function of the MILP model;
- dv is the decision variables vector ($i \times 1$) of the MILP model;
- dv_L and dv_U are the lower and upper bounds vectors ($i \times 1$) of the decision variables;
- A is the constraints coefficient matrix ($j \times i$) of the MILP model.

- b_L and b_U are the lower and upper bounds vectors ($i \times 1$) of the constraints. Equality constraints are defined by setting the lower bounds equal to the upper bounds for the respective elements of vectors b_L and b_U

Detailed formulation and programming techniques in implementing the MILGP model for oil sands long term production planning and waste management can be found in Ben-Awuah et al. (2018).

3.5 Summary and conclusions

This chapter has presented the uncertainty-based MILGP model that integrates oil sands long-term production planning and waste disposal management. The interactions and interrelations of the various processes and procedures in an oil sands conceptual mining system were discussed. The model provides an optimum production schedule that aims to: (i) maximize the NPV of the oil sands mining operation; (ii) maximize the pseudo backfilling revenue through backfilling of in-pit mined areas with tailings; (iii) minimize the risk associated with the production schedule; (iv) minimize reclamation material rehandling costs; (v) minimize the dyke construction cost; and, (vi) minimize deviations from production goals. 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 modeling development similar to Ben-Awuah et al. (2018).

CHAPTER 4

APPLICATION OF THE MILGP FRAMEWORK AND DISCUSSION OF RESULTS

4.1 Background

The research proceeds with the application and verification of the developed model. This chapter presents discussions on the experimental design and application methodology for the mathematical programming framework for an oil sands dataset, and the analysis of results for three case studies. The mathematical formulations, mining concepts and strategies presented in Chapter 3 were developed as numerical models representing the uncertainty-based MILGP framework application in this chapter. An ordinary kriging methodology is used to construct a geologic block model. The block model is used to define the orebody for reserve estimation and the economic block model for the oil sands deposit. The UPL of the oil sands mine was generated using Whittle software (Geovia Dassault Systems, 2017), based on the 3D LG algorithm (Lerchs and Grossmann, 1965). The optimized pit shell serves as a guide in designing the final pit in GEMS software (Geovia Dassault Systems, 2018). The blocks within the UPL were used as the input data for the MILGP model for subsequent integrated LTPP and waste management.

A set of nested pushbacks are generated based on the methodology developed by Lerchs and Grossmann (1965). An agglomerative hierarchical clustering algorithm is used in clustering blocks within each intermediate pushback into mining-cuts (Tabesh and Askari-Nasab, 2011). The intersection between benches and intermediate pushbacks are used in creating mining-panels. Mining-cells are created by dividing the final pit into a pattern of evenly spaced areas. Each area represents a vertical unit that spans from the topography to the bottom of the pit and is referred to as a mining-cell, m. The mining-cuts are used to control ore material tonnage for the processing plant while mining-panels are used to control total tonnage of pit material extracted. Mining-cells are used to control the design of tailings-cells for waste management. MATLAB (Mathworks, 2017) application is used as the programming platform to define the MILGP framework and IBM/CPLEX (ILOG, 2017) solver which uses a branch and cut optimization algorithm is employed to solve the resulting production scheduling problem. The model was run on a ThinkStation with CPU E5-1650 v4 at 3.60 GHz and 64.0 GB of RAM. The three case studies implemented demonstrate the contributions this research makes in oil sands mine planning and waste management.

Section 4.2 explains the concept of verifying the uncertainty-based MILGP model. The experimental design for the model implementation is presented in Section 4.3. Information on the oil sands deposit final pit design characteristics, the economic parameters and material quality requirements are presented in Section 4.4. Case study I, which is presented in Section 4.5, estimates the production schedule financial risk associated with grade uncertainty and reinforces how waste management is successfully integrated with oil sands mine planning. Case study II in Section 4.6 highlights the use of APT constraints for oil sands production scheduling considering ORS content in processing plant recovery in addition to the traditional use of bitumen grade and fines content. Finally, Case Study III in Section 4.7 investigates the integration of oil sands mine planning and tailings-cells optimization for waste management. The developed APT constraints and processing plant recovery factor considering ORS content are deployed.

4.2 Verification and validation of the uncertainty-based MILGP model

Verification aims to determine whether a system has been designed to the set standard or specification. To verify the implementation of the uncertainty-based MILGP model, it is necessary to determine whether the developed framework conforms to the specifications of the objectives it sought for. The developed formulations are implemented on a small oil sands dataset to ensure it is behaving as intended and subsequently the results are analyzed for verification and validation. The verification steps are as follows:

- The model generated uniform and practical production schedules all through the life of mine using the mining and processing goal functions or the automated production targeting constraints. The generated NPV was within known limits of optimality;
- The practical inspection of schedules and the extraction sequence of the mining-panels was uniform and followed the defined directional mining strategy;
- The upper and lower bound of the stockpile were easy to control and all stockpiled ore was reclaimed within the limited duration set by the planner;

- The bitumen and fine grade profiles were within the upper and lower bounds as required by AER for the bitumen and the requirements for dyke construction;
- The model quantified and minimized the grade uncertainty risk associated with production schedule;
- The bitumen processing recovery was modified using ORS content and the generated schedules and NPV were as expected;
- The tailings-cells were generated with capacities within the upper and lower bounds, with reasonable shape and location.

The available mine planning software packages used by industry such as Mintec (Minesight, 2014), MineMax (MineMax planner, 2018) and Whittle (Geovia Dassault Systems, 2017) have limited benefit due to the nature of their modeling and solution techniques (Moreno et al., 2016). Whittle, the leading industry standard software that was used in this research to generate the UPL, does not contain tools for integrated oil sands waste management. Also, it does not use optimization techniques to model the stockpile (Moreno et al., 2016). Therefore, Whittle cannot be used for validation of the developed model. The practicality of the generated production and waste disposal schedules has been considered as a measure for model validation. The proposed model was implemented on a real-size oil sands dataset and the obtained results were analyzed in detail in terms of uniformity and practicality of production schedules, stockpile capacity boundaries, bitumen and fine grade profiles, bitumen processing recovery based on ORS content and the design of tailings-cells as well as quantification and minimization of grade uncertainty risk. All the steps, workflow and parameter calibration for the formulations are documented in an implementation manual as well as the codes developed for the research.

As highlighted in Chapter 3, the main objectives of the MILGP framework are to (i) maximize the NPV of the mining operation; (ii) maximize the pseudo backfilling revenue through backfilling the in-pit mined-out areas; (iii) minimize financial risks associated with the production schedule; (iv) minimize the reclamation and dyke construction costs; and (v) minimize deviations from the production goals. These objectives are subject to practical and technical constraints, and goals in oil sands mining. The MILGP framework includes two implementation approaches: Implementation A uses predetermined pushback mining strategy for waste management and is deployed for Case studies I and II; Implementation B optimizes tailings-cells designs for waste management and is deployed for Case study III.

4.3 Experimental design layout for implementation of the MILGP model

A solution scheme based on branch and cut optimization algorithm (Horst and Hoang, 1996; Wolsey, 1998; Mitchell, 2009) is used for implementation of the MILGP framework for the integrated oil sands mining and waste management problem. To obtain consistent experimental results, the solution scheme used in solving the problem should capture the complete definition of the integrated oil sands production scheduling and waste disposal planning problem. That includes the conceptual mining framework, the tailings storage management strategy, the production schedule financial risk associated with grade uncertainty, limited duration stockpiling, and modified processing plant recovery factor based on ORS content. The modelling assumptions stated are based on prior knowledge of practical mining environments and the framework for the application of operations research methods in mining.

The uncertainty-based MILGP framework presented in Chapter 3 is verified with three case studies using dataset from an oil sands mining company. Figure 4-1 shows the summary of the case studies in this thesis. Case study I includes two implementation scenarios showcasing different aspects of the developed MILGP framework. These scenarios are designed to highlight features of the MILGP framework including 1) integrating waste management, reclamation works, and limited duration stockpiling strategy into oil sands mine planning (Scenario I-1); and 2) estimating the production schedule financial risk associated with grade uncertainty (Scenario I-2). For both scenarios, a fixed processing plant bitumen recovery of 90% is assumed.

Case study II outlines the determinations of mining and processing annual targets as part of the production scheduling optimization process. Two implementation scenarios highlighting different aspects of the developed MILGP model are 1) determining the NPV considering revenue calculated based on AER recovery (Scenario II-1); and 2) determining the NPV considering revenue calculated based on ORS recovery (Scenario II-2). For both scenarios, a 2-year pre-stripping production requirement is enforced.

Case Study III focuses on a different approach for creating tailings-cells to support the waste management plan. Four implementation scenarios are deployed based on changing the size and number of mining-cells and their impact on the tailings-cells designs and NPV. Figure 4-1 summarizes the differences between the case studies.

For all case studies, mining, processing, reclamation and dyke material scheduling are implemented with mining-panels as the mining scheduling units and mining-cuts as the processing, reclamation and dyke material scheduling units. Additionally, mining-cells are implemented as the scheduling units for tailings-cells designs in Case Study III. The MILGP framework is deployed using IBM CPLEX solver (ILOG, 2017) which uses a branch and cut optimization algorithm where an optimization termination criterion, EPGAP, is set up to define how far our generated solution is from the optimal solution; subject to the practical and technical mining constraints.

Cumulative development of MILGP framework and implementation		Objective Function	Implementation Parameters	Exclusions	
Case Study I	**Scenario I-1**	Revenue + Revenue$_{sp}$ + Pseudo Revenue from backfilling operation - mining Cost - grade uncertainty Cost - ore stockpiling Cost - reclamation material Cost - dyke material Cost	Goal functions for mining and processing capacities (Fixed recovery)	• No backfilling • No production schedule financial risk assessment (no grade uncertainty cost)	**Implementation A**: Predetermined pushbacks for waste management
	Scenario I-2			• No stockpiling • No backfilling • No dyke material • No reclamation material	
Case Study II	**Scenario II-1**		APT* constraints for mining and processing capacities (AER recovery)	• No backfilling • No production scheduling financial risk assessment (no grade uncertainty cost)	
	Scenario II-2		APT* constraints for mining and processing capacities (ORS recovery)		
Case Study III	**Scenario III-1**		APT* constraints for mining and processing capacities (ORS recovery)	• No production scheduling financial risk assessment (no grade uncertainty cost)	**Implementation B**: Tailings-cells optimization for waste management
	Scenario III-2				
	Scenario III-3				
	Scenario III-4				

APT*: Automated Production Targeting

Figure 4-1: Summary of experimental design layout for case studies

4.4 General information on case studies data

Table 4-1 summarizes the details of the oil sands final pit and the materials contained in it while Table 4-2 and Table 4-3 give the details of the economic parameters and material quality requirements respectively. It should be noted that haulage cost is part of the extra cost mentioned in Equations (3.6) to (3.9). The discount rate mentioned in Table 4-2 is used to discount the revenue from the mining project over time. This parameter is a function of risk. This means as risk increases the discount rate should be increased as well. It has been found that the NPV is sensitive to the discount rate. The NPV decreases when a higher discount rate is used as it reduces the revenue generated in later years. The sensitivity of NPV to a range of discount rates between 5% and 12% has been tested. The results show that a higher NPV is generated at a 5% discount rate and dropped significantly (about 32%) at 12% discount rate (Badiozamani, 2014). This implies that a realistic rate should be chosen especially in feasibility study analysis. However, for this research, as the focus is to develop a robust mathematical model to be used in decision making, all case studies were carried out at a 10% discount rate.

Table 4-1: Oil sands deposit final pit design characteristics

Description (unit)	Value	Description (unit)	Value
Total tonnage of material (Mt)	5,735.6	Number of blocks	79,095
Total ore tonnage (Mt)	1,906.9	Number of mining-cuts	4,494
Total TCS dyke material tonnage (Mt)	1,813.83	Number of mining-panels	131
Total OB dyke material tonnage (Mt)	1,515.51	Number of benches	8
Total IB dyke material tonnage (Mt)	1,813.83	Block dimensions (m)	50 × 50 × 15
Total RM tonnage (Mt)	373.78	Mine life (years)	25
Stockpiling duration limit (years)	2		

Table 4-2: Economic parameters

Parameter (unit)	Value	Parameter (unit)	Value
Mining cost ($/tonne)	4.6	OB dyke material cost ($/tonne)	1.38
Processing cost ($/tonne)	5.03	IB dyke material cost ($/tonne)	1.38
Ore re-handling cost ($/tonne)	0.5	RM cost ($/tonne)	0.5

Selling price ($/bitumen %mass)	4.5	Discount rate (%)	10.00
TCS dyke material cost ($/tonne)	0.92		

Table 4-3: Material quality requirements

Parameter (unit)	**Value**
Upper / Lower bound of ore bitumen grade (wt%)	16 / 7
Upper / Lower bound of ore fines percent (wt%)	30 / 0
Upper / Lower bound of IB dyke material fines percent (wt%)	50 / 0

4.5 Case study I: Estimation of production schedule financial risk due to grade uncertainty

4.5.1 Introduction to Case study I

Geological uncertainty is usually present because of lack of enough geological information. Grade uncertainty affects the optimality of the production scheduling problem. Thus, an uncertainty-based mathematical programming model is developed based on MILGP. The developed model uses kriged estimates with a variance penalty scheme to minimize the financial risk from grade uncertainty associated with the production schedule. The developed model is capable of simultaneously integrating waste management into the production schedule for oil sands mining. A limited duration stockpiling option is introduced in the model for the extra-mined ore. The model aims to maximize the NPV, minimize reclamation material rehandling cost, minimize dyke construction cost and minimize the production schedule financial risk from grade uncertainty. The uncertainty-based model is implemented for an oil sands mine case study with two scenarios.

4.5.2 Block modeling, variography and kriging

For oil sands resource modeling, it has been found that ordinary kriging (OK) with a large number of search data results in a low observed mean squared error (Deutsch et al., 2014). This makes OK a preferred resource estimation technique. The creation of interpolation profiles was required to determine the spatial correlation between the observations. A semi-variogram was used for this purpose. Semi-variogram models are used in kriging estimation procedures, and help to define search parameters for interpolation techniques. To create a semi-variogram model, an experimental semi-variogram was calculated for the oil sands McMurray Formation (MMF) being used as case study in Geovia GEMS software (Geovia

Dassault Systems, 2018). Omnidirectional variograms for bitumen grades were prepared to identify the sill while vertical variograms were used to identify the nugget effect. Primary variogram maps were calculated to determine the orientation of the major axis in the presence of anisotropy. The directional horizontal variogram (major axis) and the secondary variogram maps (semi-major axis) were calculated and modeled. The variograms were extracted along the ellipse axis. The major, semi-major and minor axes were selected for final modeling. The spatial continuity for bitumen and fines grades were modeled with semi-variograms, so that patterns and anisotropy are incorporated into the estimation using OK. The general equation for anisotropic spherical variogram is given by Equation (4.1). The semi-variogram models for bitumen and fines consist of two nested spherical models are defined in Table 4-4. Search ellipse and semi-variogram profiles were updated for the semi-variogram models and used for interpolation within the ore rock types for bitumen and fines grades.

Ordinary Kriging estimates were calculated for each block in the block model. Using the concept of Block Kriging (Gringarten and Deutsch, 2001), these kriging estimates are used together with the sill, the nugget effect and the range to calculate the OK grade and variance for each mining-cut and mining-panel in the ultimate pit limit (UPL). The estimated kriged variances for all mining-panels are used to calculate the frequency and probability of occurrence of the kriged variance. The latter is used to calculate the expected variance for the mining-panels. The kriged estimates together with a variance penalty scheme are used for mine planning to estimate the production schedule financial risk associated with grade uncertainty as explained in Section 4.5.3.

$$\gamma(h)=\begin{cases} C_0 & if\ \ h=0.0 \\ C_0+C\times\left(1.5\left(\frac{h}{r}\right)-0.5\left(\frac{h}{r}\right)^3\right) & if\ \ 0<h<r \\ C_0+C & if\ \ h\geq r \end{cases} \tag{4.1}$$

Table 4-4: Semi-variogram models for bitumen and fines grades

Element	**Nugget Effect, C_0**	**Spherical 1**		**Spherical 2**	
		Sill, C	Range, r	Sill, C	Range, r
Bitumen	0.026	0.673	46.34	0.292	46.61
Fines	0	0.6	29.15	0.4	44.13

4.5.3 The effect of grade uncertainty and a variance penalty scheme

Grade uncertainty affects the metal content in the material sent to the plant which will subsequently affect the NPV of the project. This uncertainty exists because of the ignorance and lack of knowledge of the researchers. It is not an inherent feature of the deposit (Isaaks and Srivastava, 1989). For this research, the effect of grade uncertainty on the mine plan is investigated through the grade variance. The technique adopted is to minimize the grade-variance effect while the expected value of NPV is maximized. This approach works based on the mean-variance method referred to as the Modern Portfolio Theory (MPT) for risk-based portfolio optimization (Markowitz, 1952). MPT requires calculating the expected value and expected variance of a portfolio’s return considering a weighted average combination of the assets’ return (Figure 4-2). MPT is a quadratic optimization problem that maximizes the expected return and minimizes the standard deviation. The decision variables are the weights or the portions of each asset’s contribution towards the objective function.

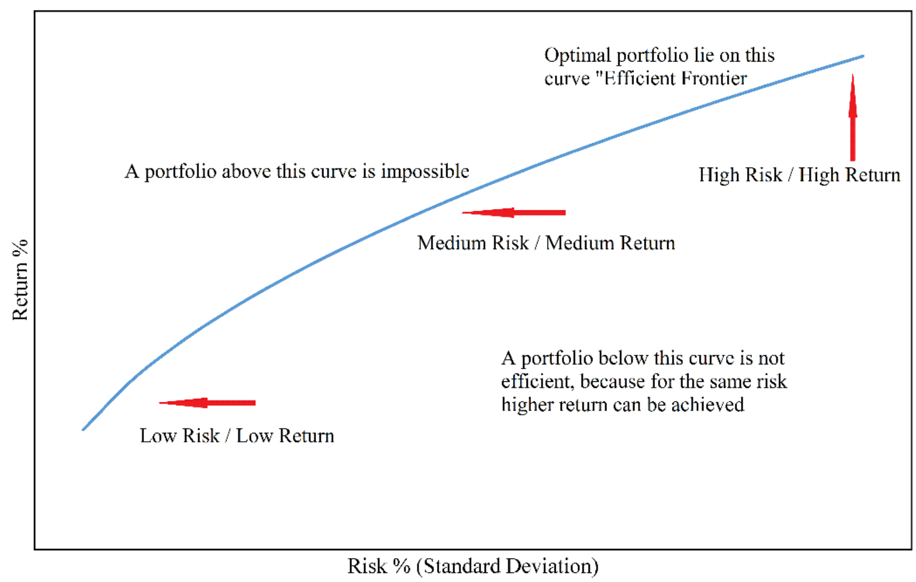


Figure 4-2: Return versus standard deviation, modified after dos Santos and Brandi (2017)

In this research, the mean-variance method is adapted and applied to production planning optimization in the presence of grade uncertainty using an uncertainty-based MILGP model to reduce mine project risk. The kriged mean and kriged variance for each mining block, mining-cut and mining-panel are calculated as well as the Economic Block Values (EBVs). The main concept of the mean-variance method deployed for long-term mine planning is to find the low-variance mining blocks, mining-cuts or mining-panels to be extracted earlier, such that the project NPV is maximized and the extraction of high-variance mining blocks, mining-cuts or mining-panels is deferred to later years to minimize risk.

In the proposed uncertainty-based MILGP model, the kriged variance for mining-panels together with a penalty scheme is used to minimize the risk associated with the production schedule. Applying the penalty postpones extraction of high variance mining-panels to later years. Figure 4-3 shows the kriged variance and expected variance for mining-panels within the UPL for the case study. The research investigates two options in applying the variance penalty for mining-panels. The first option is to apply the penalty for high variance mining-panels only. In this option, the expected variance for all the mining-panels in the deposit is set as the threshold above which the variance of a mining-panel is classified as high. Mining-panels with kriged variance greater than the expected variance will be penalized. The second option is to apply the penalty for all mining-panels. The optimizer will give preference to the extraction of low-variance mining-panels earlier in the mine life to reduce the financial risk associated with achieving the production schedule. The term "grade uncertainty cost" is used in this research to represent a pseudo cost for each mining-panel calculated as a product of a penalty value and the mining-panel kriged variance. Subsequently, the grade uncertainty cost is used to enforce the preferential extraction of low-variance mining-panels early in the mine life to reduce project risk. The "overall uncertainty cost" is therefore a quantitative parameter which estimates the difference in NPV of the production schedule from the MILGP model and uncertainty-based MILGP model due to grade uncertainty. The grade uncertainty cost is calculated from Equation (4.2).

$$\text{Grade uncertainty cost } \left(PN_u\right) = \text{Penalty cost} \times \text{mining-panel kriged variance} \tag{4.2}$$

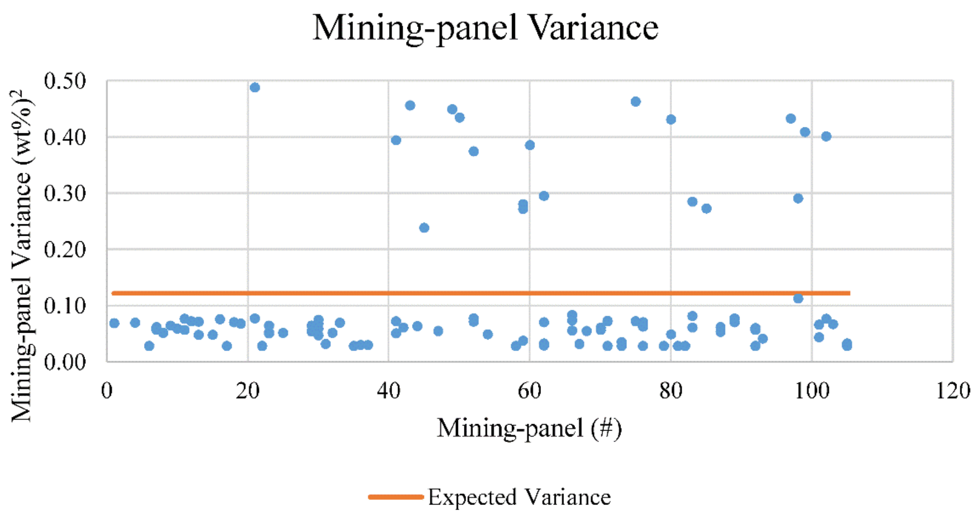


Figure 4-3: Kriged variance and expected variance for mining-panels within the ultimate pit limit

4.5.4 Penalty cost determination

The penalty cost is controlled by the mine planner. It starts from zero and increases gradually until the production schedule starts to change and consequently the NPV. As the penalty applied increases, the optimizer changes the production schedule, looking for low-variance mining-panels to be extracted earlier to minimize the financial risk associated with the production schedule. At some point, increasing the penalty cost has no effect on the production schedule and subsequently the NPV (Figure 4-4). Low penalty means high NPV and high risk, and vice versa. Increasing the penalty minimizes the financial risk resulting in a high-degree of confidence in the NPV of the mining project.

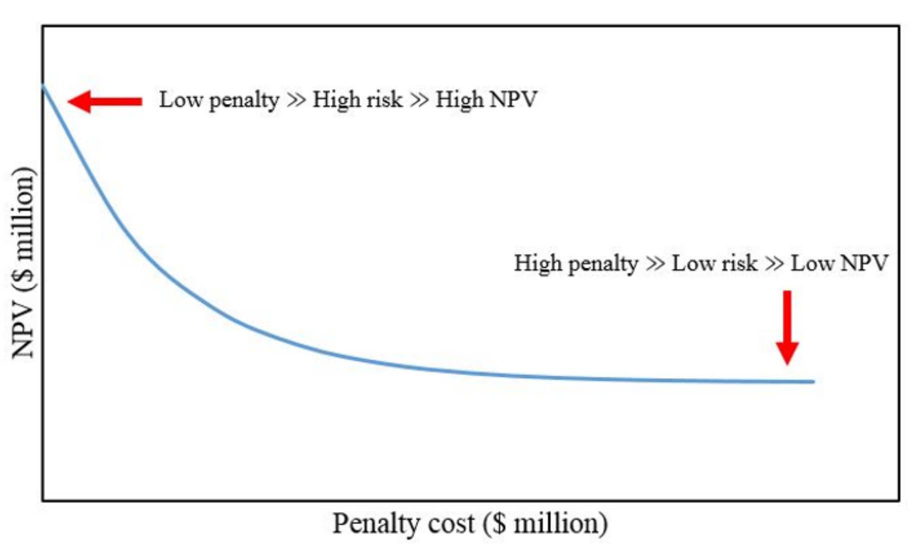


Figure 4-4: Net present value versus penalty cost

4.5.5 Implementation of the MILGP framework: Case study I

This section documents the details of Case study I experimental design and application of the developed MILGP framework for an oil sands dataset. For this case study, the ultimate pit was divided into four pushbacks to be used as tailings-cells for waste management. Two implementation scenarios as outlined in Figure 4-5 were investigated. The deposit is to be scheduled for 25 years for the processing plant, reclamation stockpile and dyke construction destinations. Summarized information on the oil sands material contained in the final pit design is presented in Table 4-1. Table 4-2 shows the economic parameters while Table 4-3 defines the upper and lower bounds of material quality requirements for ore and interburden dyke material. Table 4-5 presents the operational capacities for production scheduling. The economic data are extracted and compiled based on Ben-Awuah and Askari-Nasab (2013). The EPGAP, which is 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 was set to 5% for the optimization runs.

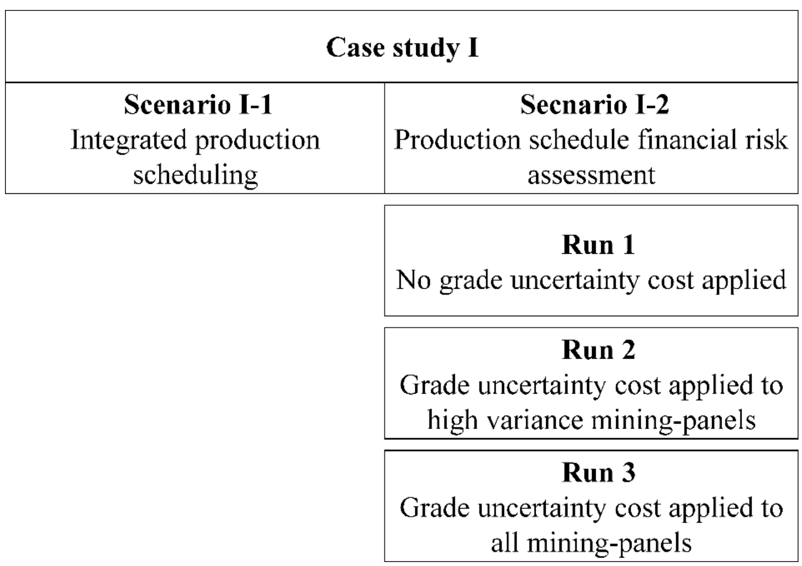


Figure 4-5: Implementation scenarios of Case study I

Table 4-5: Operational capacities for production scheduling

Parameter (unit)	**Value**	**Parameter (unit)**	**Value**
Mining capacity (Mt/year)	239.76	IB capacity (Mt/year)	200
Processing capacity (Mt/year)	82.59	TCS capacity (Mt/year)	75
RM capacity (Mt/year)	220	Processing recovery (%)	90
OB capacity (Mt/year)	230		

These implementation scenarios are designed to highlight different features of the MILGP model including: 1) integrating waste management, reclamation and limited duration stockpiling strategy into oil sands mine planning (Scenario I-1); and 2) estimating production schedule financial risk associated with grade uncertainty (Scenario I-2).

4.5.6 Scenario I-1: Integrated production scheduling

The proposed MILGP model for Scenario I-1 features goal functions for mining, processing, dyke material and reclamation material, and a stockpiling strategy for ore. The ore that exceeds the processing capacity in each period will be stockpiled for a limited duration controlled by the mine planner. The grade uncertainty cost is set to zero. No backfilling activity is implemented and the processing plant recovery factor for bitumen is assumed to be 90%. The MILGP model generates a smooth and practical production schedule, and a NPV with known limits of optimality. In Scenario I-1, the mining operation is limited by mining, processing, reclamation and dyke construction activities through the operational capacities in Table 4-5 and material quality requirements in Table 4-3. The main focus of this experiment is to achieve a smooth processing rate throughout the mine life and generate a uniform production schedule that generates the highest NPV. The overall NPV generated excluding dyke material costs is $18,108 M and the results of the production schedule are shown in Table 4-6, Figure 4-6 and Figure 4-7.

Table 4-6: Production schedule with a two-year ore stockpiling duration (Scenario I-1)

Period	Average bitumen grade (wt%)	Material mined (Mt)	Material processed (Mt)
1	8.33	239.76	13.49
2	10.33	239.76	62.43
3	9.96	239.76	67.08
4	10.32	239.76	58.24
5	10.44	239.76	82.59
6	10.51	239.76	82.59
7	10.16	239.76	82.59
8	10.74	239.76	82.59
9	10.8	239.76	82.59
10	11.13	239.76	82.59
11	10.94	239.76	82.59

12	10.44	239.76	82.59
13	9.58	239.76	82.59
14	9.6	239.76	82.59
15	10.64	239.76	82.59
16	11.28	239.76	82.59
17	10.67	221.39	82.59
18	10.58	209.76	82.59
19	10.84	209.76	82.59
20	10.38	209.76	82.59
21	10.65	209.76	82.59
22	9.79	209.76	82.59
23	10.23	209.76	82.59
24	8.89	209.76	82.59
25	9.37	209.76	53.89

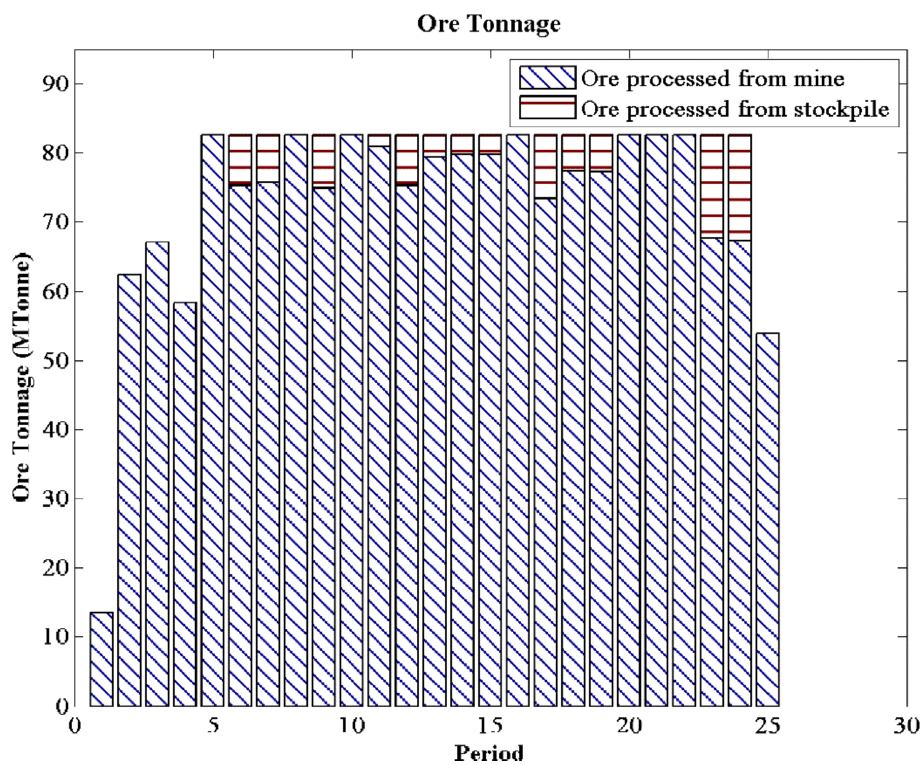


Figure 4-6: Processing schedule with a two-year ore stockpiling duration (Scenario I-1)

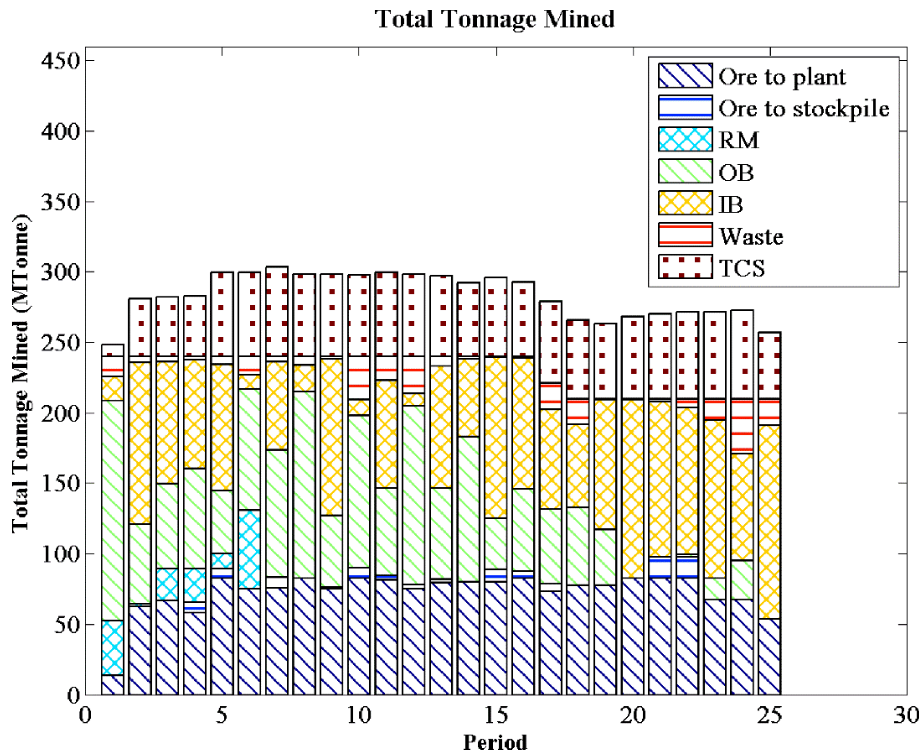


Figure 4-7: Production schedule with a two-year ore stockpiling duration (Scenario I-1)

4.5.7 Scenario I-2: Production schedule financial risk assessment

The proposed MILGP model for Scenario I-2 is implemented with a mining-panel grade variance penalty scheme through the grade uncertainty cost to estimate the financial risk associated with a production schedule. The mining operation is limited by mining and processing activities using the operational capacities in Table 4-5 and material quality requirements in Table 4-3. To investigate in detail the features of the uncertainty-based MILGP model, Scenario I-2 was setup with zero target for stockpiling, reclamation material and dyke materials. No revenue is generated from backfilling activities and the processing plant recovery factor for bitumen is assumed to be 90%. Scenario I-2 is implemented using three different uncertainty-based techniques (Figure 4-5): 1) no grade uncertainty cost is applied for mining-panels as a base case (Run 1); 2) grade uncertainty cost applied to high variance mining-panels (Run 2); and 3) grade uncertainty cost applied to all mining-panels (Run 3). In Runs 2 and 3, different production schedules are generated as the penalty cost is varied resulting in a range of NPVs. An estimated overall financial risk value associated with the production schedule can then be calculated. This uncertainty-based MILGP model: generates a smooth and practical production schedule; is easy to setup with more flexibility for the optimizer; provides a quantified risk value associated with the production schedule;

and generates NPVs corresponding to the varying penalty cost values with known limits of optimality. As the penalty cost values increase, the grade uncertainty cost increases, which forces the optimizer to preferentially mine lower variance mining-panels thereby affecting the NPV.

The general relationship between NPV and penalty cost can be seen in Figure 4-8 with some selected data points. Figure 4-9 shows the production schedule for Scenario I-2 Run 1 which is similar to Run 2 and Run 3 except for grades. It can be noticed from Table 4-7 that the extraction sequence is postponed to later years for some of the high variance mining-panels such as mining-panel number 15, 43, 51, 91, 96, 98, 100 and 103. At the same time, the extraction sequence for some low-variance mining-panels are brought forward such as mining-panel number 12, 35, 38, 45, 64, 65, 70, 83 and 93. In addition, there is an exceptional effect of penalty cost on some low-variance mining-panels such as mining-panels 26, 44, 52, 55 and 87 as they have to provide access to lower variance mining-panels. It is important to note that, the primary objective function of the uncertainty-based MILGP model is to maximize NPV and hence the optimizer simultaneously looks for high-grade mining-cuts in addition to low-variance mining-panels.

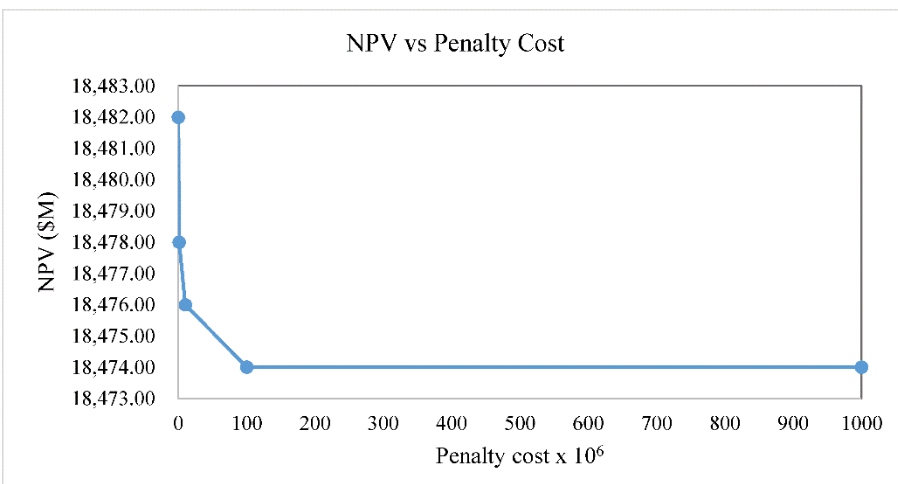


Figure 4-8: General relationship between net present value and penalty cost

Table 4-7: Production schedule for Scenario I-2 for selected mining-panels

Mining-Panel #	**Mining-Panel Variance (wt%)^2**	**Extraction Sequence (year)**		
		Run 1	**Run 2**	**Run 3**
12	0.0691	4	3	3
15	0.2809	3	4	4
26	0.0697	5	6	6
35	0.0291	10	10	8
38	0.0743	7	6	6
43	0.2721	6	7	7
44	0.0487	6	7	7
45	0.0724	8	7	7
51	0.2911	7	8	8
52	0.0485	7	8	8
55	0.0613	10	11	11
64	0.0291	21	17	17
65	0.0328	25	22	22
70	0.0526	18	17	17
83	0.0291	22	21	21
87	0.0617	18	19	19
91	0.4013	17	18	18
93	0.0723	22	19	20
96	0.4564	19	20	20
98	0.409	20	23	22
100	0.4883	23	24	23
103	0.3747	23	24	24

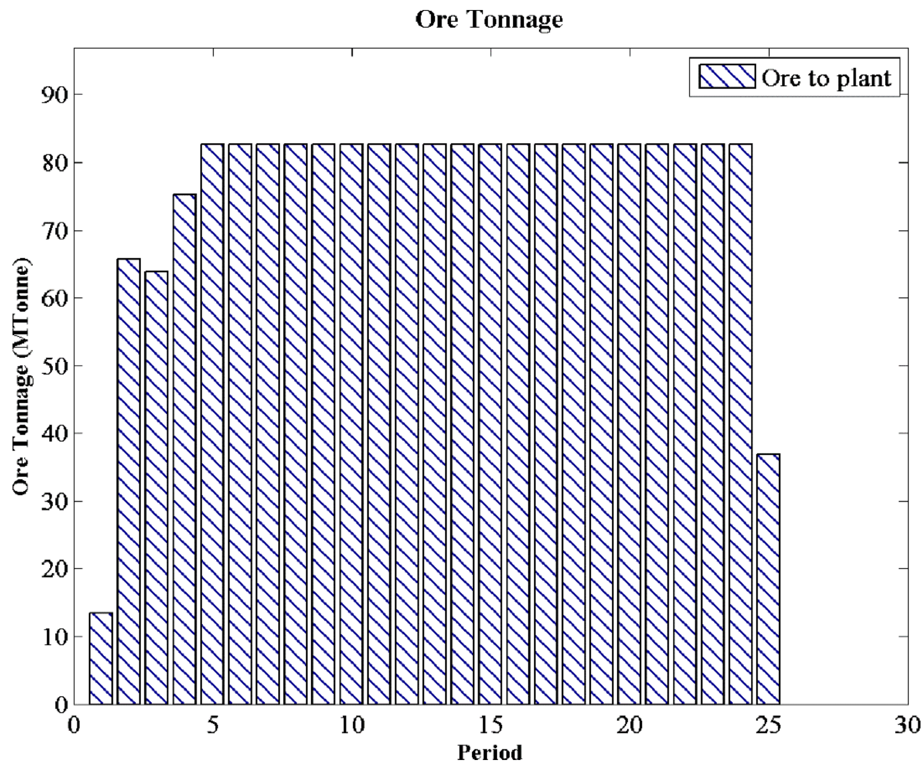


Figure 4-9: Processing schedule for Run 1 (Scenario I-2)

4.5.8 Discussion of the results for Case study I

The performance of the MILGP model in Scenario I-1 was analyzed based on: NPV, mining and processing production targets and smoothness and practicality of the generated schedules. Scenario I-1 generates smooth schedules for mining, processing, reclamation and dyke materials. The total material mined was 5,735.6 Mt. This is made up of 1,906.9 Mt of ore, 218.74 Mt of RM, 1,515.5 Mt and 1,925.5 Mt of OB and IB dyke materials respectively. Ore processing also generated 1,351.6 Mt of TCS dyke material. The model generated a uniform production schedule for ore, OB, IB and TCS dyke material over the 25 period. This ensures the effective utilization of the mining fleet and processing plant throughout the mine life.

For the uncertainty-based MILGP model in Scenario I-2, during the first run (Run 1) no penalty was applied and the NPV obtained was \$18,482 M. For Run 2, the optimizer penalizes mining-panels with grade variance higher than the expected grade variance, calculated as 0.1219 wt%^{2}. The penalty cost applied starts from zero (no grade uncertainty cost) and increases gradually until the production schedule starts to change by postponing the mining of high variance mining-panels to later years. As the penalty cost increases, the

NPV of the project decreases due to the changes in the production schedule. At some point, increasing the penalty cost has no effect on the production schedule and subsequently the NPV. The NPV obtained for Run 2 decreases from $18,482 M to $18,474 M. Thus, the potential financial risk associated with the production schedule can be estimated as a loss of $8 M in the most pessimistic case. For Run 3, the optimizer penalizes all mining-panels and gives preference to low-variance mining-panels to be mined earlier. The NPV obtained decreases from $18,482 M to $18,475 M. Thus, the potential financial risk associated with the production schedule can be estimated as a loss of $7 M in the most pessimistic case. Among other things, by taking into consideration the NPV range and the production schedule risk, investors can make more reasonable choices when managing their mining investment risk profile. Table 4-8 shows the production schedules and grade profiles over 25 periods for Run 1, Run 2 and Run 3. Figure 4-10 shows the grade profile comparisons when no penalty was applied and when penalty was applied for the two uncertainty-based runs.

Table 4-8: Production schedules and grade profiles for Scenario I-2 (Run 1, Run 2 and Run 3)

Period	**Mining Schedule (Mt)**	**Processing Schedule (Mt)**	**Grade Profile (wt%)**		
	Run 1, Run 2 & Run 3	Run 1, Run 2 & Run 3	Run 1	Run 2	Run 3
1	239.76	13.49	8.33	8.33	8.33
2	239.76	65.71	10.37	10.37	10.37
3	239.76	63.8	9.89	9.89	9.89
4	239.76	75.24	10.41	10.41	10.41
5	239.76	82.59	10.37	10.37	10.37
6	239.76	82.59	10.34	10.34	10.34
7	239.76	82.59	10.44	10.44	10.44
8	239.76	82.59	10.77	10.77	10.77
9	239.76	82.59	10.74	10.74	10.74
10	239.76	82.59	10.86	10.89	10.86
11	239.76	82.59	11.11	11.07	11.11
12	239.76	82.59	10.43	10.43	10.43
13	239.76	82.59	9.64	9.66	9.66
14	239.76	82.59	10.22	10.16	10.21

15	239.76	82.59	10.86	10.23	10.85
16	239.76	82.59	10.17	10.63	10.19
17	209.76	82.59	9.88	10.07	9.87
18	209.76	82.59	10.7	10.79	11.07
19	209.76	82.59	11.15	11.08	10.77
20	209.76	82.59	10.93	10.92	10.93
21	209.76	82.59	10.67	10.64	10.66
22	209.76	82.59	10.03	10.06	10.05
23	210.92	82.59	9.98	9.93	9.93
24	209.76	82.59	9.25	9.29	9.29
25	209.76	36.88	8.93	8.93	8.93

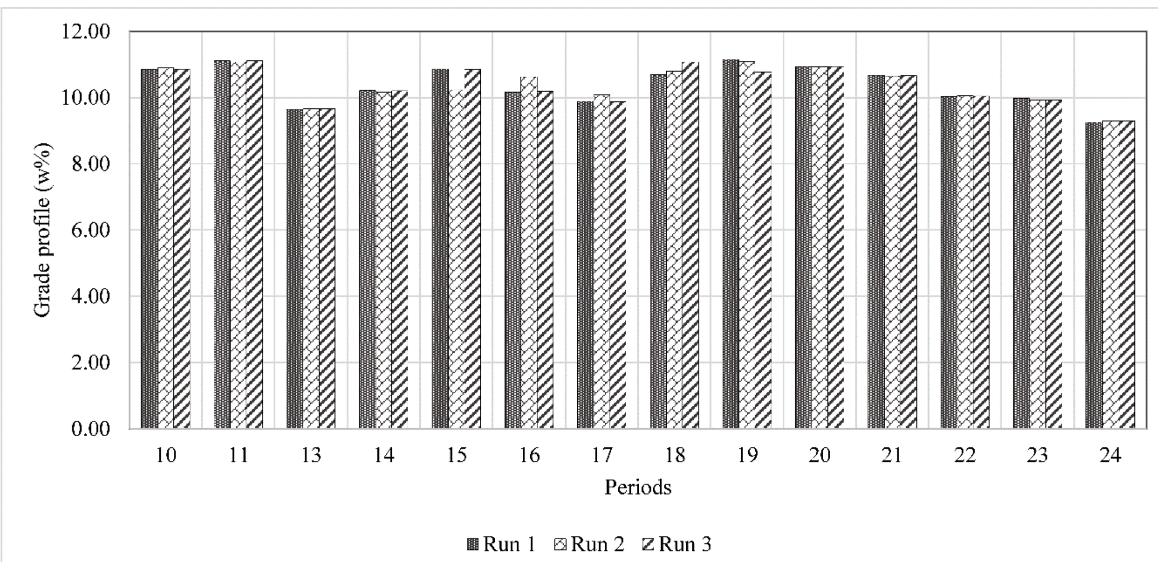


Figure 4-10: Grade profile comparisons for selected periods

4.5.9 Conclusion of Case study I

The proposed uncertainty-based MILGP model for oil sands LTPP involves the interactions of their three main subcomponents: the objective function, the goal functions and the constraints in an optimization framework to achieve the research objectives. The model generates a strategic production schedule for the ore, reclamation material and dyke materials for two different scenarios. In Scenario I-1, with grade uncertainty cost set to zero, the MILGP model illustrates how production scheduling with limited duration stockpiling strategy for ore can be effectively integrated with waste disposal planning and reclamation material stockpiling in oil sands mining. Based on dyke construction requirements, schedules are generated to provide the required dyke materials to support engineered dyke construction that will help in reducing environmental impacts. These schedules give the planner good control over dyke materials and provide a solid platform for effective dyke construction and waste management planning.

The effect of grade uncertainty on the NPV of a mining project is investigated using the uncertainty-based MILGP model in Scenario I-2 (Run 1, Run 2 and Run 3). This investigation is based on the concept of mean-variance analysis, which is the process of weighing risk (variance) against expected NPV. The main experimental focus in Scenario I-2 is to feed the plant with ore that has less potential grade variation especially in the early years of mine life. By deferring ore with highly uncertain grades to later years, the risk associated with generating the estimated mineral content from the production schedule will be reduced. The cost of uncertainty is a good indicator of the level of financial risk associated with generating the expected NPV from the mine plan.

4.6 Case study II: Automated production targeting considering organic rich solids in processing recovery

4.6.1 Introduction to Case study II

Clark Hot Water Extraction Process (CHWEP) is used to extract bitumen from oil sands ore. Conventionally, bitumen and fines contents are used to predict ore processability. However, it is evident that certain solid fractions known as organic rich solids (ORS) still exist even after the treatment of oil sands ore by multiple extraction with toluene. Ore processability results show that ORS are active solids as they carry any associated bitumen into the aqueous tailings thereby reducing the overall bitumen recovery. In general, oil sands ore contains about 5 wt% of ORS that could be used as an additional parameter for predicting ore processability, in conjunction with the traditional use of bitumen and fines content. In Case study II, the proposed MILGP model for oil sands production scheduling and waste management is further deployed with additional functionalities. Bitumen recovery is adjusted based on the ORS content. The model features automated production targeting (APT) constraints that optimize the annual capacities for material mined and processed over the mine life. The APT constraints replace the need for setting annual mining and processing goals. Two years pre-stripping production requirement in addition to limited duration stockpiling were implemented.

4.6.2 Oil sands processing and organic rich solids

In oil sands mining, CHWEP is used to separate bitumen from the watery froth (slurries) that contain significant amounts of solid fractions and emulsified salty water (Masliyah, 2010). CHWEP depends on the surface characterization of solid particles in the ore matrix. Oil sands particles are primarily water-wet. The water forms film around the particles, which prevents the oil from sticking to the surface of mineral solids (Clark, 1944). The tailings slurry is classified into coarse and fine sands. It is collected in tailings ponds where it settles to intractable Mature Fine Tailings (MFT) with a maximum solids content of about 30 wt%. The froth from the extraction process is diluted with recycled naphtha before upgrading, then filtered and centrifuged. This results in a diluted bitumen with about 0.5 wt% solids which are believed to impact bitumen processability and should be removed prior to upgrading (Sparks et al., 2003). Measurements of fines (<45 µm) are used to predict the processability of the ore, however, it is not always effective. It has been found that certain solid fractions known as ORS still exist even after the treatment of oil sands by multiple extraction toluene. The total ore comprises about 5 wt% of ORS that potentially affect the processability of oil sands ore (O'Carroll, 2002; Sparks et al., 2003). During the bitumen separation process, ORS carry any associated bitumen into the aqueous tailings, thus reducing overall bitumen recovery. In this sense, these solids are considered to be active and their associated quantity per tonne of ore can be estimated and used as an additional predictor of ore processability, augmenting the traditional use of ore fines content (O'Carroll, 2002). O'Carroll (2002) noted that losses in bitumen recovery is associated with higher ORS content in the ore. Oil sands ore sample analysis shows that bitumen to ORS ratio increases with higher bitumen content and hence has the potential for use as an index in the characterization of oil sands ore processability.

4.6.3 Processing recovery for revenue calculations

4.6.3.1 Recovery calculations based on Directive 082: Alberta Energy Regulator (AER)

For oil sands mining, AER Directive 082 (2016) identifies the operating criteria that must be adhered to by oil sands operators during mining. The in-situ oil sands cut-off grade, minimum mining thickness, the ratio of cut-off total volume to bitumen-in-place and processing plant recovery are the four criteria that must be followed to establish the volume of bitumen that an operator extracts each year. The criteria allow greater operational transparency in the oil sands mining industry as well as making efficient use of oil sands resources.

The processing recovery is a variable factor based on the average bitumen content of the as-mined ore. The variable factor is equal to 90% if the average bitumen content is 11 wt% or greater, otherwise it is determined by Equation (4.3), (Alberta Energy Regulator, 2016):

$$RECOV_{AER} = -2.5 \times (BIT)^2 + 54.1 \times (BIT) - 202.7 \tag{4.3}$$

4.6.3.2 Recovery calculations including Organic Rich Solids (ORS)

ORS associated with oil sands ore is modeled from the experimental work of O'Carroll (2002). An exponential correlation exists between bitumen and ORS as can be seen in Equation (4.4) with a coefficient of determination (R-squared) of 62.6%. R-squared shows how close the data are to the fitted regression line. The higher the R-squared, the better the model fits the data. For the ultimate pit block model in this case study, ORS ranges from zero to 2.6 wt% with an average of 0.88 wt%. The processing recovery for ore is also modeled from the experimental work of O'Carroll (2002) as can be seen in Equation (4.5) (with R-squared of 99.8%). Equation (4.5) is plotted in Figure 4-11 showing bitumen recovery versus BIT:ORS ratio. Recovery levels-off at 90% for BIT:ORS ratio of 8 or more.

$$ORS = 3.8145 \times e^{-0.094 \times Bit} \tag{4.4}$$

$$RECOV_{ORS} = -0.02 \times \left(\frac{BIT}{ORS}\right)^2 + 0.33 \times \left(\frac{BIT}{ORS}\right) - 0.38 \tag{4.5}$$

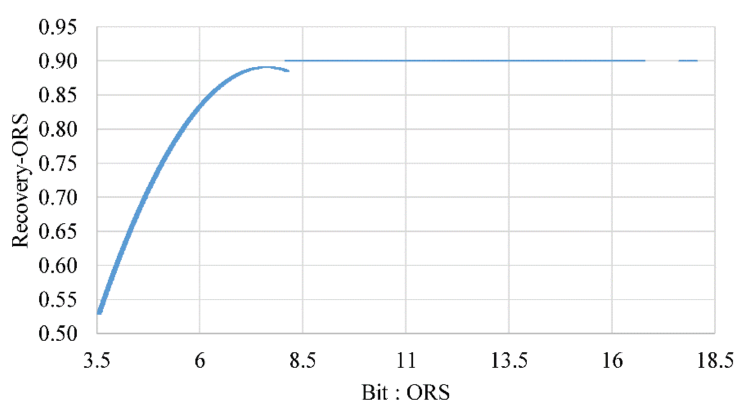


Figure 4-11: Recovery vs. BIT to ORS ratio

The bitumen recoveries from Equations (4.3) and (4.5) are subsequently used in calculating revenues generated from the sale of bitumen. The MILGP framework features APT constraints to achieve the mining and processing goals as part of the production scheduling optimization process with a limited duration stockpiling strategy for ore. No backfilling activities are implemented and grade uncertainty cost is set to zero. Scenario II-1 uses processing recovery calculated from the AER equation (Equation (4.3)) to determine revenue while Scenario II-2 uses processing recovery adjusted based on ORS content Equation (4.5). The effect of ORS on the ore processability compared to the processing recovery recommended by AER is investigated and discussed.

4.6.4 Implementation of the MILGP framework: Case study II

As mentioned in Section 4.6.2, oil sands ore contains about 5 wt% of ORS and it reduces overall bitumen recovery by carrying any associated bitumen into the aqueous tailings (O'Carroll, 2002; Sparks et al., 2003). In this sense, these solids are considered to be active and their associated quantity per ore tonne can be estimated and used as an additional predictor for ore processability, augmenting the traditional use of ore fines content. Subsequently, the bitumen recovery is adjusted based on the ORS content and termed as ORS recovery. It is noted that the recovery calculated based on AER requirements is always greater than or equal to the modified recovery based on ORS content. The recovery difference ranges between 0.01% and 4% for lower bitumen grades (<11%) (Figure 4-12).

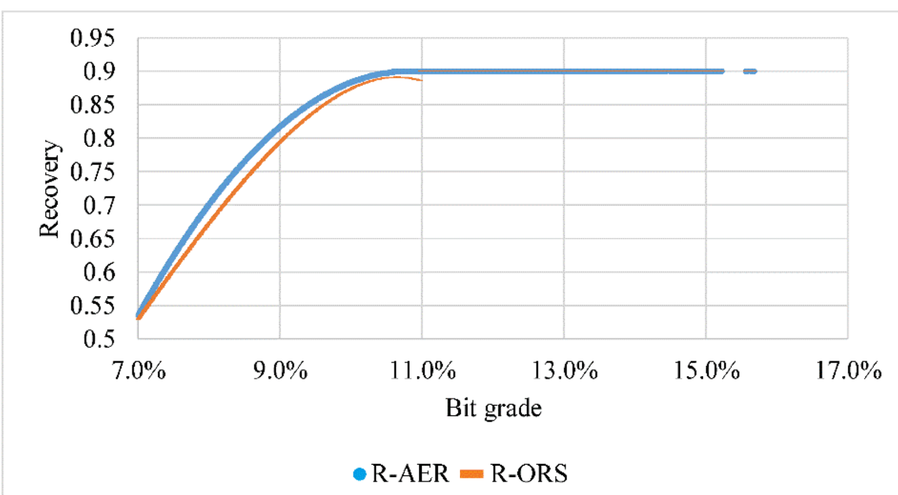


Figure 4-12: Profile for recovery vs bitumen grade based on AER requirements and ORS impact

The new robust APT constraints control the Cumulative Periodic Tonnage Fluctuation (CPTF) parameters for mining and processing material. The APT constraints eliminate the need to directly set mining and processing targets. It requires the mine planner to set an acceptable $CPTF_m$ and $CPTF_p$ throughout the mine life, together with any production ramp up or ramp down requirements. The optimizer then determines the appropriate mining and processing targets that meet the tonnage fluctuation requirements. The $CPTF_m$ and $CPTF_p$ values also control the maximum possible mining and processing capacities indirectly. The APT constraints provide varying practical production schedule options for mine planners depending on the deposit configuration. Two years of pre-stripping and two years stockpiling duration are enforced to minimize oxidation of stockpiled material. This MILGP model generates a smooth and practical production schedule, an NPV with known limits of optimality and is easy to set-up with more flexibility for the mine planner.

Two implementation scenarios as presented in Figure 4-13 highlighting different aspects of the formulated MILGP model are deployed, including 1) determining the mining and processing annual targets as part of the production scheduling optimization process using the APT constraints and CPTF parameters and; 2) determining the NPV based on the revenue generated using AER recovery (Scenario II-1) as compared to ORS recovery (Scenario II-2).

Case study II	
Scenario II-1: AER recovery	**Secnario II-2**: ORS recovery

Figure 4-13: Implementation scenarios of Case study II

For this case study, to create mining-panels, the ultimate pit was divided into four pushbacks. Two implementation scenarios were investigated. The deposit is to be scheduled for a maximum of 25 years for the processing plant, reclamation and dyke construction destinations. Summarized data on the oil sands deposit final pit design and the economic parameters are presented in Table 4-1 and Table 4-2, respectively. The material quality requirements are presented in Table 4-3. Table 4-9 presents operational capacities for production scheduling. The stockpiling duration was limited to a maximum of 2 years. The

EPGAP, which is 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 was set to 5% for the optimization runs.

Table 4-9: Operational capacities for production scheduling

Description	**Value**	**Description**	**Value**
$CPTF_m$* (Mt)	500	IB capacity (Mt/year)	200
$CPTF_p$* (Mt)	180	TCS capacity (Mt/year)	75
RM capacity (Mt/year)	22	Processing recovery (%)	Variable**
OB capacity (Mt/year)	210		

(*): Cumulative Periodic Tonnage Fluctuation

(**): Changes based on the bitumen, fines and ORS contents

In Scenarios II-1 and II-2, the annual mining and processing capacities are not required to be set. The mine planner decides on an acceptable CPTF value and the applicable periods for the mining and processing operations, and allows the optimizer to determine the optimal annual mining and processing limits that meet the CPTF values using Equations (3.24) and (3.25). The planner also controls how many ramping up years is allowed at the beginning of the operation and ramping down years is allowed at the end of mine life. In this case study, 1 year and 2 years ramping up is allowed for mining and processing respectively, and 1 year ramping down is allowed for both mining and processing. The CPTF values indirectly control the maximum possible mining and processing capacities available. It should be stated that the $CPTF_m$ and $CPTF_p$ values for both scenarios are the same. The focus of this experiment is to achieve a smooth processing rate throughout the mine life and generate a uniform production schedule that maximizes NPV.

Table 4-9 presents the annual targets for RM, OB, IB and TCS dyke materials for Scenarios II-1 and II-2. The goal functions defined by Equations (3.20) to (3.23) are used to achieve the required annual targets. These goal functions make use of deviational variables to ensure feasible solutions are obtained for the set goals. The deviational variables provide a continuous range of tonnes that the optimizer can choose from to satisfy the set goals. The waste management strategy used in the case study is to schedule all the RM, OB, IB and TCS material associated with the production schedule using the penalty and priority parameters in the objective function (Equation (3.17)). The penalty and priority parameters ensure that the optimizer prefers to schedule these dyke and reclamation materials rather than sending them to waste dumps.

4.6.5 Case study II: results and discussions

The developed MILGP model presented in Chapter 3 was used to schedule for ore, reclamation and dyke materials over 25 periods. The performance of the developed model is analyzed based on mining and processing material schedules, bitumen grade, processing recovery profile, smoothness and practicality of the generated schedules and the NPV of the project. The developed model aims to generate uniform schedules based on the availability of material, the processing plant requirements taking into consideration the effect of ORS on the ore processability, and dyke construction requirements.

The results presented in Table 4-10 and Figure 4-14 to Figure 4-21 show smooth and uniform mining and processing schedules using the APT constraints for both case study scenarios. During the first two years, due to the formation of the oil sands deposit, overburden, interburden and reclamation materials were the most abundant and must be stripped to make the ore available for mining. Any ore that is extracted in the first two years is sent to the ore stockpile area and is reclaimed within a 2-year stockpiling duration. Processing the ore starts from Period 3 until the end of the mine life as can be seen in Figure 4-14 and Figure 4-15. Comparatively, the production schedules for Scenarios II-1 and II-2 are uniform throughout the mine life. This ensures the effective utilization of the mining fleet and processing plant throughout the mine life. The optimizer completes the mining operation in 24 years for Scenario II-1 with an annual mining capacity of 238.98 Mt while for Scenario II-2, the mining operation is completed in 25 years with an annual mining capacity of 232.86 Mt. To achieve smooth and uniform schedules, two years ramping up at the beginning of the mining operations and one year ramping down at the end of the mine life are allowed.

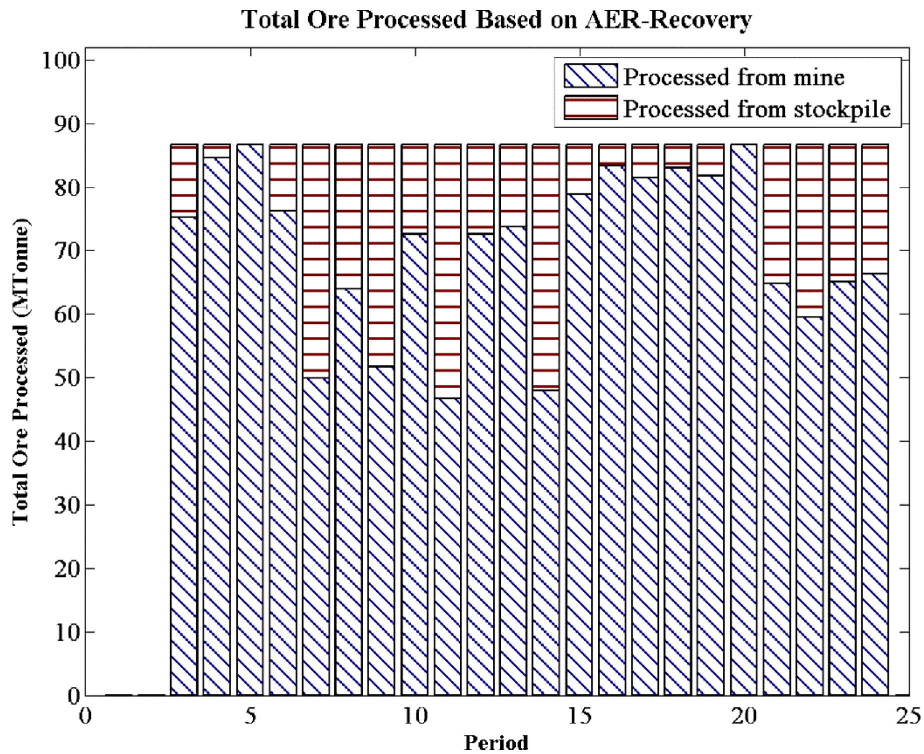


Figure 4-14: Processing schedule for Scenario II-1 (based on AER recovery)

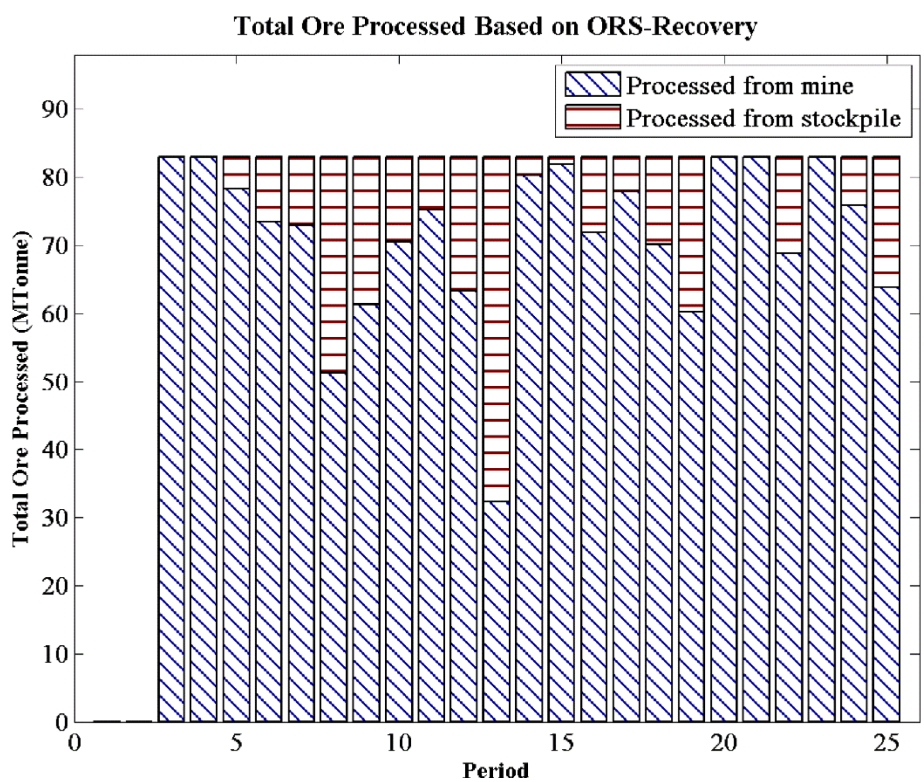


Figure 4-15: Processing schedule for Scenario II-2 (based on ORS recovery)

Although 1,906.88 Mt of total ore was extracted and processed for both scenarios, the annual ore tonnages sent to the processing plant in Scenario II-2 was always less than in Scenario II-1 by 3.77 Mt. As presented in Table 4-10 and Figure 4-16, the plant bitumen head grade was successfully achieved in all the periods for both scenarios. It was between 8.8 wt% and 11.4 wt% for Scenario II-1 and 8.6 wt% and 11.9 wt% for Scenario II-2. That was due to the differences in the annual reclamation of the stockpiled ore as presented in Figure 4-17. Regarding the average oil sands bitumen recovery, the annual AER recovery which was calculated based on the regulatory requirement, ranges between 84.7% and 89.8% (Figure 4-16). AER recovery was always higher than the ORS recovery, which ranges between 70.2% and 89.2% due to the presence of ORS that reduces the ore processability (Figure 4-16).

Table 4-10: Average bitumen processing recovery and bitumen head grade for Scenarios II-1 and II-2

Period	**Processing Recovery (%)**		**Bitumen Grade (wt%)**	
	Scenario II-1	Scenario II-2	Scenario II-1	Scenario II-2
3	84.72	83.56	10.17	10.42
4	86.66	83.86	10.47	9.83
5	88.93	86.66	10.66	10.47
6	88.58	87.23	10.67	11
7	87.85	86.02	10.38	11.02
8	88.33	86.02	10.85	10.73
9	88.62	86.36	10.21	10.15
10	89.78	86.97	11.38	10.87
11	86.34	85.1	10.43	11.56
12	88.86	86.38	10.49	9.77
13	86.13	85.92	10.4	9.83
14	87.09	85.83	9.46	9.9
15	87.63	85.39	10.15	10.77
16	89	86.99	11.02	10.26
17	87.7	86.01	10.39	11.69

18	87.98	85.69	10.92	10.05
19	89.55	89.18	11.12	11.86
20	89.32	87.05	11.22	10.04
21	88.25	86.89	10	10.88
22	85.27	83.78	9.75	9.78
23	85.46	83.88	8.8	9.45
24	87.14	84.08	9.04	9.4
25	-	70.23	-	8.59

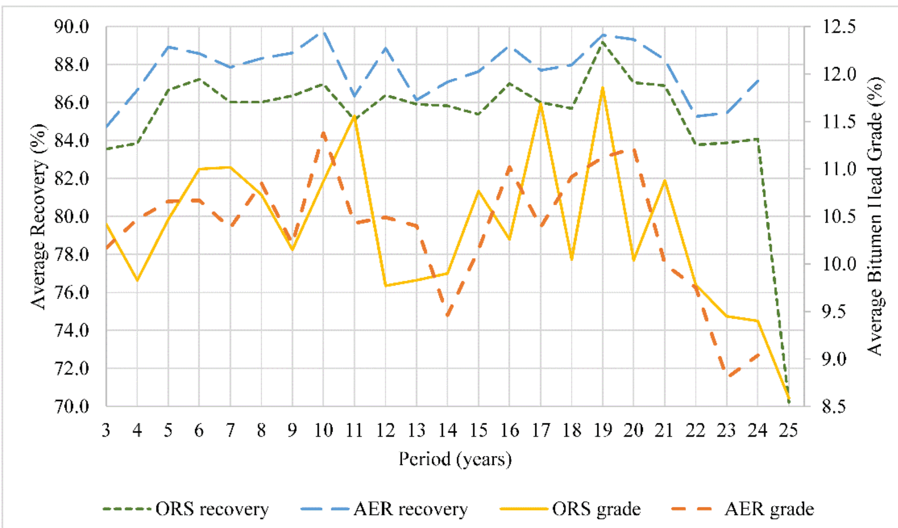


Figure 4-16: Average processing recovery and bitumen head grade for Scenarios II-1 and II-2

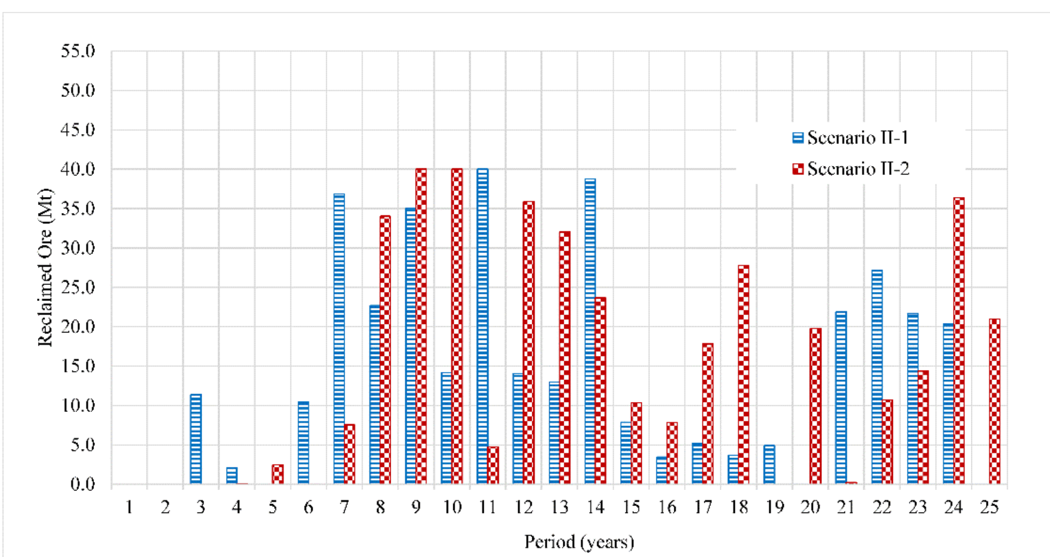


Figure 4-17: Material reclaimed from the stockpile in each period for Scenarios II-1 and II-2

The overall NPVs generated, excluding dyke material costs are \$10,150 M and \$9,800 M for Scenarios II-1 and II-2, respectively. That represents a 3.46% overestimation of NPV (equivalent to \$351.4 M) arising mainly from not taking into consideration the impact of ORS on bitumen recovery during mine planning. More specifically, there are three main reasons that explain the differences in the generated NPV. The primary reason is the adverse effect of the ORS content on the ore processability and consequently the NPV (Figure 4-16). Secondly, the MILGP model incorporates a limited duration stockpiling option for the extracted ore that exceeds the plant capacity. In the case study, the stockpiling duration was set not to exceed 2 years to prevent the oxidation of ore. The average bitumen head grade was slightly different in Scenarios II-1 and II-2 due to the periodic differences in the use of the stockpiled ore (Figure 4-17). Finally, the annual ore tonnages sent to the processing plant in Scenario II-2 was consistently less than Scenario II-1 by about 3.77 Mt which results in more time being needed to complete the mining operation (24 and 25 years for Scenarios II-1 and II-2, respectively).

The production scheduling is effectively integrated with waste disposal planning based on the waste management strategy of the mine. The schedules were generated to provide the required dyke materials based on dyke construction requirements. The use of the integrated MILGP model framework results in better environmental management and sustainable oil sands mining by ensuring mine planners have effective control over waste disposal planning in terms of material movement, in-pit tailings deposition and in-pit and ex-pit dyke construction. Figure 4-18 and Figure 4-19 show the OB, IB and TCS dyke materials generated throughout the mine life. Figure 4-18 and Figure 4-19 also show the reclamation material extracted to reclaim the disturbed landscape during or at the end of the mining operation.

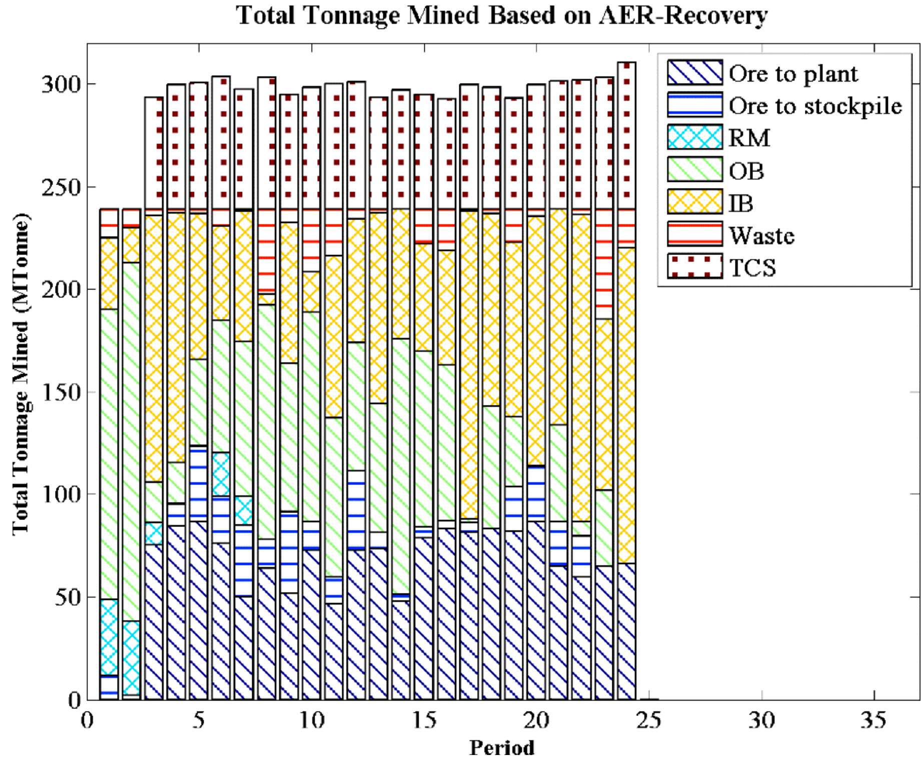


Figure 4-18: Production schedule for Scenario II-1

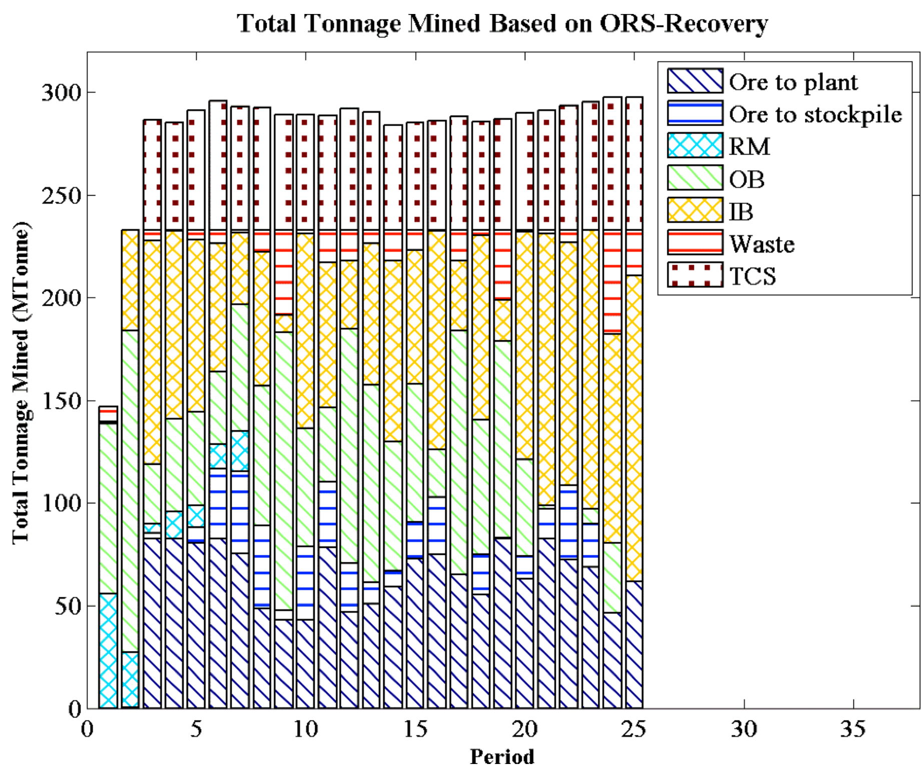


Figure 4-19: Production schedule for Scenario II-2

Figure 4-20 and Figure 4-21 show the directional extraction of material from West to East to ensure in-pit dyke construction and tailings deposition proceeds sequentially.

Table 4-11 shows a summary of the waste management cost for the two scenarios. Scenario II-1 stockpiled 32% of the total RM during the first 7 years at a cost of $45.8 M while Scenario II-2 stockpiled 39% of the total RM over 7 years at a cost of $54.6 M. For OB, IB and TCS dyke materials, Scenario II-1 scheduled approximately 100% of the available dyke materials for in-pit and ex-pit dyke construction at a cost of $2,250 M, while Scenario II-2 scheduled 98%, 100% and 73% of the OB, IB, and TCS dyke materials respectively, for in-pit and ex-pit dyke construction at a cost of $2,120 M throughout the mine life. It should be noted that using the RM, OB, IB and TCS material goal functions, different quantities of reclamation and dyke materials could be scheduled to support the reclamation and waste management plan for the mine.

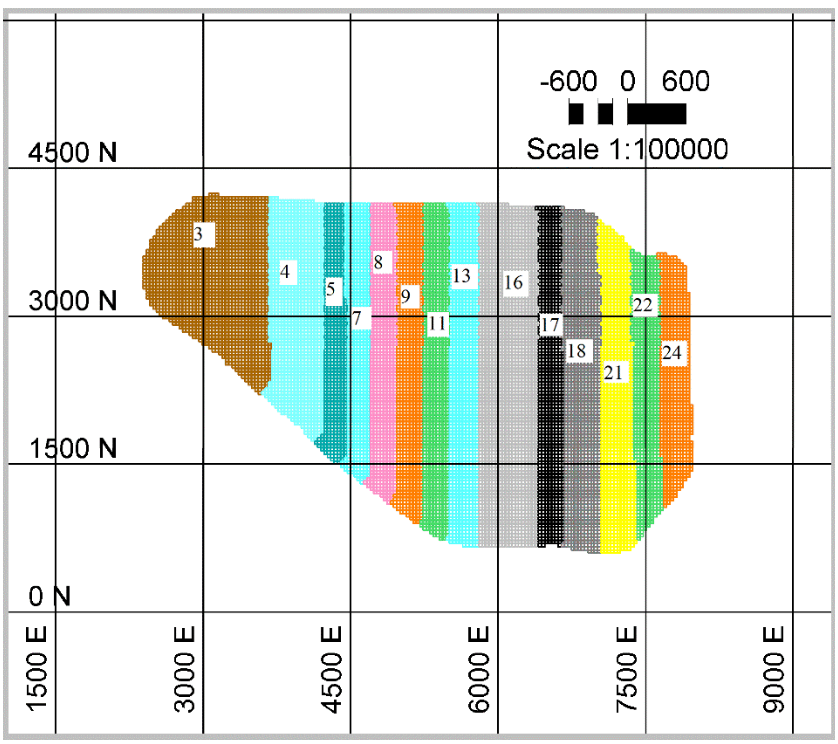


Figure 4-20: Mining sequence on level 310 m with West-East mining direction for Scenario II-1

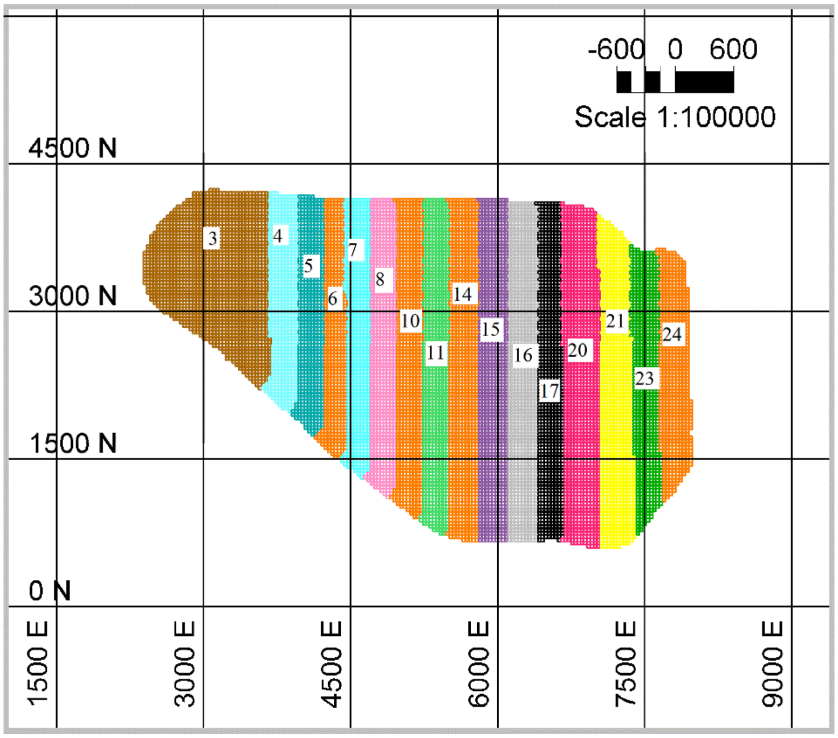


Figure 4-21: Mining sequence on level 310 m with West-East mining direction for Scenario II-2

Table 4-11: Waste management costs

Material (unit)	**Scenario II-1**	**Scenario II-2**
Reclamation material cost, RM ($M)	45.78	54.58
Overburden cost, OB ($M)	950.88	863
Interburden cost, IB ($M)	856.12	818.5
Tailings coarse sands cost, TCS ($M)	397.69	384.64
Total waste management cost ($M)	2,250.46	2,120.72

4.6.6 Summary and conclusions: Case study II

The MILGP model for oil sands long-term production planning and waste management involves the interactions of the objective function, the goal functions and the constraints in an optimization framework to achieve the research objectives. The MILGP model uses the APT constraints for mining and processing. The APT constraints minimize the risk of having variations in the production targets throughout the life of mine by setting the CPTF. The $CPTF_m$ and $CPTF_p$ control the allowable deviation for any range of periods for mining and processing respectively. The APT constraints also provide the planner the option to introduce controlled production ramp up or ramp down at the beginning and end of the mine life. These constraints are easy to set up and do not require the mine planner to define the annual mining and processing targets. This ensures robust and practical production scheduling options for mine planners.

The model generates a strategic production schedule for ore, reclamation and dyke materials for the case study in two scenarios. For both scenarios, the MILGP model illustrates how production scheduling with a limited duration stockpiling strategy for ore can be effectively integrated with waste disposal planning and reclamation material stockpiling in oil sands mining. Based on dyke construction requirements, schedules are generated to provide the required dyke materials to support engineered dyke construction that will help in reducing environmental footprints. The schedule also gives the planner flexible control over dyke materials and provides a solid platform for effective dyke construction and waste management planning. The MILGP framework integrates a production planning strategy that uses ORS content to additionally adjust bitumen recovery and subsequently the NPV. The results show a 3.46% overestimation of NPV (equivalent to $351.4 M) arising mainly from not taking into consideration the impact of ORS on bitumen recovery during mine planning.

4.7 Case study III: Multi-objective integrated mine planning and tailings-cells optimization

4.7.1 Introduction to Case study III

In oil sands mine planning and waste management, tailings-cells are created and used as dedicated disposal areas for tailings backfilling. Dyke construction and backfilling activities require well-managed techniques to facilitate progressive reclamation at the earliest opportunity, which directly affects the profitability and sustainability of oil sands mining operations. This case study implements a MILGP model that simultaneously determines: 1) the production schedule with limited duration stockpiling and directional mining; 2) the dyke construction schedule; 3) the optimal size, shape and location of tailings-cells; and 4) the optimal mining and processing production targets.

4.7.2 Implementation of the MILGP framework: Case study III

The robust MILGP model to solve the LTPP and waste management problem has been progressively developed and functionally implemented over a period of time. In this case study, the ore bitumen processing recovery is additionally adjusted based on the ORS content and the grade uncertainty cost is set to zero. The APT constraints are used to optimize the mining and processing capacities in addition to defining the mining-cells belonging to each tailings-cell.

The area to be mined is divided into a pattern of regularly spaced areas that represent mining-cells. A group of mining-cells gets accumulated into a tailings-cell based on the required capacity, shape, location and the timelines required in making the tailings-cell areas available for tailings-containment. Tailings-cells optimization constraints are used to control backfilling activities in the in-pit mined areas. For this case study, it was decided to create four tailings-cells with the same upper bound capacities. Initially, the lower bound was set to zero and the upper bound was calculated approximately by dividing the total rock volume of the ultimate pit by the required number of tailings-cells taking into consideration the size of the last tailings-cell that will not be used for backfilling.

To achieve the optimal production targets for material mined and processed, APT constraints are used to minimize the periodic fluctuation in the production schedules. The mine planner sets an acceptable CPTF throughout the mine life, taking into account any required production ramping up and down. The mining and processing $CPTF_m$, $CPTF_p$ values indirectly control the maximum possible mining and processing capacities that satisfy the tonnage fluctuation requirements. The APT constraints provide varying practical production schedule options for mine planners (Maremi et al., 2020).

4.7.3 Case study III: results and discussions

In solving the MILGP optimization problem, 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 10% for the optimization of the mining project. The deposit is to be scheduled for 25 years for the processing plant, and tailings-cells need to be constructed every 5 to 6 years. The remaining tailings-cell area at the end of mine life could be used as a waste dump or for tailings deposition if there are additional pits. Table 4-9 provides information about the operational capacities.

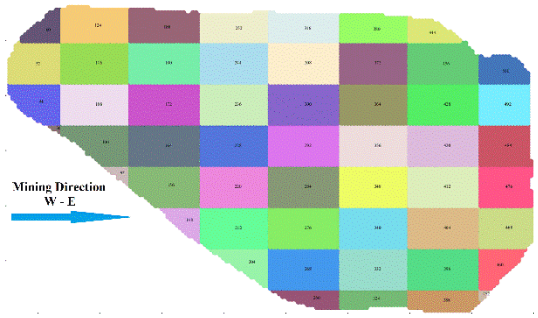
Mining will proceed generally from west to east. Dyke material requirements for dyke construction destinations will be scheduled concurrently with the ore to processing plant. It is assumed that all dyke construction destinations are ready to receive dyke material as soon as mining starts. Four implementation case study scenarios highlighting different approaches in creating the tailings-cells using the formulated MILGP model are presented in Figure 4-22. The dimensions of the mining-cells used in creating the tailings-cells are varied for each case study scenario (Figure 4-23).

The performance of the proposed MILGP model was analyzed based on the NPV, mining and processing production targets, smoothness and practicality of the generated schedules, availability of tailings-containment areas at the required time, percentage of remaining in-pit volume not backfilled, pseudo backfilling revenue, and computational time required for convergence. The implemented scenarios focus on a practically integrated oil sands production planning and tailings-cells optimization strategy that generates value and is sustainable. This includes west-east directional mining and making tailings-cells available for timely tailings deposition. That reduces the environmental footprints of the external tailings facility. An initial directional mining production schedule run in Whittle (Geovia Dassault Systems, 2017) was used to decide the mining direction with the best NPV. Directional mining ensures minimum mobility and increased utilization of loading equipment.

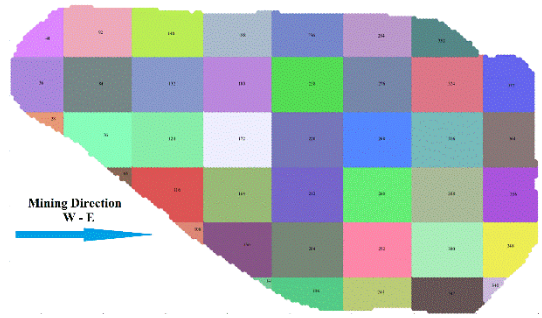
Case study III			
Scenario III-1	**Scenario III-2**	**Scenario III-3**	**Scenario III-4**
Different sizes of mining-cell units for creating tailings-cells			

Figure 4-22: Implementation scenarios of Case study III

For all four case study scenarios: (a) the mining and processing annual targets are determined as part of the production scheduling optimization process using the APT constraints in Equations (3.24) and (3.25); and (b) a two-year maximum stockpiling duration is enforced. The four experiments were carried out with varying waste management strategies at a 10% discount rate and 10% EPGAP. The number of mining-cuts, mining-panels and mining-cells are different for each case study scenario. As the dimensions of a unit mining-cell increases, the total number of in-pit mining-cells decreases and vice versa. Details about each scenario can be found in Figure 4-23 and Table 4-12.

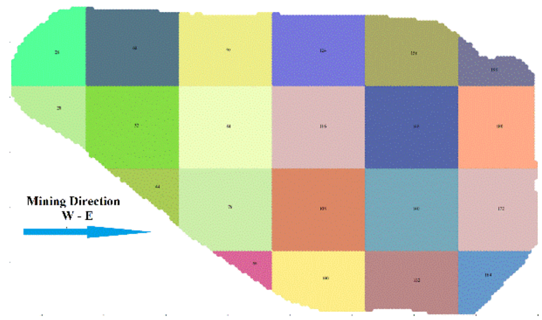


a) Scenario III-1: 1,125 m × 750 m



b) Scenario III-2: 1,125 m × 1,000 m

c) Scenario III-3: 1,500 m × 750 m



d) Scenario III-4: 1,500 m × 1,500 m

Figure 4-23: In-pit mining-cell unit dimensions for each scenario on level 319 m

Table 4-12: Mining-blocks, mining-cuts, mining-panels and mining-cells contained in the final pit for each scenario

Description	**Scenario III-1**	**Scenario III-2**	**Scenario III-3**	**Scenario III-4**
No. of Blocks	79,095	79,095	79,095	79,095
No. of mining-cuts	4,543	4,537	4,528	4,491
No. of mining-panels	503	379	380	191
No. of mining-cells	54	42	42	21
Mining-cell unit dimensions (m × m)	1,125 ×750	1,125 ×1,000	1,500 ×750	1,500 ×1,500

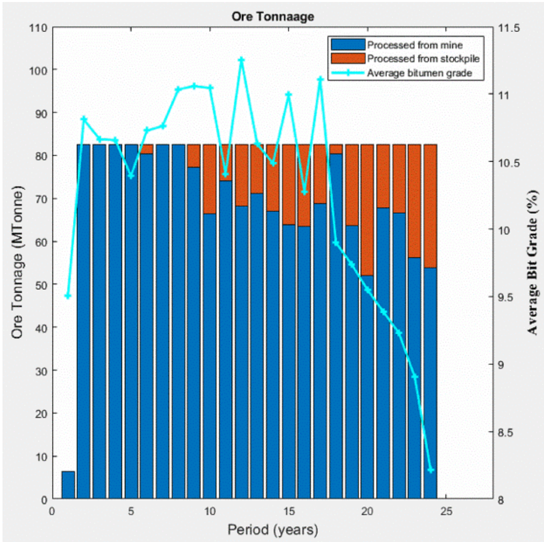
All implemented scenarios focus on the optimization of mining and processing targets, and the waste management strategy over the mine life. This includes directional mining and the availability of tailings-cells for in-pit dyke construction, and subsequently tailings deposition. This reduces the environmental footprints of the external tailings facility by commissioning in-pit tailings facilities on time.

Evaluation of the oil sands deposit with the integrated MILGP model indicates that Scenario III-1 generates the highest NPV at $12,040 M, followed by Scenario III-2. While Scenario III-4 generated the lowest NPV. Summary of results from the MILGP model including NPV (excludes dyke construction cost and backfilling pseudo revenue), dyke construction cost and backfilling pseudo revenue for each scenario can be found in Table 4-13.

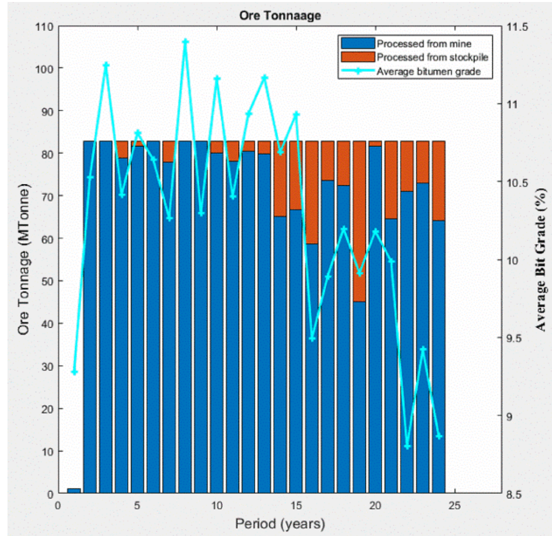
Table 4-13: Summary of results for the MILGP model with different tailings-cells scenarios

Scenarios #	**Scenario III-1**	**Scenario III-2**	**Scenario III-3**	**Scenario III-4**
Tonnage mined (Mt)	5,545.73	5,528.55	5,553.57	5,497.07
Ore tonnage (Mt)	1,906.9	1,906.9	1,906.9	1,906.9
OB dyke material tonnage (Mt)	1,381.4	1,415.4	1,425.3	1,461.9
IB dyke material tonnage (Mt)	1,925.4	1,924	1,924.73	1,925.4
TCS dyke material tonnage (Mt)	1,150.9	1,007.8	1,011.7	843.83
NPV (M$)	12,040	11,854.4	11,350	11,252
Dyke construction cost (M$)	2,310	2,344	2,330	2,409
Backfilling pseudo revenue (M$)	5,380	5,443.6	5,160	5,191.3
In-pit volume backfilled (%)	91.8	93	85.7	87.4
No. of continuous variables	73,515	73,223	73,08	72,173
No. of binary variables	503	379	380	191
CPU time (hrs.)	6.75	106.7	16.86	181.6

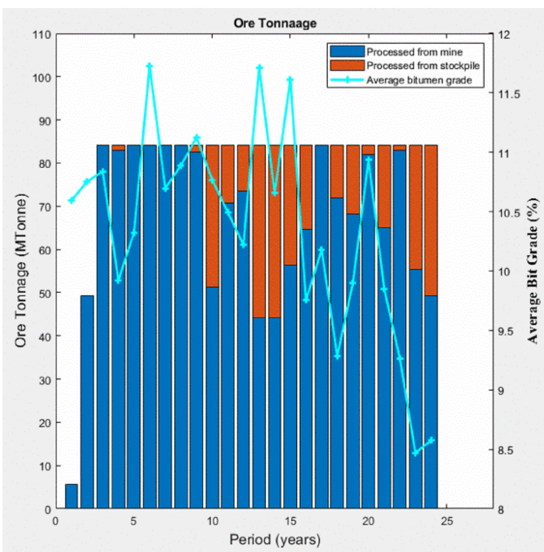
From Figure 4-24, the total material processed in the first four years is highest in Scenario III-1. Also, the average bitumen head grade is slightly different in each scenario due to the rehandling of stockpiled material resulting in varying NPVs. Figure 4-24 illustrates how limited duration stockpiling is well integrated into the life of mine processing schedule using the APT constraints. This ensures efficient utilization of the processing plant capacity through a consistent maximum throughput feed. APT constraints are easy to set up especially for less experienced mining engineers, as the optimizer has more control on the material handling strategy. Although the life of mine was setup for 25 years, the APT constraints completed ore processing in 24 years. All stockpiled ore was processed within 2 years duration to minimize oxidation, which adversely affects bitumen recovery. For all scenarios, the optimizer generally extracts high-grade mining-cuts earlier and postpone low grade mining-cuts to later years.



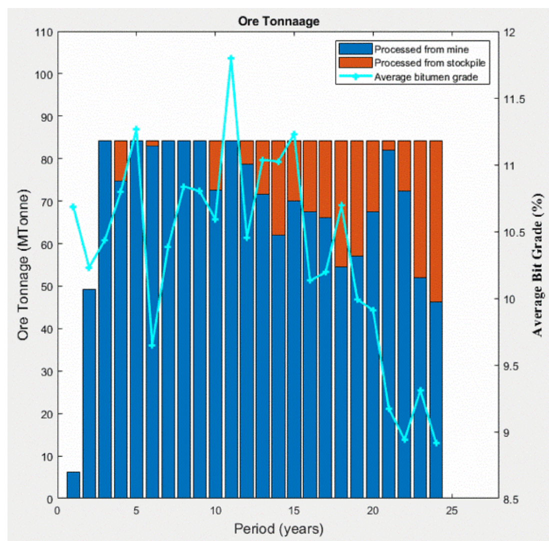
(a): Scenario III-1



(b): Scenario III-2



(c): Scenario III-3



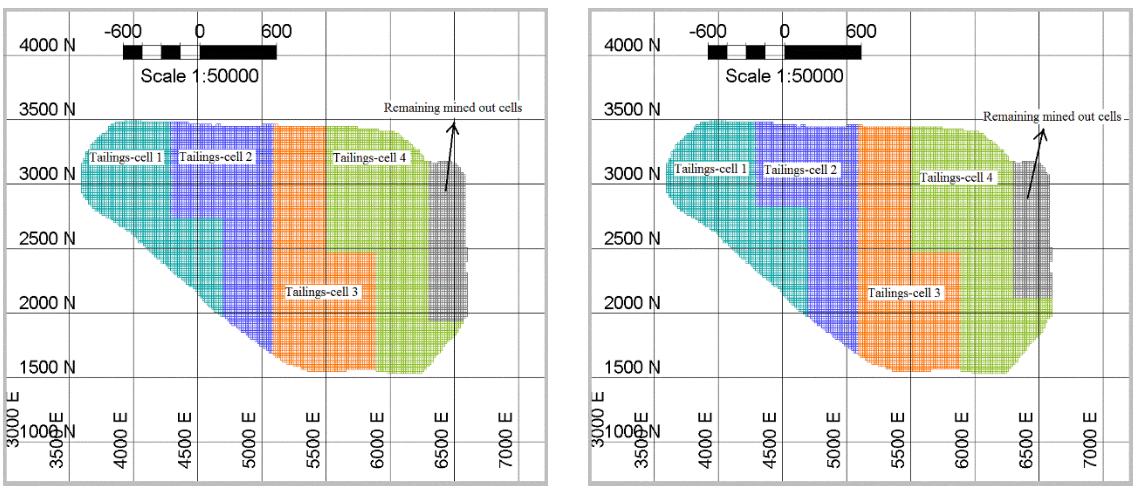
(d): Scenario III-4

Figure 4-24: Processing schedule with limited duration stockpiling

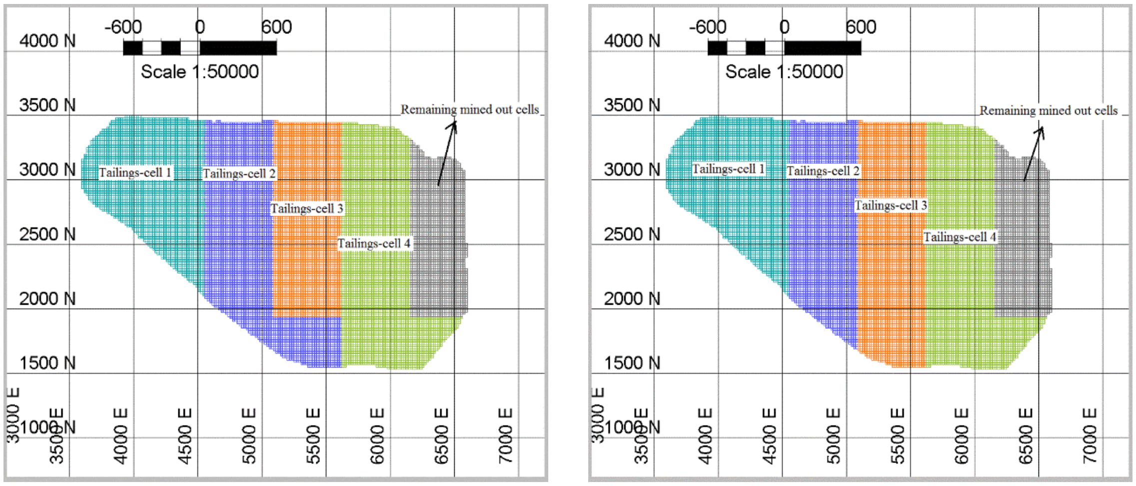
4.7.4 Sustainable waste management: in-pit tailings-cells and dyke material optimization

The availability of in-pit volumes for tailings deposition before the end of mine life is a preferred and a regulated strategy for continuous reclamation. In general, the results from the case study show that all tailings-cells are ready at the scheduled time or earlier. For example, Tailings-Cell 1 was ready for tailings deposition in the fourth year for Scenario III-1 and in the fifth year for Scenarios III-3 and III-4. Increase in the in-pit volume backfilled results in increased pseudo revenue generated from backfilling. Continuous backfilling ensures early reclamation during mine life. Results from Table 4-13 show that Scenario III-2 generates the highest in-pit volume for backfilling by the end of year 21 followed by Scenario III-1. Scenario III-2 therefore results in the most efficient waste management strategy ensuring that about 93% of the in-pit volume is available for backfilling before the end of mine life.

Table 4-14 presents the volumes of all tailings-cells generated in each scenario. The backfilled and remaining tailings-cells shape and location can be seen in Figure 4-25. The tailings-cells are created progressively following the west-east mining direction. It should be noted that the site tailings dam engineer must provide inputs regarding the design of the tailings-cells. Multiple optimization runs may be required to modify the tailings-cells designs by varying the tailings-cells capacities.



(a): Scenario III-1 (b): Scenario III-2



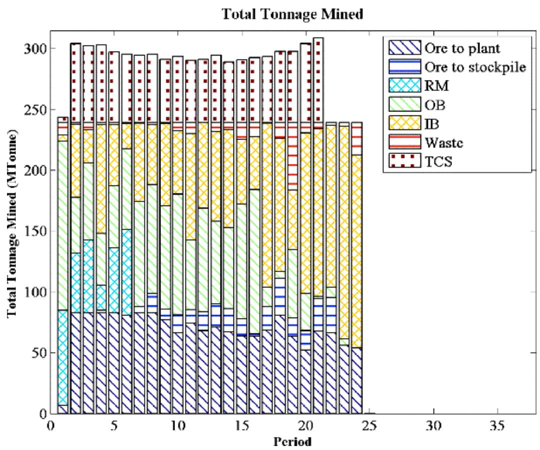
(c): Scenario III-3 (d): Scenario III-4

Figure 4-25: Tailings-cells generated in each scenario

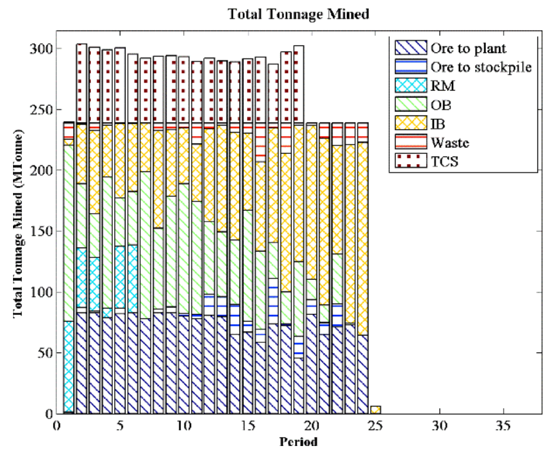
Table 4-14: Volume of tailings-cells generated in each scenario

Scenario #	**Tailings-cell volume, (m^3)**			
	Tailings-cell 1	Tailings-cell 2	Tailings-cell 3	Tailings-cell 4
III-1	481.8	636.4	787	817.3
III-2	506.4	611.8	787	853.7
III-3	539	708.8	572.7	720
III-4	539	579.2	702.4	770.9

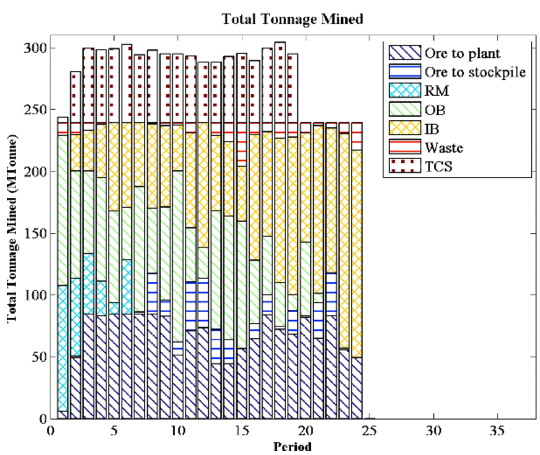
The type and quantity of dyke material used for in-pit tailings-cells dykes in a timely manner and at a minimum cost can be seen in Figure 4-26. Dyke material is needed when all mining-cells required to create a specific tailings-cell are mined-out and dyke construction is ready to take off. The dyke material mined is sent directly to the scheduled dyke construction destination. OB and IB dyke materials are initially required to construct the dyke foundation and TCS dyke material is needed for the main dyke. The integrated production schedule provides a robust platform for effective dyke construction planning and tailings storage management.



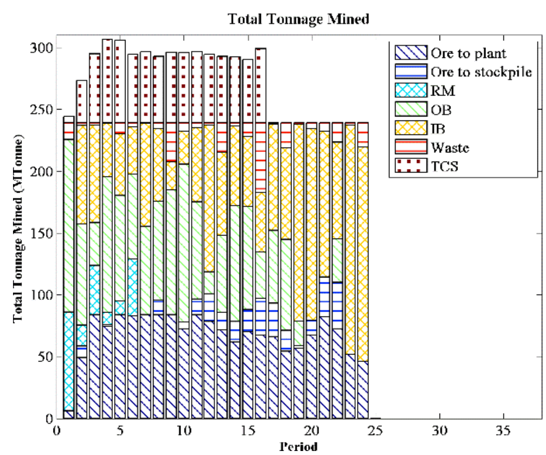
(a): Scenario III-1



(b): Scenario III-2



(c): Scenario III-3



(d): Scenario III-4

Figure 4-26: Integrated production scheduling and waste management

In summary, four waste management optimization scenarios were executed to assess the effect of different waste disposal approaches on the mining operation in terms of the NPV, waste management cost, backfilling pseudo revenue and CPU run time. Each scenario has its own inherent advantages depending on conditions at the mine and priorities of the mining operation. If the total volume of in-pit tailings-cells created has the highest priority as part of an environmental policy and reclamation plan, then Scenario III-2 may be preferred. On the other hand, if there is the need to increase the NPV regardless of the availability of in-pit tailings storage areas, then Scenario III-1 may be preferred.

Scenario III-4 with the least number of mining-cells is not desirable. It generates the lowest NPV due to the reduced operational flexibility and the highest dyke construction cost.

Scenario III-1 has the lowest CPU time. Increasing the number of mining-cells in the east-west direction gives the optimizer more flexibility when generating the tailings-cells as part of the integrated production schedule. This results in higher NPV and backfilling pseudo revenue. Comparatively, decreasing the number of mining-cells in the north-south direction has significant effect on the CPU time as can be seen in Scenarios III-2 and III-4.

4.7.5 Conclusions and recommendations: Case study III

The integrated oil sands mine planning problem involves the incorporation of waste management into the production planning process in an optimization framework that maximizes value and generates a sustainable waste management plan. The developed MILGP model aims to maximize the revenue from the operation, maximize the backfilling pseudo revenue, minimize the reclamation material cost and dyke construction cost. The model also optimizes tailings-cells designs for waste disposal planning. Potential tailings-cells are selected based on required specifications such as capacity, shape and location. The MILGP framework investigates the effect of having different in-pit tailings-cells designs on the NPV and pseudo backfilling revenue. The schedules provide a robust platform for effective dyke construction and waste disposal planning. A limited duration stockpiling option is integrated into the oil sands production plan and this results in an increased NPV as the processing plant is provided with higher grade ore first. The bitumen recovery is additionally adjusted based on the content of organic rich solids which affects ore processability leading to more refined economic mining-cut values. The model generated practical, smooth and uniform schedules for ore and dyke material using the APT constraints. APT constraints are easy to set up and ensures that feasible mining and processing rates are determined for a given orebody configuration. It also helps to determine optimal mining and processing capacities throughout the mine life. Additionally, APT constraints can be used at the prefeasibility stage of a mining project to define sophisticated mining and processing capacity estimates for the mining fleet and processing plant.

Four waste management scenarios based on variations in the number of mining-cells are investigated. The results show that decreasing the mining-cell unit size and increasing the number of mining-cells used to create in-pit tailings-cells increases the NPV of the operation. This is as a result of increased operational flexibility as demonstrated in Scenario III-1. Comparatively, decreasing the number of mining-cells in the vertical direction (north-south) increases the CPU time as demonstrated in Scenarios III-2 and III-4. The investigated scenarios demonstrate availability of in-pit tailings storage areas early in the mine life, and efficient use of the storage areas required for sustainable operations and timely reclamation. In general, this integrated mine planning framework can be implemented for various directions of mining, and different shapes and sizes of tailings-cells. It was noticed that, some tailings-cells require subsequent runs to refine their shape through changing the tailings-cells capacity boundaries. The solution to the MILGP model exemplifies a practical mining regime with operational merits. The results highlight how integrated mining and waste management should be deployed, contrary to previous models that were an oversimplification of reality.

4.8 Summary and conclusions for Chapter 4

This chapter verifies the developed MILGP framework through three case studies and eight scenarios. Whittle's LG algorithm was used in generating the ultimate pit limit and consequently the pit design. The pit design contains a total rock of 5735.6 Mt including 1,906.9 Mt of ore. The MILGP 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 involves the use of pushbacks (or tailings-cells) and directional mining to strategically relate in-pit dyke construction with production scheduling and in-pit tailings storage. The model framework uses limited duration stockpiling for the extra ore that exceeds the plant capacity. The model also uses clustering of mining blocks to mining-cuts and paneling of mining-cuts to mining-panels to ensure practical mining environments and efficient mining fleet utilization.

The first case study minimizes the financial risk from grade uncertainty associated with the production schedule through kriged estimates and a variance penalty scheme. It also highlights the strategy used in the MILGP model to integrate waste disposal planning and reclamation material stockpiling in oil sands mining production scheduling with limited duration stockpiling strategy. Goal functions are used to control the mining and processing annual capacities and ore bitumen processing was based on a fixed recovery factor.

The second case study investigates the effect of organic rich solids content on the ore processability. The results are compared to the processing recovery based on AER recommendations. Two new robust APT constraints are introduced in the model to optimize the mining and processing annual capacities. These APT constraints are used in place of the mining and processing goal functions in Case study I. Two years of pre-stripping and a two-year limited duration stockpiling constraint are enforced. In Case studies I and II, the final pit is divided into four predetermined pushbacks that are used as dedicated in-pit tailings storage areas for waste management.

In Case study III, the MILGP framework is implemented to incorporate the optimization of tailings-cells designs for waste management. The final pit is divided into a pattern of regularly spaced areas that represent vertical units spanning from the topography to the bottom of the pit and are defined as mining-cells. Mining-cells are used to generate the in-pit tailings-cells designs, location and capacity for tailings backfilling. A two-year limited duration stockpiling constraint is implemented but no pre-stripping is enforced.

The MILGP model generated near-optimal practically integrated production schedules for all case studies. In addition, the production schedule shows uniform ore feed to the processing plant using the APT constraints and limited duration stockpiling. The results show that the MILGP framework is a powerful tool for optimizing oil sands long-term production plans whilst providing a robust platform for integrating waste disposal planning.

CHAPTER 5

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary of the research

Researchers have successfully used open pit LTPP and scheduling algorithms to determine the feasibility of mining projects. In the literature however, there are major limitations in the existing planning and optimization techniques. These include the following: (a) limitations in fully integrating waste management and reclamation planning in the optimization problems; (b) difficulties in implementing the developed algorithms on large scale problems; (c) shortcomings in integrating geological and economic uncertainties in mining projects evaluation; (d) deficiency in mathematically modelling limited duration stockpiling; (e) inability to optimize production capacities as part of the mining schedule; and (f) limitations in optimizing the size, shape and location of tailings-cells as part of the waste management strategy. These limitations in mine planning may result in sustainability, regulatory and financial challenges. For oil sands mining, it is required by regulation to generate long-term mine plans that directly integrate their waste management system.

Accordingly, an uncertainty-based MILGP framework has been developed to integrate waste disposal planning into oil sands production scheduling. It has been proven that the uncertainty-based MILGP framework is a robust mine planning tool with the capability to: (1) quantify production schedule financial risk associated with grade uncertainty; (2) optimize mining and processing capacities as part of the production schedule; (3) mathematically model limited duration stockpiling to support the processing plant; (4) incorporate ORS content as part of the ore processability indicators defined by processing recovery factor; (5) optimize tailings-cells designs specification for tailings disposal planning; and (6) schedule dyke and reclamation material as part of the waste management strategy.

A summary of the research methodology and developed framework is presented in Figure 5-1. Matlab programming platform was used in formulating and implementing the uncertainty-based MILGP framework. The main components of the framework comprise the objective function, goal functions and constraints. These components interact with the block model through the mine planner input parameter definition file, which enables the setting up of the economic, production and waste disposal parameters. For this research, a large-scale optimization solver IBM/CPLEX developed based on branch and cut algorithm is used.

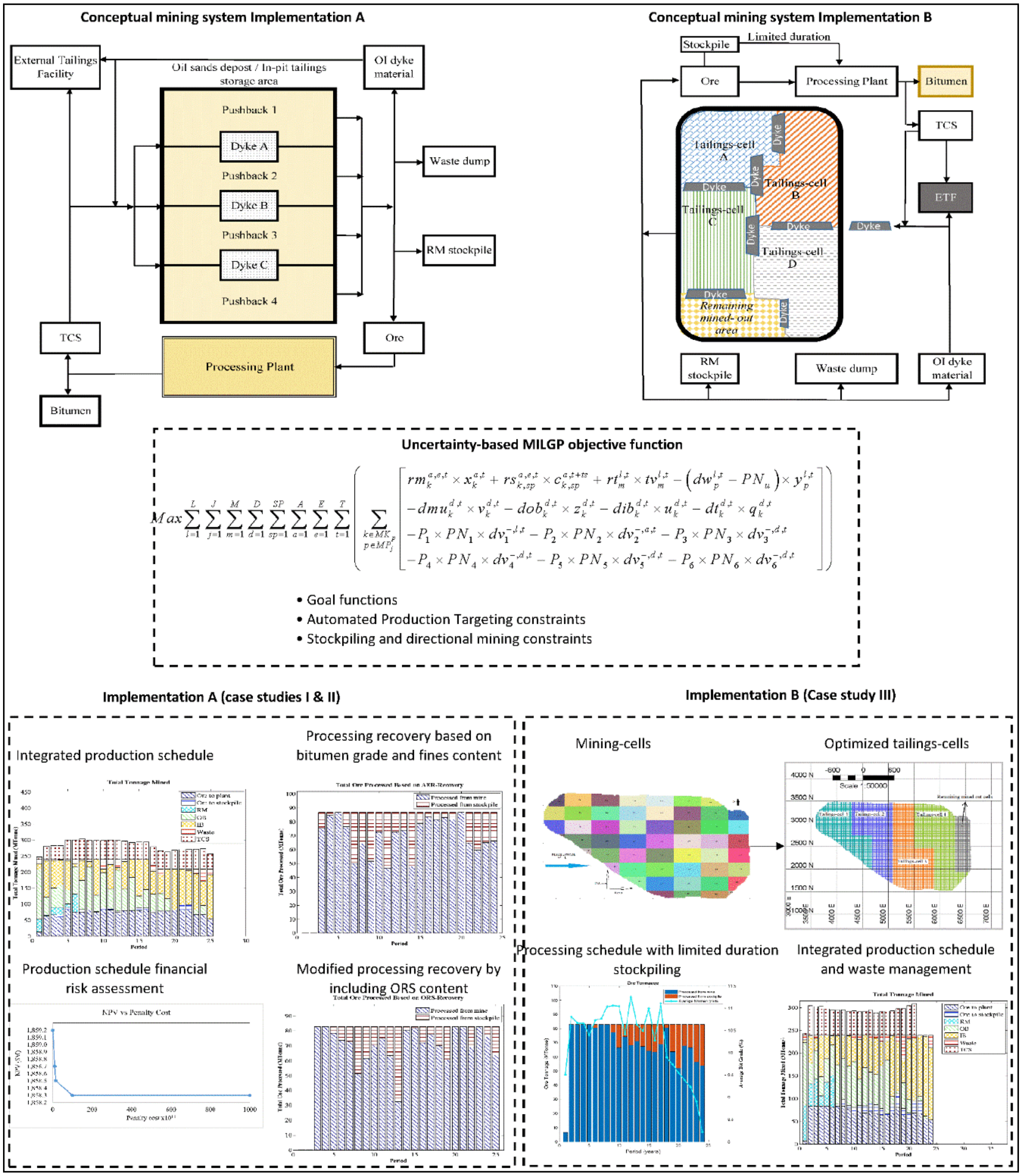


Figure 5-1: Summary of research methods and framework developed

The research aims to achieve seven main objectives: (i) maximizing the NPV of the mining operation; (ii) minimizing the dyke construction and reclamation works cost; (iii) incorporating limited duration stockpiling; (iv) minimizing the production schedule financial risk associated with grade uncertainty; (v) adjusting the bitumen recovery by integrating ORS content; (vi) maximizing the pseudo backfilling revenue from in-pit tailings disposal; and (vii) optimizing the annual production schedules. The uncertainty-based MILGP framework includes the strategic application of pushbacks (or tailings-cells) and directional mining, with the waste management scheme in oil sands mining. This strategy enables the construction of in-pit tailings facility cells in the mined-out areas as mining proceeds in the specified direction. The developed model generates a long-term production schedule for the processing plant, and reclamation and dyke materials schedules for in-pit and ex-pit tailings facilities and reclamation works. The MILGP framework was implemented for a large-scale oil sands mining project taking into consideration grade uncertainty and ORS content that effects ore processability. Mining-cuts and mining-panels are used to control mining, processing, reclamation and dyke material scheduling units, while mining-cells are used to model tailings-cell design requirements.

Numerical experiments with an oil sands dataset were used to verify the developed uncertainty-based MILGP framework. Whittle software based on the LG algorithm is used to generate the UPL which contains a total of 5,735.6 Mt of rock including 1,906.9 Mt of ore in addition to reclamation material, dyke materials and waste. The model was run on a ThinkStation with CPU E5-1650 v4 at 3.60 GHz and 64.0 GB of RAM. Three case studies were implemented to outline the different techniques and strategies used in the uncertainty-based MILGP framework to incorporate waste management planning with production scheduling in oil sands mining. The three case study scenarios were implemented with a 10% annual discount rate over 25 periods. The results show that all the considered constraints were satisfied and the developed model worked properly. Among other things, the case study scenarios were compared based on NPVs, mining and processing production schedules, smoothness and practicality of the schedules, average bitumen head grade, average processing plant recovery and pseudo backfilling revenue.

Case study I was implemented with two scenarios (Scenario I-1 and Scenario I-2) using goal functions to define mining and processing capacities, and a fixed recovery of 90% for the processing plant. Specifically, Scenario I-1 features goal functions for mining, processing, reclamation and dyke materials with a limited duration stockpiling strategy for ore. Grade uncertainty cost is set to zero and no backfilling activities are modeled. The MILGP model generates a smooth, uniform and practical production schedule with an overall NPV of $18,108 M. Scenario I-2 deploys grade uncertainty cost to investigate the effect of grade uncertainty on the NPV of a mining project. No stockpiling, reclamation and dyke materials targets, and backfilling activities are considered. The technique applied is based on the concept of mean-variance analysis, which is the process of weighing risk (variance) against expected NPV. Scenario I-2 is implemented with three different uncertainty-based techniques as follows: (1) no grade uncertainty cost applied to mining-panels (Run 1), the NPV obtained was $18,482 M; (2) applying grade uncertainty cost to high-variance mining-panels (Run 2), the NPV obtained decreases from $18,482 M to $18,474 M. Thus, the potential production schedule financial risk associated with grade uncertainty can be estimated as a loss of $8 M in the most pessimistic case; (3) applying grade uncertainty cost to all mining-panels (Run 3), the NPV obtained decreases from $18,482 M to $18,475 M. Thus, the potential production schedule financial risk associated with grade uncertainty can be estimated as a loss of $7 M in the most pessimistic case. Among other things, by taking into consideration the NPV range and the production schedule financial risk, investors can make more pragmatic choices when managing their mining investment risk profile. Additional details on the production schedule scenarios for Case study I are presented in Sections 4.5.6 to 4.5.9.

Case study II was implemented with two scenarios (Scenario II-1 and Scenario II-2) to highlight different aspects of the formulated MILGP model. Scenario II-1 determines the NPV based on revenue calculated using AER recovery and Scenario II-2 estimates the NPV based on revenue calculated using ORS recovery. The two scenarios feature the determination of mining and processing capacities as part of the production scheduling optimization process using the Automated Production Targeting (APT) constraints in place of goal functions. The grade uncertainty cost was set to zero. A two-year pre-stripping production requirement and a two-year limited duration stockpiling constraint were enforced.

Comparatively, the production schedules for Scenarios II-1 and II-2 were uniform throughout the mine life. The overall NPVs generated, excluding dyke material costs are \$10,153 M and \$9,800 M for Scenarios II-1 and II-2, respectively. That represents a 3.46% overestimation of NPV (equivalent to \$351 M) arising mainly from not taking into account the effect of ORS content on bitumen recovery during mine planning. The APT constraints are used to optimize the mining and processing annual capacities. The APT constraints minimize the periodic variations in the production schedule throughout the life of mine. The integrated MILGP model results in better environmental management and sustainable oil sands mining by ensuring mine planners have effective control over waste disposal planning in terms of material movement, in-pit tailings deposition and in-pit and ex-pit dyke construction. Additional details on Case study II results are presented in Sections 4.6.5 and 4.6.6.

Case study III was implemented with four waste management scenarios based on the differences in the size and number of unit mining-cells used in creating tailings-cells for tailings backfilling. Scenario III-1 was implemented with smaller size unit mining-cells and larger number of unit mining-cells. In general, for the same UPL, as the size of the unit mining-cells increases, the number of unit mining-cells decreases. For all scenarios, grade uncertainty cost was set to zero, while limited duration stockpiling and ORS recovery are deployed for production scheduling. No pre-stripping was enforced. The investigated scenarios make in-pit tailings storage areas available early in the mine life to ensure sustainable operations and timely reclamation. The model generated optimal mining and processing capacities as well as practical, smooth and uniform schedule for ore using the APT constraints. Excluding pseudo backfilling revenue, Scenario III-1 generated the highest NPV of \$12,040 M, followed by Scenario III-2 with NPV of \$11,854.4 M while Scenario III-4 generated the lowest NPV of \$11,282 M. The results show that, decreasing the volume of unit mining-cells used in creating the in-pit tailings-cells increases the NPV of the operation due to increased operational flexibility. On the other hand, decreasing the number of mining-cells in the (north-south) direction increases the CPU run time significantly. Additionally, as the percentage of in-pit volume to be backfilled increases as observed in Scenario III-1, more savings is generated from not sending tailings to external facilities at a higher cost. Additional details on Case study III results can be found in Sections 4.7.3 to 4.7.5.

In comparison, Case study I has a higher NPV than Case study II and Case study III due to the assumed processing plant bitumen recovery of 90%. In addition, Case study III generated a higher NPV than Case study II since no pre-stripping was enforced. The developed MILGP framework was verified through the numerical experiments and analysis of results obtained from the implementation of the proposed model on a real-size dataset. Since current industry-standard software such as Whittle does not contain tools for integrated uncertainty-based mine planning and waste management, it cannot be used for validation of the proposed model. Instead, the practicality of the generated production and waste disposal schedules has been considered as a measure for model validation.

5.2 Conclusions

In pursuing this research, the literature review showed that there has never been any previous attempt to integrate grade uncertainties into integrated production scheduling and waste management optimization for oil sands mining. Specifically, there has not been any previous research to optimize tailings-cells capacity, shape and location for waste management. The literature also showed that there are some limitations in production scheduling optimization applications such as: (i) limited literature in integrating oil sands waste management and reclamation planning in the production scheduling optimization process as required by the regulator; (ii) limitations in mathematically modeling limited duration stockpile usage to support the processing plant capacity; (iii) limitations in accurately modelling oil sands ore processability through the processing plant recovery factor; and (iv) limitations in determining the mining and processing targets as part of the optimization problem. These limitations affect the practicality and optimality of the generated mine plans. This research therefore, pioneers the effort to employ a mathematical programming framework to contribute to the body of knowledge and provide a novel understanding in the area of uncertainty-based integrated mine planning and waste management optimization.

In this research, an uncertainty-based mathematical programming framework for long-term production scheduling and waste management optimization of open pit mines using MILGP was developed. The theoretical framework was implemented and verified on a real oil sands dataset. The objectives of the research outlined in Chapter 1 have been achieved within the research scope. The following conclusions are drawn:

1. The integration of waste management into production scheduling by the uncertainty-based MILGP model is implemented using two different strategic approaches; pushback mining and mining-cells extraction for creating tailings-cells.
2. The MILGP model concurrently generates production schedules for the processing plant, and reclamation and dyke materials providing the platform for robust waste management planning leading to sustainable mining.
3. The uncertainty-based MILGP model simultaneously minimizes production schedule financial risk associated with grade uncertainty while maximizing the NPV of the mining operation.
4. The MILGP model deploys mining-cells to optimize the size, shape and location of in-pit tailings containment areas referred to as tailings-cells.
5. The MILGP model determines mining and processing capacities as part of the optimization problem using sophisticated APT constraints.
6. The MILGP framework introduces ORS content in addition to bitumen and fines content to adjust processing plant bitumen recovery.
7. The MILGP model uses limited duration stockpiling to support the processing plant feed while reducing the oxidation of stockpiled ore material.
8. The MILGP framework provides a systematic workflow towards promoting integrated sustainable mining as directed by the AER Directive 082 regulation.

These results prove that the uncertainty-based MILGP model is a robust tool for optimizing oil sands long-term production schedules whilst taking into account grade uncertainty and waste disposal planning.

5.3 Contributions of PhD research

This research has developed an integrated uncertainty-based MILGP model for oil sands mine planning and waste management. The MILGP model seeks to generate practical and optimal mine plans through risk-based multi-objective optimization. This research contributes significantly to the body of knowledge on open pit mine planning and waste management, and creates the platform for developing specialized mine planning software packages. The main contributions of this research are:

1. This is a novel effort in developing an integrated uncertainty-based MILGP model that is capable of evaluating and quantifying the production schedule financial risk associated with grade uncertainty. The developed model uses kriged estimates with a variance penalty scheme to minimize the financial risk. The model generates a range of NPVs representing the financial risk profile, thus mine planners and investors can make more pragmatic choices when managing their mining projects.
2. The MILGP framework is a pioneering endeavor to strategically optimize the capacity, shape and location of tailings-cells for waste disposal planning and tailings management.
3. The research has introduced new APT mining and processing constraints that optimize the annual capacities for the plant and the mining operation in the MILGP framework. The strength of the APT constraints to determine the appropriate production levels expands the frontiers of mine planning and optimization in generating refined and sophisticated mining and plant capacity estimates based on deposit configuration.
4. Unlike current mathematical programming models, introducing limited duration stockpiling strategy for the mined ore that exceeds plant capacity in the MILGP model results in production schedules with improved net present value.
5. The MILGP framework incorporates ORS content to additionally adjust processing plant recovery providing a more accurate prediction of ore processability and NPV.
6. The MILGP framework provides a systematic workflow towards promoting sustainable mining as directed by Directive 085 issued by Alberta Energy Regulator. The framework enables step-changes in the planning and managing of oil sands mines by the industry.

5.4 Recommendations for further research

Despite the pioneering framework and workflow that integrates oil sands production scheduling and waste disposal planning in this thesis, there is still the need for continued investigation into the application of MPMs for integrated mine planning in the mineral industry. The following thematic areas and recommendations could improve and add to the body of knowledge in this research area:

a) Although the MILGP framework for this research evaluates the effect of grade uncertainty on the production schedule, it still considers deterministic values such as future cost and price data for the economic block model. This assumption means that as cost and price change in the future, there is a need for re-optimization of the production schedules. To be able to deal with these limitations, the MILGP framework should be extended to include uncertain variables like mining costs and mineral prices during optimization.
b) In this research, the optimization of tailings-cells shape, size and location are integrated in the MILGP framework for waste management. This ensures that sufficient and timely in-pit tailings-containment areas are made available for tailings backfilling. To push forward the frontiers of mining, further research into extending the MILGP framework to integrate additional tailings-cell shape constraints during optimization should be carried out.
c) To make it more user friendly for mine planners, the efficiency of the MILGP model should be improved by reducing the CPU runtime.

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