An Integrated Optimization Model for Strategic Open-Pit Mine Planning and Tailings Management

by

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ABSTRACT

A strategic mine planning model determines the best order of extraction and destination of material over the mine-life, in a way that maximizes the net present value of the produced minerals. In case of oil sands open-pit mining, further processing of the extracted oil sands generates massive volumes of slurry containing water, sands, clay and fine material known as tailings. Since the tailings volume significantly influences the mine production and site reclamation, it is reasonable to consider tailings management within the frameworks of long-term mine planning. One of the current practices in Alberta oil sands industry is to process the tailings slurry and make composite tailings (CT), through adding coagulant aids to the mature fine tailings (MFT), to accelerate its dewatering and make it ready for reclamation. To save space and also to avoid higher reclamation costs, the processed tailings is deposited in in-pit tailings containments constructed by internal dykes using mine waste material. In this research, an integrated mine planning framework is proposed, implemented and verified using mixed-integer linear programming technique, to optimize the production schedule with respect to mine waste management in terms of dyke construction and in-pit tailings deposition. A tailings model is developed and integrated to the mine planning model that calculates the volume of tailings slurry and composite tailings based on the processed material. Two small case studies and one large-scale case are carried out to verify the performance of the proposed optimization model. Two variable reduction techniques are implemented to increase the efficiency of the run time. The model solves the large-scale problem to optimality over 30 periods within 0.5 to 1.5 hours of CPU time, depending on the model resolution. In the generated schedule, the produced tailings is being deposited in the excavated mining-pit as the mining operations proceed and the in-pit dykes are constructed using mine waste material.

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LIST OF ABBREVIATIONS

AFD	Atmospheric Fines Drying
CHWE	Clark Hot Water Extraction
CT	Composite Tailings
ERCB	Energy Resources Conservation Board
ETF	External Tailings Facility
ILP	Integer-Linear Programming
LP	Linear Programming
LR	Lagrangian Relaxation
MILP	Mixed-Integer Linear Programming
NPV	Net Present Value
NST	Non-Saturated Tailings
OI	Over-burden and Inter-burden
SAGD	Steam-Assisted Gravity Drainage
TCS	Tailings Coarse Sand

LIST OF NOMENCLATURE

Tailings Model Parameters

$B\%_{SET}$	SET bitumen percent
BDD_{DT}	Beach dry density (DT)
BDD_{RunOff}	Beach dry density (Run off)
BDD_{SET}	Beach dry density (SET)
CDD	Cell dry density
$CT\%_{Tremie}^{Spec}$	On spec CT to Tremie (%)
E_{Cell}	Cell Efficiency
$F\%_{Beach}$	Fines content in beach solids (%)
$F\%_{CT}^{Seg}$	Fines in segregated CT (%)
$F\%_{SET}$	SET fine percent
$F\%_{Cell}$	Cell % fines in solids
FC_{Cell}	Cell physical capture
HPW	HPW
R	SET recovery percent
$Rj\%$	Reject percent
$Rj\%_{B}$	Bitumen rejects percent
$Rj\%_{F}$	Fines reject percent
$Rj\%_{Sd}$	Sand reject percent
$Rj\%_{W}$	Water reject percent

$S\%_{CT}$	Solid % (CT)
$S\%_{CT}^{Dep}$	Solids in CT deposit (%)
$S\%_{DT}$	DT solid content (%)
$S\%_{MFT}$	MFT solid content (%)
$SCBD$	Density of segregated CT at beach
$Sd\%_{SET}$	SET sand percent
SFR	Sand to fine ratio (target)
$Sd\%_{UF}$	Sand content of the underflow
SG_f	Fines specific gravity
SG_s	Sand specific gravity
$Sl_{solid\%}$	Solid percent of slurry sent to cyclone
$UF_{F\%}$	Fine percent in cyclone underflow
$UF_{Sd\%}$	Sand percent in cyclone underflow
$UF_{W\%}$	Water percent in cyclone underflow
V_{Cell}	Cell volume (m3)
$W_{Make-up}$	Make up water
$W\%_{SET}$	SET water percent

MILP Sets and Indices

$a \in \mathbf{A}, \mathbf{A} = \{1,.....,A\}$ Index and set of all the possible mining locations (pits) in the model.

$c \in \mathbf{C}, \mathbf{C} = \{1,......,C\}$ Index and set of all CT cells in the model.

$d \in \mathbf{D}, \mathbf{D} = \{1,......,D\}$ Index and set of all dyke units in the model.

$e \in \mathbf{E}, \mathbf{E} = \{1,.....,E\}$ Index and set of all the elements of interest in the model.

$j \in \mathbf{J}, \mathbf{J} = \{1,......,J\}$ Index and set of all the phases (push-backs) in the model.

$k \in \mathbf{K}, \mathbf{K} = \{1,.....,K\}$ Index and set of all the mining cuts in the model.

$p \in \mathbf{P}, \mathbf{P} = \{1,.....,P\}$ Index and set of all the mining panels in the model.

$t \in \mathbf{T}, \mathbf{T} = \{1,.....,T\}$ Index and set of all the scheduling periods in the model.

$u \in \mathbf{U}, \mathbf{U} = \{1,.....,U\}$ Index and set of all the possible destinations for materials in the model.

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

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

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

$O_p(L)$ For each mining panel p, there is a set $O_p(L) \subset \mathbf{P}$ defining the immediate predecessor mining panels in a specified horizontal mining direction that must be extracted prior to extraction of mining panel p at the specified level, where P is the total number of mining panels in the set $O_p(L)$.

$Q_c(R)$ For each CT cell *c*, there is a set $Q_c(R) \subset \mathbf{C}$ defining the immediate predecessor CT cells below the CT cell *c* that must be filled in prior to filling of CT cell *c*, where *R* is the total number of CT cells in the set $Q_c(R)$.

$S_d(G)$ For each dyke unit *d*, there is a set $S_d(G) \subset \mathbf{D}$ defining the immediate predecessor dyke units that must be constructed in prior to constructing of dyke cell *d*, where *G* is the total number of dyke units in the set $S_d(G)$.

$T_c(D)$ For each CT cell *c*, there is a set $T_c(D) \subset \mathbf{D}$ defining the immediate predecessor dyke units that must be constructed in prior to filling of CT cell *c*, where *D* is the total number of dyke units in the set $T_c(D)$.

$X_d(P)$ For each dyke unit *d*, there is a set $X_d(P) \subset \mathbf{P}$ defining the immediate predecessor mining panels that must be extracted in prior to construction of dyke unit *d* to guarantee that the dykes foot print is cleared, where *P* is the total number of panels in the set $X_d(P)$.

MILP Parameters

$cl^{u,t}$ Extra cost in present value terms for mining, shipping, and using a tonne of OI material for dyke construction at destination u.

$cm^{a,t}$ Cost in present value terms of mining a tonne of waste in period t from mine a.

$cp^{u,e,t}$ Discounted extra cost for mining and processing one tonne of ore at dest. u.

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

$ct^{c,t}$ Cost in present value terms of sending a volume unite of CT in period t to cell c.

$cu^{u,t}$ Extra cost in present value terms for mining, shipping, and using a tonne of tailings sand for dyke construction at destination u.

$d_p^{a,u,t}$ Discounted profit obtained by extracting mining panel p from location a and sending it to destination u in period t.

d_k OI dyke material tonnage in mining-cut k.

f_k Fines tonnage produced from extracting all of the ore from mining-cut k.

f_k^c Average percentage of fines in the OI dyke material portion of mining-cut k.

$\underline{f}^{u,t,c}$ Lower bound on the required average fines percentage of OI dyke material in period t at destination u.

$\overline{f}^{u,t,c}$ Upper bound on the required average fines percentage of OI dyke material in period t at destination u.

f_k^o Average percentage of fines in the ore portion of mining-cut k.

$\underline{f}^{u,t,o}$ Lower bound on the required average fines percentage of ore in period t at processing destination u.

$\overline{f}^{u,t,o}$ Upper bound on the required average fines percentage of ore in period t at processing destination u.

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

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

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

h_c Total volume of CT cell c.

h_k MFT volume produced from extracting all of the ore from mining-cut k.

k_d Total volume of dyke unit d.

l_k Tailings coarse sand tonnage in mining-cut k.

$m_k^{u,t}$ Extra discounted cost of producing tailings sand from mining cut k in period t and sending it for dyke construction in destination u.

$n_k^{u,t}$ Extra discounted cost of mining the OI material of the mining cut k in period t and sending it for dyke construction in destination u.

o_k Ore tonnage in mining cut k.

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

p_k CT volume produced from extracting all of the ore from mining-cut k.

p_p Mining panel p.

$q_p^{a,t}$ Discounted cost of mining all the material in mining panel p in period t as waste from location a.

r_k Water tonnage produced from extracting all of the ore from mining-cut k.

$r^{u,e}$ Proportion of element e recovered if it is processed at destination u.

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

s_k Sand tonnage produced from extracting all of the ore from mining-cut k.

t_k Tailings tonnage produced from extracting all of the ore in mining-cut k.

$T_{Mu}^{a,t}$ Upper bound on mining capacity (tonnes) in period t at location a.

$T_{Ml}^{a,t}$ Lower bound on mining capacity (tonnes) in period t at location a.

$T_{Pu}^{u,t}$ Upper bound on processing capacity (tonnes) in period t at destination u.

$T_{Pl}^{u,t}$ Lower bound on processing capacity (tonnes) in period t at destination u.

$T_{Cu}^{u,t}$ Upper bound on OI material required for dyke construction (tonnes) in period t at destination u.

$T_{Cl}^{u,t}$ Lower bound on OI material required for dyke construction (tonnes) in period t at destination u.

$T_{Nu}^{u,t}$ Upper bound on tailings sand required for dyke construction (tonnes) in period t at destination u.

$T_{Nl}^{u,t}$ Lower bound on TCS required for dyke construction (tonnes) in period t at destination u.

$T_{Tu}^{u,t}$ Upper bound on capacity of tailings facility (tonnes) in period t at destination u.

$T_{Tl}^{u,t}$ Lower bound on capacity of tailings facility (tonnes) in period t at destination u.

$T_{Fu}^{u,t}$ Upper bound on capacity of fine material (tonnes) in period t at destination u.

$T_{Fl}^{u,t}$ Lower bound on capacity of fine material (tonnes) in period t at destination u.

$T_{Su}^{u,t}$ Upper bound on capacity of tailings sand (tonnes) in period t at destination u.

$T_{Sl}^{u,t}$ Lower bound on capacity of tailings sand (tonnes) in period t at destination u.

$T_{Wu}^{u,t}$ Upper bound on capacity of tailings water (tonnes) in period t at destination u.

$T_{Wl}^{u,t}$ Lower bound on capacity of tailings water (tonnes) in period t at destination u.

$T_{Xu}^{u,t}$ Upper bound on capacity of MFT (tonnes) in period t at destination u.

$T_{Xl}^{u,t}$ Lower bound on capacity of MFT (tonnes) in period t at destination u.

$T_{Yu}^{u,t}$ Upper bound on capacity of CT (tonnes) in period t at destination u.

$T_{Yl}^{u,t}$ Lower bound on capacity of CT (tonnes) in period t at destination u.

w_k Waste tonnage in mining-cut k.

CHAPTER 1
INTRODUCTION

The oil sands is one of the fastest growing industries in North America. Most of the bitumen resources of the world are located in northern Alberta boreal forests. An oil sands deposit is a mixture of bitumen and water in sands and clay. It is a thick, sticky, heavy and viscous material and needs rigorous extraction treatment to refine its bitumen. Depending on the reserve's depth, two methods are available for bitumen extraction: surface mining and steam-assisted gravity drainage (SAGD) technology. Surface mining is used for near-surface reserves, requiring an open-pit mine operation. The oil sands are dug up with shovels, loaded to the trucks, and transferred to the processing facilities, where the recoverable oil is separated by the means of hot water. SAGD technology is used for deeper reserves where surface mining is not economical.

A mine production plan determines the best schedule for extraction and the destination of the extracted material, in such a way that maximizes the net present value of the production. In oil sands surface mining, the extracted material will be sent to the processing plants for extraction of bitumen through hot water extraction process. Bitumen extraction generates massive volume of slurry - a mixture of water, fine material, sand, and residual bitumen - known as tailings.

Tailings is the main unwanted by-product of oil sands processing because of its two associated consequences. First, there are a number of environmental issues around tailings impoundment and dewatering, such as fresh water table contamination through leaking of the contaminated tailings water. The oil sands companies must address the requirements of Directive 074 (McFadyen, 2008) and are responsible to reclaim the mine site and tailings ponds before leaving the site. A number of technologies are developed for dewatering of tailings slurry and preparing the tailings ponds for reclamation. Composite tailings (CT) production is one of the current technologies used extensively in Alberta for tailings dewatering. CT is produced by adding gypsum as a coagulant aid to the mature fine tailings (MFT) to increase the dewatering rate of the MFT. The second issue with tailings storage is that tailings ponds occupy a considerable surface from the limited lease areas. This will constrain the mining operations, as each tonne of mined and processed material generates further volume of tailings slurry for which the tailings facility may not have enough storage space.

In the current practice, the tailings and reclamation plans are prepared and optimized after optimization of the long-term mine production planning. The resulting schedule from mine planning is considered as an input to the tailings and reclamation plans. However, the material used in dyke construction for tailings storage, and the material used for capping in reclamation phase are mainly the waste material generated in mining operations as over-burden or inter-burden (OI), and tailings coarse sand (TCS) captured downstream from bitumen processing. This fact advocates the idea of integrating waste management, tailings planning, and reclamation planning within the long-term mine planning optimization framework. Hence, the main goal in this research is to develop, implement, and verify an integrated mine planning model which includes oil sands waste management in terms of dyke construction and CT deposition.

The mixed-integer linear programming (MILP) is a powerful tool extensively used in the literature for mine planning optimization. The proposed MILP model in this research maximizes the net present value (NPV) and at the same time minimizes the costs of dyke construction and CT deposition. The optimization is subject to a number of constraints, including the mining, processing, and tailings storage capacities and extraction precedence constraints. Also a tailings model is developed to calculate the potential volume of different tailings products resulting from the hot water extraction process. The result of tailings model is used in tailings constraints of the MILP model.

This chapter continues by the statement of the problem, followed by a summary of the literature review. The objectives of the research and its scope and limitations are discussed. Further, the research methodology, the scientific contribution of the research and its significance to the industry are provided as well, followed by presenting the organization of the thesis in the next chapters.

1.1. Statement of the Problem

Typical mine planning models maximize the NPV over the mine-life, with respect to the mining and processing capacities, ore blending constraints, and spatial precedence among mining blocks (Johnson, 1969; Askari-Nasab and Awuah-offei, 2009; Askari-Nasab et al., 2011b). Further than the pure long-term mine planning models, few works are published addressing the linkage between mine planning and tailings production (Kalantari et al., 2013). The solid waste disposal management and dyke construction planning in oil sands are also integrated into the long-term mine planning framework (Ben-Awuah and Askari-Nasab, 2011; Ben-Awuah et al., 2012; Ben-Awuah, 2013). Moreover, the material procurement for reclamation planning are included in long-term mine planning as well (Badiozamani and Askari-Nasab, 2014a). A schematic view of the current state in long-term mine planning and related domains in oil sands surface mining is presented in Figure 1.

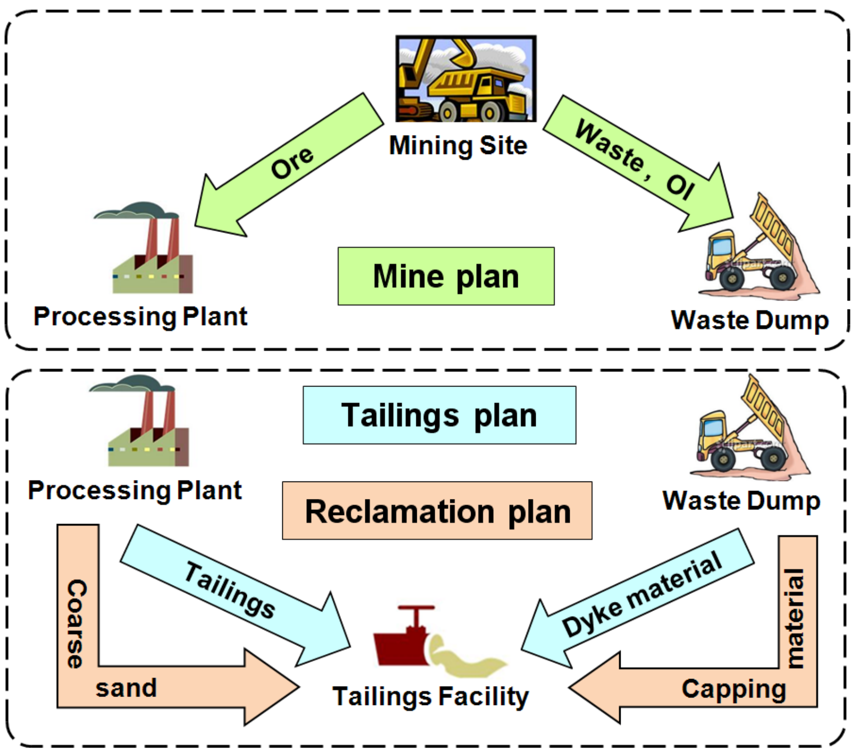

Figure 1: The current separated frameworks of mine planning, tailings planning, and reclamation planning, modified after (Badiozamani and Askari-Nasab, 2014a).

However, the gap in current literature is the integration of all these areas: maximization of profit in pure mine planning, minimization of dyke construction costs, minimization of material handling costs for reclamation, and minimization of tailings disposal costs. Such integration is supported by the following facts: (1) the mining cannot be scheduled regardless of potential tailings slurry production, as the capacity for tailings storage is limited to the lease area, (2) the material used for dyke construction is coming either from the mining operations as OI, or from the processing plant as TCS, and (3) the same source of material - the OI and TCS - will be used also for capping purpose in reclamation phase. These facts show that the mining, processing, dyke construction and reclamation are all dealing with the same material and a change in any of them will influence the rest. Further, the maximized NPV with respect to all these aspects will generate a globally-optimized schedule for mining that is always a better solution comparing to separately-optimized schedules for sub problems in a convex space. The solid waste management, dyke construction, tailings management, and reclamation planning can be all integrated within the long-term mine planning framework, as schematically proposed in Figure 2. Proposing such an integrated framework motivates this research.

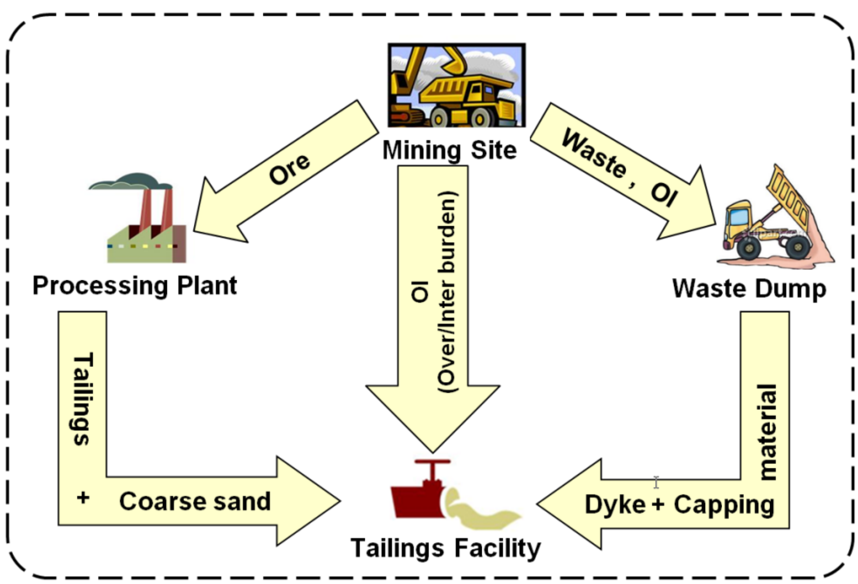

Figure 2: The proposed integrated mine planning model,
modified after (Badiozamani and Askari-Nasab, 2014a).

In this research, it is assumed that the same material (OI and TCS) is used for dyke construction and reclamation. Hence, the reclamation material is not considered further in this research to reduce the model complexity. The proposed integrated mine planning model has the following structure:

Maximize: NPV – Dyke construction costs - CT deposition costs

Subject to:

Mining capacity constraints

Processing capacity constraints

OI and TCS requirements for dyke construction

Tailings, fines, sand and water capacity constraints

CT and MFT capacity constraints

Ore blending constraints

Mass balance constraints for mining, produced CT, and dyke material

Mining precedence

CT deposition precedence

Dyke construction precedence

1.2. Summary of Literature Review

Mine planning determines the order of extraction and destination of the blocks as the imaginary 3-dimensional spatial units defined to model the mass of the material considered for extraction. Open-pit mining is known as an economical method for extraction of near-surface deposits. A considerable portion of northern Alberta oil sands reserves are located near surface, currently being extracted through open-pit mining using truck-shovel system. The extracted oil sands will be sent to the processing plants for extraction of bitumen trough Clark hot water extraction (CHWE) method (Clark and Pasternack, 1932; Clark, 1939). The added hot water, plus the fine material, sand and residual bitumen contents make downstream tailings slurry. The oil sands operators are supposed to dewater the slurry and make the tailings containments trafficable for further reclamation in closure phase.

Oil sands surface mining triggers a number of environmental issues, mostly around mining solid waste and downstream tailings slurry resulting from CHWE process. Tailings is a mixture of fine material, sand and clay in water and includes residual bitumen. The foot prints of mining operations, the toxic tailings ponds, and the green house gas emissions resulting from CHWE process are the main environmental concern around oil sands surface mining (Woynillowicz et al., 2005; Rodriguez, 2007; Singh, 2008). Despite of the environmental issues, the massive volume of generated tailings is a critical issue that affects the mine planning since the available area for tailings storage is limited to the lease areas. These facts raise the idea of considering the tailings management in an integrated framework with long-term mine planning. However, the tailings plans and long-term mine plans are prepared separately in current practice (Suncor, 2009; CNRL, 2010; Imperial-Oil, 2010; Syncrude-Canada-Ltd., 2010; Shell-Canada-Energy, 2010a; Shell-Canada-Energy, 2011a; Shell-Canada-Energy, 2011b).

Solid waste management is the other related concept to the long-term mine planning. Mining operations generates considerable volumes of solid waste mostly as overburden and the low-grade interburden material in order to access the mineralized zone. The current practice is to dump the waste material for later use in dyke construction and reclamation, which are planned separately after the mine planning. The requirements of Directive 074 (McFadyen, 2008) issued by the Energy Resources Conservation Board (ERCB) mandates the oil sands operators to publish their waste disposal and tailings plans. Currently, the waste disposal is planed separately from the mine planning. However, the main source of the required material for dyke construction is OI material coming from mining operations, and the TCS coming from processing plant (Fauquier et al., 2009; Ben-Awuah, 2013). Hence, waste disposal, reclamation planning, and dyke construction planning can be integrated with the mine planning framework. In the literature, few works have addressed such integration, but none of them has covered the mentioned domains completely (Ben-Awuah and Askari-Nasab, 2011; Ben-Awuah et al., 2012; Badiozamani and Askari-Nasab, 2013; Ben-Awuah, 2013; Badiozamani and Askari-Nasab, 2014a; Badiozamani and Askari-Nasab, 2014b).

Since 1960s, operations research techniques such as linear programming, integer programming, mixed-integer linear programming (Johnson, 1969) and dynamic programming (Tan and Ramani, 1992) have been used to find the optimized pattern of extraction and determine a destination for the extracted material in open-pit mining and block caving (Newman et al., 2010). The most common way to control the precedence order of extraction for mining blocks is to define integer variables, which makes the mine planning problem NP-hard for large-scale problems (Gleixner, 2008). Due to the large number of integer variables corresponding to mining blocks over large number of periods, it takes considerably a long time for the current solvers to solve the problem.

Review of the literature reviled that a number of techniques have been used to simplify the model and make it tractable. In LP relaxation, the integer nature of variables is ignored to solve a reduced problem, which provides an upper bound for the NPV maximization (Tan and Ramani, 1992; Bienstock and Zuckerberg, 2010; Alvarez et al., 2011; Chicoisne et al., 2012; Epstein et al., 2012). However in most of the cases, the LP relaxation does not provide a feasible solution for the original integer problem and hence, the solution must be modified using some heuristic algorithms. Lagrangian relaxation (Jünger et al., 2010) is the other technique implemented extensively in mine planning problems (Dagdelen and Johnson, 1986; Akaike and Dagdelen, 1999; Kawahata, 2006; Gaupp, 2008; Cullenbine et al., 2011). In Lagrangian relaxation (LR), the constraints are classified into soft versus hard constraints assuming that the problem can be solved easily, e.g. as a knapsack problem, in presence of only soft constraints. to adjust the relaxation of each constraint, a penalty function is added to the objective function to control the violation from the corresponding constraint. When choosing LR, the values to be determined are the penalty multipliers. The sub-gradient method (Fisher, 1981; Fisher, 1985) is one of the algorithms used in determining the multipliers values. However, there is a limitation involved in using LR: the sub-gradient algorithm is not an exact method and does not guarantee to find the optimal penalty values. Therefore, the solution may or may not be feasible for the original problem and needs further heuristic modifications. In conclusion, the LP relaxation and LR methods need supplementary heuristic algorithms to adjust the solutions. Therefore, they both fail in guaranteeing an optimal feasible solution to the MILP problem.

Aggregation of mining-blocks to form larger units as mining-cuts is another technique used in the literature to tackle the issue of dimensionality. There are different data clustering methods (Barbakh et al., 2009), including hierarchical clustering (Johnson, 1967), k-means clustering (MacQueen, 1967), and fuzzy c-means clustering (Dunn, 1973). All of the algorithms have been used for mining-block aggregation. The idea behind aggregation is to merge the similar mining-blocks to make larger mining-cuts, according to mining-block properties such as spatial location, grade and rock type (Smith, 1999; Zhang, 2006; Boland et al., 2009; Tabesh and Askari-Nasab, 2011a). Defining fundamental trees is the other method to aggregates the mining-blocks and reduces the problem size (Ramazan et al., 2005; Ramazan, 2007). Mining-panels, the intersections of pushbacks and mining benches, also can be considered as larger aggregate units (Ben-Awuah, 2013). In this case, the mining-cuts are defined within the boundaries of mining-panels and can be used for destination decisions. For large-scale problems, the blocks must be clustered through heuristic or meta-heuristic algorithm, since the clustering problem is NP-hard itself. However, the clustering and paneling can be used as a powerful technique to provide larger units that follow the practical selective mining units and at the same time, reduce the number of decision variables.

Preprocessing techniques have been used to eliminate a number of decision variables by fixing their values before solving the problem. Since the mining capacity is limited in each period, the accumulated mining capacity up to each period is known in advance. Due to the precedence order of extraction, the total mass tonnage laid on top of each block or in a certain horizontal direction must be extracted to access that specific block. By comparing the accumulated mining capacity and the tonnage of the predecessor blocks, it can be determined if the mining-block is accessible in certain periods or not. With the same logic, more variables may be cancelled from the model by considering processing capacity (Amaya et al., 2009; Bley et al., 2010; Cullenbine et al., 2011; Martinez and Newman, 2011; Tabesh and Askari-Nasab, 2011b).

In conclusion, review of the oil sands regulations, specifically the requirements of Directive 074, motivates the consideration of tailings management and waste disposal planning within the long-term mine planning framework. Such integration is also supported by the fact that most of the material used in dyke construction or reclamation is generated either in mining operations or oil sands processing. The MILP is a powerful operations research technique that has been used extensively to optimize the mine production schedule. However for large scale mine planning problems, the resulting MILP is NP-hard and cannot be solved in acceptable solution time. Inclusion of more features such as tailings and waste disposal planning even adds to the complexity of the model. Review of the literature reviled that heuristic algorithms have been used to solve the mine production scheduling problem, either directly or in LP relaxation and LR algorithms. Heuristic approaches are also used in block aggregation to reduce the problem size. Knowing that heuristic methods do not guarantee the optimality of the solution, the goal of this research is to solve the MILP model with a minimum use of heuristics (only in block aggregation), and implement other available problem-size reduction techniques.

The following research question motivates this research: “How an integrated mine production schedule can maximize the NPV of the production and minimize the cost of dyke construction and tailings deposition over the mine life-time, using an MILP framework?”

1.3. Objectives of the Research

The main goal of this research is to develop, implement, verify and validate an integrated mine planning optimization framework using an MILP model, that maximizes the net present value of the operation over the mine life. This optimization is constrained by tailings management requirements, waste disposal and material procurement for reclamation. In order to develop such an integrated model, the available mine planning MILP models are revised to control the flow of material from the mine site to the processing plant and other destinations for various purposes such as dyke construction.

The second objective in this research is to develop and verify a tailings model containing the required formulations for calculation of tailings slurry volume and its contents such as fine material, sand and water. In oil sands mining, the available area for tailings storage is restricted to the lease areas and the volume and contents of tailings slurry influence on other operational aspects in mine planning.

The third objective in this research is to implement efficient techniques for problem-size reduction. The resulting integrated MILP model will be an NP-hard problem. That is because numerous number of integer variables are involved in the model to control the precedence orders in mining the blocks, building the dykes, and filling the tailings containments. Preprocessing techniques, period aggregation and implementing larger mining units are the techniques that will be investigated for problem-size reduction.

In brief, the theoretical framework development will aim at:

- Development of a mathematical model to maximize the NPV of the mining operations for the case of open pit mining, considering minimization of costs associated with dyke construction and tailings deposition.
- Development of a framework for tailings volume calculation on the basis of mass balance relation between the ore feed and tailings products such as CT, MFT, sand, fine material and water.
- Implementation of clustering algorithms for aggregation of mining-blocks in order to generate a mining sequence that follows practical selective mining units.
- Development and implementation of techniques for problem size reduction to make the NP-Hard problem solvable within a reasonable solution time,
- Development of computer codes to implement the solution algorithm on the formulated model, using TOMLAB/CPLEX (Holmström et al., 2009),
- Verification of the developed model by carrying out case studies on actual oil sands data sets, and model validation through checking the practicality of the generated results.

1.4. Context and Scope of Work

This reserach is about development of an integrated mine plan with respect to tailings management and waste disposal planning. The proposed MILP model maximizes the NPV over the active mine-life, subject to (1) mining and processing capacities, (2) requirements on the tonnage and quality of different mined materials for each destination such as processing plant and dyke construction sites, (3) capacity of in-pit and external tailings facilities, and (4) vertical and horizontal precedence constraints regarding directional mining. There are a number of limitations to the research as well. The following assumptions define the scope and limitations of this research:

- Among the complete list of environmental impacts corresponding to the oil sands industry (Woynillowicz et al., 2005; Rodriguez, 2007), the focus in this research is on tailings ponds, in terms of in-pit tailings storage and tailings pond reclamation. The reason is that the foot print left after mining is directly related to the amount of mined material and generated tailings, and can be controlled in mine planning phase through reclamation planning and tailings management. The rest of environmental impacts are not addressed in this research because the mine planning does not have significant ties with them.
- The formulations in the proposed tailings model are based on a tailings flow sheet for hot water extraction method used by Suncor. Although different oil sands operators may have their specific hot water extraction processes, the differences are negligible. The proposed tailings model can be used with minor modifications for other cases.
- Investigation of different aggregation algorithms is out of the scopes of this research. The algorithm used in this research for block aggregation is the one proposed and implemented by Tabesh and Askari-Nasab (2013), as a hierarchical clustering algorithm. The parameters of the algorithm are tuned for the case of oil sands.
- It is assumed that the geological block model is provided through geo-statistical methods. The block model is a three dimensional representation of the mining pit

with different attributes of the imaginary cubic blocks, including the spatial coordinates of the blocks, the grade and tonnage of bitumen, potential dyke and reclamation material and waste. The details involved in collecting and sampling of drilling data for developing the geologic block model are not included in the framework of this research.

- The data from geologic block models are deterministic values and no uncertainty or fuzziness are involved in the data. The input parameters to the model, such as the mining and processing capacities, selling price of the bitumen and mining costs are assumed to be constant. The model needs to be optimized in future if the assumed values change. This assumption is aligned with the current industry practice.
- Procurement of required material for dyke construction is considered in this integrated framework. The technical details of tailings production, dyke design and dyke construction are out of the scopes of this research.
- Only the operational costs are included in the proposed integrated optimization framework. The capital costs are not considered as part of optimization, since they are essential to initiate any project and under any scenario. Particularly about dyke construction costs, the costs involved in construction of the external tailings facility are considered as the capital costs, as an ETF is required to start processing of the extracted material, while the cost of internal dyke construction is assumed to be operational cost and is present in the model calculations.

The results of the strategic mine planning model can be used later for short-term planning through optimization or simulation, with more details on the pit design, dyke construction design, tailings deposition methods, and capping operations, models.

1.5. Research Methodology

Development and implementation of an integrated long-term mine planning framework motivates this research. The main goals of this research are to address the related domains of tailings management, dyke construction, and waste disposal planning in a comprehensive optimization model and generate a production schedule that meets the requirements of the mentioned areas. To approach the research goal, the related literature is reviewed, including the applications of the operations research in mine planning, clustering and block aggregation, the main environmental impacts in oil sands surface mining, and the tailings and solid waste management.

Afterwards, a tailings model is developed based on Suncor hot water extraction flow sheet. It calculates the potential volume of tailings slurry, CT, MFT, and slurry contents (water, sand, fines) corresponding to each tonne of the ore feed entering the mill. The calculated values are used as coefficients in MILP constraints.

The next part of the research involves finding the final pit limits for a real-case oil sands block model, using the 3-dimensional LG algorithm (Lerchs and Grossmann, 1965). This is done in Whittle software (Gemcom, 2012). A number of scenarios are investigated in Whittle to generate the final pit shell and pushback design for different mining directions. The block model, the pit limits and the pushbacks corresponding to the directions with higher NPV values are then used for experimental studies through the proposed MILP model.

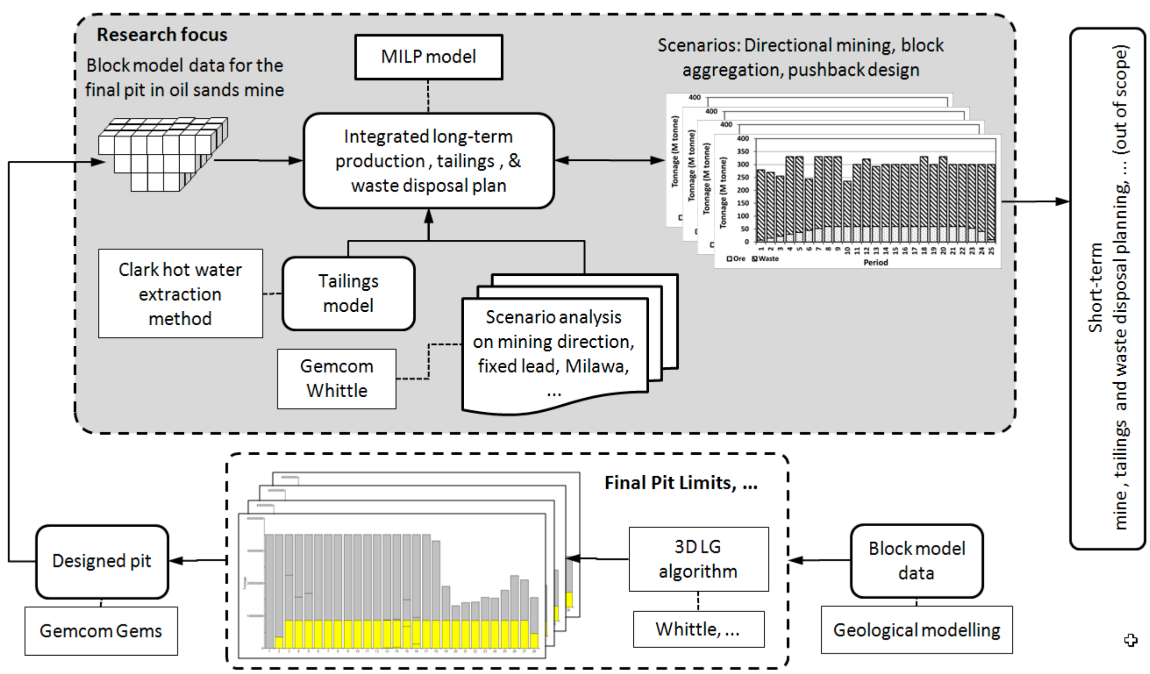

Figure 3: Summary of research methodology.

The research focus has been on the development and implementation of an MILP model for an integrated mine planning problem, to (1) maximize the NPV over the mine-life, (2) minimize the costs associated with dyke construction, and (3) minimize the CT deposition costs. The proposed model provides long-term production schedule, tailings production and deposition schedule, and dyke construction schedule, simultaneously. A number of metrics such as annual stripping ratio, ore and waste production, average grade, and the NPV are involved in model verification. Further, the long-term schedule will be used later for short-term production planning, tailings management, and dyke construction planning. Figure 3 illustrates a summary of the research methodology.

The required matrices for the MILP model are prepared in Matlab (MathWorksInc., 2011), and the TOMLAB/CPLEX (Holmström et al., 2009) has been used to solve the MILP model. CPLEX uses a branch-and-cut algorithm, which is a combination of branch-and-bound and cutting plane algorithms to solve the integer programming. It continues to search for best integer solutions up to the point that finds an integer solution within an acceptable gap (EPGAP) to the LP-relaxation optimal solution.

The tasks that are completed to achieve the research objectives can be summarized as:

- Propose and develop the theoretical framework for an MILP model to be used in optimizing a long-term strategic production schedule for mining production, tailings management and dyke construction, and waste disposal.
- Develop a framework based on the regulatory and technical requirements governing oil sands mining operations, that classifies the oil sands block model into different material types.
- Propose and develop a tailings model to formulate the volume of tailings slurry, slurry contents, and the CT and MFT that potentially will be produced downstream of hot water extraction process.
- Investigate and implement the proper techniques to increase the efficiency of the solution by reducing the problem size.
- Test and calibrate the MILP model and the tailings model, using a small dataset.

- Verify the MILP and tailings models through analyzing the results obtained from implementation of the proposed model on a real-size dataset. Since the current industry-standard software such as Whittle do not contain tools for integrated waste management, they 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.

The following gradual progress briefly shows how the research is advanced and the research objectives are obtained: the first step includes development of the initial version of the MILP formulation, including the NPV maximization and reclamation cost minimization (Badiozamani and Askari-Nasab, 2012; Badiozamani and Askari-Nasab, 2013; Badiozamani and Askari-Nasab, 2014a). At this step, the MILP controls the material procurement for reclamation and a set of constraints for controlling the total volume of generated tailings slurry. The model solves the problem in cut resolution, both for mining operations and ore processing. In the next step, more details are added to the tailings model and it becomes capable of calculating the volume of CT resulting from further process of the MFT. In addition, the MILP model includes minimization of CT deposition costs. Also the deposition of produced CT is controlled through precedence constraints (Badiozamani and Askari-Nasab, 2014b). At this step, the mining-panels are used to schedule the mining operations, while the mining-cuts are used in determining the material destinations. Finally in the latest phase of the research, a new feature is added to the MILP model to control sending the required material for dyke construction, which enables the model to construct the tailings containments and filling them with the CT, simultaneously. It considers the precedence order in construction of tailings containments and filling them with CT in a certain horizontal direction. The resulting MILP model integrates long-term production schedule with dyke construction and tailings management.

1.6. Scientific Contributions and Industrial Significance of the Research

The main contribution of this research is development of an integrated framework for optimizing the mine production schedule for long-term, with respect to tailings management and waste disposal planning. The problem is modeled as a mixed-integer linear programming model. The model is capable of classifying the material dynamically by determining the material destination as the processing plant for oil sands, dyke construction for OI and TCS, and waste dumps for waste. The model maximizes the NPV over the mine-life, minimizes the dyke construction costs, and minimizes the costs associated with deposition of composite tailings in tailings containments. Also a tailings model is developed to calculate the volume of tailings slurry and tailings products, such as MFT and CT, to be used in tailings-control constraints in the integrated MILP model. The model in its general form is capable of handling multiple pits, multiple elements, multiple destinations, and imposing certain horizontal directions for mining. A pre-processing method and the period aggregation technique are implemented to reduce the problem size through reducing the number of decision variables and making the model tractable for current optimization software and hardware. The integrated MILP model finds the optimal integer solution that maximizes the NPV, minimizes the dyke construction and CT deposition costs, guarantees to provide the required material for dyke construction, and meets the tailings capacity constraints.

The industrial significance of this research is providing an integrated framework that optimizes the mine production schedule, dyke construction and CT deposition simultaneously. The requirements of sections 4.0, 4.2, and 4.5 of Directive 074 issued by the ERCB (McFadyen, 2008) make Alberta oil sands operators responsible for preparation of a strategic production and dyke material schedule, and submit their tailings management plans. The proposed framework in this research provides the right tool for addressing such requirements. The integration of tailings equations within the mine planning framework enables the oil sands industrial user of the model to study the consequent effects of any modifications in tailings model on the tailings volume and production schedule. The implementation of problem size-reduction techniques has made the solution algorithm so efficient that can solve the problem in a reasonable time, which is essential in sensitivity analysis and choosing among decision alternatives regarding mining direction, size of aggregate units, mining and processing capacities, and details on tailings production and deposition.

1.7. Organization of Thesis

Chapter 1 of this thesis provides a general overview of the research. It includes statement of the problem, summary of the literature review, objectives of the research, context, scope and limitations of the work, the research methodology, and the research contributions.

In the first part of the Chapter 2, the related literature to the research is reviewed, including the implementation of operations research techniques in mine planning such as mixed-integer linear programming, the LR and the LP relaxation. It also provides a literature review on aggregation algorithms and their use in mine planning problems. The second part starts with a review of the important environmental impacts of the oil sands and continues with a review of integrated mine planning frameworks, including tailings planning and waste disposal management. The chapter concludes with a summary of the literature gap and a highlight on the research rationale.

Chapter 3 provides the theoretical framework for the proposed MILP model. It starts with background on oil sands processing, different tailings facilities and the tailings formulations. The chapter is continued by block aggregation, including clustering and paneling. The main part of the chapter is the introduction of the MILP model, which includes different versions of the proposed model showing the gradual progress of the research, the objective functions, and the model constraints. It also includes the concepts of directional mining and the preprocessing technique that has been used for problem-size reduction.

Chapter 4 includes the results of implementing the proposed MILP on oil sands datasets. Three case studies, covering a total of 13 experiments are designed and carried out to verify the performance of the model in presence of each contributing feature of the integrated framework. For each case study, the specifications of the dataset and experiments are provided, and the numerical results of the experiments are discussed followed by a conclusion for each case study. The chapter ends with running the most complete version of the proposed model on a large-scale oil sands data set and concluding remarks.

Chapter 5 contains the summary of the research methodology and case studies. It highlights the conclusions made from the case studies, scientific contributions and industrial significant of the research, and provides recommendations for the further research under the topic of integrated long-term mine planning optimization.

CHAPTER 2
LITERATURE REVIEW

2.1. Introduction

The literature on modeling and solving the long-term mine planning problem in oil sands is reviewed in this chapter. In the first section, different operations research techniques that have been used in solving the mine planning model, such as LP relaxation and Lagrangian relaxation (LR) are reviewed. The concept of block aggregation and its implementation in the related literature is discussed as well. The second section provides a review on different aspects that can be integrated into the mine planning framework, mainly from an environmental point of view, to generate a sustainable mine plan. Also, tailings planning and solid waste management, including dyke construction and reclamation planning are discussed. The chapter is concluded with a summary of the reviewed researches and comments on the oil sands long-term mine planning literature gap.

2.2. Operations Research and Mine Planning

Mine planning is about planning for the best order of extraction of mining units. It is assumed that the optimal limits of the mining-pit are already known as inputs to mine planning. The dominant algorithm for open-pit mine design is developed by Lerchs and Grossmann as LG algorithm (Lerchs and Grossmann, 1965). It determines which blocks are within the optimal pit limits. With having the optimal pit limit, the decision to be made is the order that the blocks should be extracted so to generate the maximum NPV.

A typical method for solving the mine planning problem is implementation of an exact solution method through mathematical programming. The related literature to solution methods will be discussed further in this section. The mine planning models are divided based on the planning horizon into short-term and long-term models. Strategic decisions such as overall capacity of mining and processing are involved in long-term mine planning framework, while operational considerations such as route selection for trucks within the mining-pit are discussed in short-term planning. Since the subject of this research is long-term planning for oil sands open-pit mining, the literature of long-term mine planning and different approaches for solving the mine planning models are reviewed and will come next.

The subject of long-term mine planning is maximization of NPV over the mine-life, subject to a number of constraints. Most of the constraints in typical mine planning models are technical constraints. Examples of constraints are the capacities of mining and processing in each period, the limitations on the grade ranges as required by processing plants and the precedence constraints to control the vertical order of extraction of the mining-blocks.

The first comprehensive mathematical model for long-term open-pit mine production planning is developed by Johnson (1969). The author introduces integer variables to control the precedence of extraction between mining-blocks. The proposed MILP model is solved through Dantzig-Wolf decomposition technique for small-size data sets. In this model, the author considers multiple destinations for extracted material and dynamic cut-off that optimizes the material destination. However, the proposed model is not tractable for large scale problems, as the problem is NP-hard (Gleixner, 2008) and the solution time increases exponentially for millions of mining-blocks and large number of time periods in long-term planning.

After Johnson (1969), two main streams of research have been followed in parallel; (1) inclusion of new decisions in mine planning, depending on the special considerations for different ore types, and (2) implementing new techniques to overcome the curse of dimensionality and make the models tractable for large-scale problems. The literature related to integration of new aspects into mine planning framework will be discussed later for the case of oil sands surface mine planning.

Newman et al. (2010) review the applications of operations research technique in modeling and solving mine planning problems. This comprehensive literature review covers the applications of operations research in surface mining, underground mining, and emerging areas in mining industry. For open-pit mining, the papers that have addressed the following three categories in mine planning are reviewed: ultimate pit limit design and mine layout models, tactical block-sequencing models, and equipment allocation models. The authors mention some of the emerging areas in mine planning and conclude with stating that with advances in software and hardware, the direction in mining industry is towards modeling more complicated problems and solving them faster. The improvements in software and hardware also make it possible to tackle the large-scale problems with exact solution methods such as LR. In the following sections, the operations research techniques that are used for modeling and solving mine planning problems are reviewed under four titles of LR, LP relaxation, block aggregation and other methods.

2.2.1. The Lagrangian Relaxation

The Lagrangian relaxation method was first used by Held and Karp in 1970 (Gass and Assad, 2005). The method has been used to make complicated integer linear programming problems solvable. The basic idea in LR is dividing the constraints into two sets as soft versus hard constraints. It is assumed that the problem is easily solvable in presence of only soft constraints. Each relaxed constraint will be adjusted by a corresponding penalty term added to the objective function to penalize any violation from the constraint. The key in LR is to determine the magnitude of Lagrangian multipliers to be used in penalty functions. There are a number of algorithms for determination of multipliers. The sub-gradient method is one of the non-heuristic algorithms. The mathematical basis for the LR method is introduced by Arthur M. Geoffrion (Jünger et al., 2010).

Fisher in (1981) and (1985) publishes an application oriented guide to the LR method. The author discusses the basic concepts of LR through operations research framework and simple mathematical model examples. The list of critical issues in using the LR are counted as: (1) how to select appropriate value for multipliers, (2) how the dual solutions can be feasible for the primal problem, (3) how the lower and upper bounds reached by the Lagrangian problem can be integrated in the branch-and-bound algorithm, and (4) how to choose between LR and LP relaxation. The author answers to these four questions and lists a number of LR implemented cases in different applications of operations research such as general IP, location problem, assignment problem, and scheduling problem. The author proposes the sub-gradient algorithm as a method to find the Lagrangian multipliers' values.

Dagdelen and Johnson (1986) use LR to solve the open-pit production planning problem. The objective function is to maximize the NPV, subject to block precedence and production capacity constraints. The authors relax the mining capacity constraints and add penalty in the objective function accordingly. The sub-gradient algorithm is used to update the Lagrangian multipliers for small-scale problems. Akaike and Dagdelen (1999) extend the work done by Dagdelen and Johnson (1986), using an iterative procedure to update the values of Lagrangian multipliers. The iterative algorithm is continued to find an optimal solution for the relaxed problem that is feasible for the original MILP problem.

Kawahata (2006) uses LR to solve the mine production scheduling problem. By using the concept of Lagrangian relaxation, the author defines two smaller sub-problems that are tractable; one for the most aggressive case of mine sequencing and the other for the most conservative case. The proposed algorithm continues to solve the sub-problems iteratively up to reach to a predetermined level of optimality. Some of the decision variables and constraints will be eliminated from the MILP model to reduce the problem size, based on the solutions of two sub-problems. The model assumes a dynamic cut-off grade that optimizes the destination for each parcel of extracted material; either as processing plant, stockpile, or waste dump. The solution time has been improved significantly for large-scale problems through variable and constraint reduction.

Gaupp (2008) proposes three methodologies that make the open-pit mine production scheduling problem more tractable. The methodologies include (1) preprocessing by applying the earliest and latest possible start times, to fix the value of some integer variables before solving the problem, (2) presenting a series of cut generation algorithms to tighten the problem formulation, and (3) employing a LR technique to relax hard constraints and solve the model faster. The sub-gradient algorithm is applied to determine the Lagrangian multipliers and update them. A feasing subroutine is also developed to make the Lagrangian dual solutions feasible for the monolith problem. Applying the three methodologies has expedited the solution time by over 95% as the result of reducing the problem size.

Cullenbine et al. (2011) develop a sliding time window heuristic to solve the block sequencing integer programming problem. The authors use LR to increase the computational efficiency in solving the sub-models they define over time windows. In each of iterations, the proposed heuristic algorithm solves a restricted Lagrangian sub-problem that partitions the time period of the original problem into three sub-sets as T1, T2, and T3. The algorithm finds feasible solutions for corresponding variables in T1 periods, all of the constraints of the original integer programming are enforced for T2 periods, and a Lagrangian relaxation version of the original model will be solved for T3 periods. The authors' experiments show that using LP relaxation can increase the computational time by a factor of 20 comparing to using the LR, yet without any improvement in the quality of the solution. This happens because the large Lagrangian relaxation version of the original integer programming is totally tractable for the solver.

Lagrangian relaxation schemes such as sub-gradient algorithm can reduce the primal problem to a tractable "easier" problem to solve. This will happen by partitioning the constraints into two groups of soft and hard constraints, relaxing the hard ones, and adding penalty function with Lagrangian multipliers to the objective function. The structure of the relaxed problem is such that the problem is tractable. Thus, the LR approach is reliable method for large size problems (Newman et al., 2010). However, the Lagrangian-based algorithms are too slow to achieve convergence (Bienstock and Zuckerberg, 2010). The other shortcoming about the method is that the optimal solutions for the Lagrangian dual problem are usually infeasible for the primal problem. Although some further processing can be done to make the solutions feasible for the primal problem such as feasing subroutine (Gaupp, 2008), it takes more computational time and the resulting solution is no longer optimal. This means that the Lagrangian Relaxation alone is not reliable and should be used as part of other algorithms, like how Bienstock and Zuckerberg (2010) have used it in an LP relaxation iterative algorithm.

2.2.2. LP Relaxation

Integer variables are defined to control the precedence of extraction in the block sequencing problem. Having integer variables changes the problem from a linear programming (LP) to an integer linear programming (ILP), or in most of the cases, a mixed integer linear programming (MILP) problem. The feasible region in ILP mathematical models includes only integer points, not the whole convex region in LP. Therefore, the feasible region is not convex anymore and the typical LP solution algorithms, such as simplex, do not work for ILP problems. In order to solve ILP problems, the first step is to solve the corresponding LP version of the model - the relaxed version of the original model- by considering all of the variables as continuous ones. In a maximization problem, the optimal solution of the LP relaxation is an upper bound for the original ILP problem, which can be used in branch-and-bound algorithm to find the optimal integer solution of the problem within a certain gap.

Tan and Ramani (1992) ignore the binary nature of the decision variables in block extraction. The authors solve the LP relaxation of the mine planning problem and use LP and dynamic programming to schedule the extraction of blocks over time periods and constrain the optimization to the equipments capacity. Since the integrality of decision variables is ignored, the optimal solution does not satisfy the block sequencing constraints. The proposed LP model solves the production scheduling problem under consideration of different equipment capacities and interest rates.

Bienstock and Zuckerberg (2010) propose an iterative algorithm that solves the LP relaxation of the original problem in each iteration. The proposed algorithm suits the integer programming problems where the decision is about scheduling jobs over time periods, subject to precedence constraints and side constraints such as capacities. The proposed algorithm is not restricted to block sequencing problem. Open-pit mine planning is a typical example of such IP problems, with mining-blocks to be extracted (as jobs) subject to the spatial precedence among blocks and period-wise constraints such as mining and processing capacities. The authors use LR and column generation at a low level, but the algorithm is based on the combinatorial structure of the precedence constraints. A synthesized and three real instances are solved in seconds, with 3,000 to 200,000 blocks over 8 to 100 time periods.

Alvarez et al. (2011) replace integer programming with Continuous programming for the cases of mine design and mine planning problems. Instead of defining integer variables, the authors introduce a continuous approach, based on graph theory and differential equations that redefines the slope constraints associated with geotechnical stability. The authors address three main decision-making problems of final open-pit (FOP), capacitated final open-pit (CFOB) and capacitated dynamic open-pit (CDOP). A mathematical proof is provided for the existence of a continuous framework that solves each of the problems. The authors refer the reader to their future works for a numerical presentation of the proposed method. The proposed continuous approach does not substitute the current discrete MILP models, but it is useful in sensitivity analysis for discount rate or mining capacity. Also the authors claim the proposed framework as a potential tool for obtaining an insight to consider good starting points for integer programming based on microscopic block model.

Chicoisne et al. (2012) propose a decomposition method for solving the LP relaxation of the original MILP block scheduling problem, based on the precedence-constrained knapsack problem. The proposed algorithm considers a single capacity constraint in each period. Three steps are involved in the proposed methodology as (1) solving an LP relaxation with critical multiplier algorithm as a new decomposition method, (2) calling a rounding heuristic, which is based on topological sorting, to change fractional solutions to integer values, and (3) applying a local-search heuristic to improve the solutions obtained by the rounding heuristic. The authors propose to solve the LP relaxation of real-size mine planning instances over five million blocks in 20 periods in minutes and find integer feasible solutions by applying the topological sorting algorithm. They claim to produce integer solutions within 6% of optimality, in seconds. However, there is a chance that in each period, the blocks to be extracted are scattered all over the benches. Therefore, the resulting solutions need to be overlooked and modified by mining engineers.

Epstein et al. (2012) propose a methodology for long-term mine planning model based on a network flow formulation. The authors consider a network of open-pit and underground ore deposits, sharing a number of processing plants for the extracted ore material. An extended formulation with a tight LP relaxation is considered for open-pit mining part. For underground mining, the problem is solved considering the nature of underground mines, assuming that the ore grades increases by going vertically deep in each drawpoint. A rounding heuristic algorithm is developed to find feasible integer solutions for both cases of open-pit and underground mining. According to authors' practical experience the proposed approach has preferences over other techniques such as decomposition or LR, as it requires less operations research expertise on-site. Two independent case studies from copper mines in Chile are used to test the performance of the proposed model and rounding algorithm. By using the proposed model, the NPV has increased up to 8%, which is due to open-pit and underground mines integration and their proposed optimized plan.

LP relaxation has been used extensively in the reviewed literature of mine planning optimization. It reduces the complexity of the MILP models by ignoring the integrality of the decision variables. However, since the optimal continuous solution of the LP relaxation is not usually feasible for the original problem, there must be one sort of approximation heuristics to modify the solution and make it feasible for the MILP problem. Heuristic approximation approaches find feasible solutions that are not necessarily optimal anymore. Beside its limitations, the LP relaxation is the basis for the dominant integer programming solution algorithm; the branch-and-bound.

2.2.3. Block Aggregation

It is well accepted that the block sequencing optimization model is an NP-hard problem (Gleixner, 2008). That is because the mathematical formulation for the real cases of mine planning problems includes a large number of decision variables, corresponding to three to ten million blocks and 15-40 time periods. A great portion of mine planning decision variables are integer variables that control the precedence of extraction of the mining-blocks. Despite of the improvements in optimization software and hardware, the problem size makes the models intractable for current software and hardware, or inappropriate for the commercial software due to the relatively very large solution times. A number of techniques are proposed to reduce the size of the MILP problem and overcome the curse of dimensionality. One of these techniques is aggregation of mining-blocks and making larger units for extraction and processing purposes. The mathematical basis for block aggregation is backed up by the concept of clustering, which is the idea of merging similar entities together based on some similarity criteria. A comprehensive introduction to the clustering concept and algorithms is done by Barbakh et al. (2009).

The main criteria that are used for measuring the similarity index between pairs of blocks are distance between blocks, ore grade of the blocks, and blocks' rock types. Different weights are assigned to each of the similarity criteria to control their influence on the measured similarity. There are two main groups of clustering algorithms as hierarchical versus partitional algorithms. The hierarchical clustering results in better clusters (taking more CPU time) comparing to partitional algorithm (Tabesh and Askari-Nasab, 2011a). The aggregation of blocks may happen in different resolutions and the aggregated units may be referred to as mining-cuts, mining-clusters, mining-panels or other related terms.

Smith (1999) is among the first researchers that have used block aggregation in open-pit mining production scheduling problem. The author uses mixed-integer and goal programming to optimize the short-term mine production plan. In the studied case, the extracted ore is stockpiled for further blending in later periods. Optimization of the stockpiled material makes the model non-linear. The author implements piece wise linear formulation to keep the model linear and proposed some variable-reduction strategies to reduce the problem size. One of the proposed variable-reduction strategies is aggregating the blocks to make larger units as mining-cuts.

Ramazan et al. (2005) propose a new algorithm for aggregation of blocks in open-pit mine production scheduling, known as "the fundamental tree algorithm". The authors define a fundamental tree as a combination of blocks that are profitably minable, obey the slope constraints, and do not include a subset with the first two conditions. The fundamental trees substitute the blocks and hence, the number of decision variables decreases significantly. The trees are found by a set of LP formulations without any integer variable. For large scale instances, solving the LP model for determination of the fundamental trees is controversial, as it takes large solution times. The performance of the proposed algorithm is tested in optimization of long-term production algorithm for a large open-pit copper deposit. This work is improved by presenting the algorithm in more detailed steps, specifically by defining a new step for generating a starting network of blocks within pushbacks (Ramazan, 2007).

Zhang (2006) uses block aggregation to reduce the problem size and solve the production scheduling problem with genetic algorithm. The author compares the performance of the proposed algorithm against CPLEX in terms of CPU time, and claims that solving the problem with CPLEX takes two to four times more CPU time comparing to the proposed genetic algorithm. The paper does not include any details about aggregation procedure, nor explains the disaggregation method.

Boland et al. (2009) develop an iterative algorithm for aggregation and disaggregation of blocks. The aggregated blocks are used for block excavation, while the so called “bins”, as disaggregated units, are used for processing decisions. The main contribution of the paper is investigation of different disaggregation strategies. For disaggregation, the authors modify the adaptive clustering method by letting the blocks to be aggregated into any number of units rather than considering a fix number of aggregates in advance. The disaggregated units are refined in an iterative manner to the point that the refined aggregates produce the same optimal solution for the LP relaxation of the MIP. Four different strategies are investigated for disaggregation binning, based on structural properties of the problem. The authors claim that all of the proposed binning strategies result in achieving solutions so close to the MIP solutions in block level, without any binning for processing.

Tabesh and Askari-Nasab (2011a) present an aggregation algorithm based on a two-stage clustering approach. In the first stage, the blocks are clustered with a hierarchical clustering algorithm. A similarity index is defined to measure the similarities among blocks, according to the rock type, ore grade and blocks distances. In the second stage, the clusters will be modified through a tabu search algorithm to reduce the number of dependencies between clusters. The proposed algorithm and MILP formulation is tested on a real iron ore deposit to generate a long-term schedule. A number of input parameters are defined to control the size of mining-cuts, i.e. the average and maximum number of mining-blocks contained in each mining-cut. The authors claim that implementation of tabu search reduces the precedence relations between mining cuts. Therefore, the number of integer variables in the MILP model is decreased, resulting in 40% less CPU time on average. However, using tabu search has decreased the NPV and mining-cut homogeneity by 4 to 50 percent. As the disaggregation method, the authors consider uniform extraction from all of the blocks within each mining-cut. The authors extend the work by introducing a new version of clustering algorithm with shape control (Tabesh and Askari-Nasab, 2013). It considers mining direction in creating the clusters.

In the literature, the term “aggregation” mostly refers to clustering a number of mining-blocks into new mining-cut units. However, larger aggregation units can be defined to follow the practical selective mining units and also reduce the number of integer variables. Ben-Awuah (2013) defines mining panels as the intersections of mining benches and pushbacks. Each mining panel includes all the mining cuts that inherit the same bench number and are members of a same pushback. The author uses panels as the units for mining operations. Mining-cuts, as proposed by Tabesh and Askari-Nasab (2011a), are used for determining the destination of the extracted material. The proposed MILP model integrates waste management and dyke construction with long-term mine planning model. It maximizes the NPV and minimizes the cost of dyke construction. Introducing the mining panels reduces the size of the problem significantly. However, the resulted NPV for mining-panels is less than the NPV when the mining-cuts are used.

Preprocessing techniques are another means to reduce the number of decision variables in block sequencing problems. In preprocessing, a number of decision variables are eliminated from the model by fixing their values in advance. The spatial configuration of the blocks imposes that a particular block cannot be extracted until many other overlying blocks already have been extracted. Extraction of the overlying blocks does not leave any free mining capacity for extracting the particular block. Therefore, the decision variables corresponding to that particular block can be considered as zero for a number of periods. On the other hand, not extracting a given block after a certain period precludes extraction of underlying blocks. Thus, each particular block must be extracted prior to certain period and the corresponding decision variable can be fixed to one for the remaining periods. Cullenbine et al. (2011) define an "earliest start time" and "latest start time" for each block and fix a number of decision variables to zero or one. During recent years, variable reduction using the preprocessing technique has been used in solving a number of mine planning models (Amaya et al., 2009; Bley et al., 2010; Martinez and Newman, 2011; Tabesh and Askari-Nasab, 2011b).

In conclusion, variable reduction through aggregation and preprocessing makes the large-scale mine planning problems tractable. However, the aggregation of mining-blocks and defining larger units for mining will reduce the solution precision and implicitly causes to lose the optimality of the original problem. In real case of open-pit or underground mining, the selectivity between the mining blocks and separation of the extracted material is practically limited. Therefore, it is a reasonable assumption for long-term mine planning to consider block aggregation.

2.3. Integrated Mine Planning Models

Considering the environmental issues related to the oil sands surface mining, two concepts can be integrated into the long-term mine planning optimization framework, as tailings management and solid waste management. The solution to such an integrated model provides sustainable production planning in oil sands mining operations.

2.3.1. Oil Sands Environmental Impacts

In recent decades, many papers have been published regarding different aspects of environmental impacts in the mining industry. The authors have investigated the environmental issues that are triggered by mining operations and mineral processing and have include them in decision making. A common approach to address the environmental impacts is to audit the mining sites in accordance with environmental codes and regulations, investigate the violation from environmental regulations and report the violations to stakeholders.

Sinding (1999) reviews environmental management and communication tools in mining industry and discusses the specifications of some of them, such as environmental impact assessment, environmental management systems, environmental accounting and life cycle assessment. The author focuses on different stages in a typical mining production as mineral exploration, mine development decision-making, production phase and mine closure and decommissioning. The author suggests mining companies to consider a full range of environmental management and documentation for projects. Further, a global environmental reporting mechanism must be established so that different mining products can be comparable, and the companies put more emphasis on the effective environmental management in new projects. Increased monitoring and post audit reviews are also essential for effective environmental assessment.

Manteiga and Sunyer (2000) modify the environmental evaluation methodologies in order to make them more practical. The authors propose a simplified three-step methodology for environmental evaluation assessment, consisting of (1) establishment of an assessment framework, (2) assessment of the environmental situation and (3) environmental assessment. The steps are elaborated in detail and some indicators are defined to quantify the final results of each step. However, greater efforts are required to achieve the operational implementation of indicators, both by the environmental authorities who define indicators and by the mining operators that run projects and are responsible for recording precise data.

Audit reports will raise the awareness about environmental impacts and are essential in sustainable mining practice. Such reports are either mandatory, i.e. required by governments or regional authorities, or voluntary in which the company aims to show its differences from others in the market in terms of environmentally clean practices. However, in order to consider the environmental impacts practically in mine planning and mine design, review of reports will not be sufficient. The better strategy is to consider the environmental impacts as part of mine design and mine planning. That means to take into account the environmental costs in designing the final mine pit-limits and consider mine site reclamation in mine planning phase.

Rodriguez (2007) includes the environmental impacts in mine design phase. The author develops a heuristic algorithm that considers the environmental cost and adds it to other mining costs to find the pit limit for an open pit mining problem. The environmental cost

(EC) covers a variety of costs regarding environmental issues, such as drilling and blasting, pit excavation, waste rock dumping, tailings disposal and decommissioning. EC is deducted from the economic block value (EBV), and the revised EBV is used to find the pit limit in an iterative algorithm. The social impacts are not included in EC.

Odell (2004) uses the sustainability primer methodology, initially proposed by the association of professional engineers and geoscientists of British Columbia (APEGBC), to integrate sustainability into feasibility study and mine design process. The basis for the APEGBC process is multi-criteria analysis (MCA), also known as multiple accounts evaluation. MCA consists of a number of distinct approaches, with the same basis of defining a number of scenarios and assess them with respect to series of criteria through MCA tables. The availability of time and financial resources, availability and amount of supporting data, the analytical expertise of the project team, and the number of decision options are some of the important factors in successfulness of MCA methodology. The author applies MCA to an open pit copper deposit in Peru. Since the decision context in the case study shows a high complexity and a wide range of interested stakeholder groups, the MCA seems to be the proper choice for the problem.

Fuzzy logic is another powerful tool that is used in quantification of descriptive environmental values. In many cases, there are some quantitative environmental indicators. However, an expert must rank the indicators based on their importance and this judgment changes the quantitative nature of indicator to qualitative. Fuzzy sets, membership functions and fuzzy logic are strong tools in capturing the uncertainty and fuzzy nature of environmental variables and generate crisp values corresponding to each fuzzy variable. Shepard (2005) introduces fuzzy logic and discusses its implementation in quantification of environmental impact assessment. The author reviewes the traditional approach in environmental impact assessment and introduces fuzzy logic as a modern and successful approach in the field.

Among the environmental impacts of oil sands production, two issues seem to be the most important ones: (1) tailings slurry and its dewatering, and (2) the remaining footprint from mining operations and tailings ponds. In this research, the focus is on addressing these two issues in terms of integrating them with the long-term mine planning.

2.3.2. Mine Planning and Tailings Management

Processing of oil sands ends up in massive volumes of slurry known as tailings. The Clark hot water extraction process is the current dominant method for extraction of bitumen from the oil sands (Clark and Pasternack, 1932; Clark, 1939). In a typical oil sands processing plant, the extracted oil sands is crushed to smaller parts, hot water is added to the crushed material and the resulting blend is passed to separation cells. After the separation cells, the blend will be divided into two main streams: (1) the bitumen froth that mostly contains the bitumen with small amount of fine material and (2), the remaining slurry as a mixture of water, sand and fine material plus small residuals of bitumen, being sent to the cyclone for separation of coarse material.

The traditional approach has been pumping the tailings slurry into tailings ponds and keeping it there for segregation. A number of environmental issues are tied to the tailings ponds, such as leaking of toxic tailings to the fresh water tables and the footprint of mining operation in the mine site. In the literature, there are comprehensive lists of environmental impacts associated with oil sands tailings (Woynillowicz et al., 2005; Rodriguez, 2007; Singh, 2008).

Oil sands operators are supposed to treat the tailings ponds in such a way to minimize the environmental impacts. The tailings dewatering is the key in tailings treatment to transform the tailings ponds to trafficable landscapes, facilitate the reclamation, and re-vegetation (Sobcowicz and Morgenstern, 2010). A number of technologies have been developed for tailings dewatering (Longo et al., 2010). Producing of consolidated tailings, also known as composite tailings (CT), and the Atmospheric fines tailings (AFD) are two examples of these technologies (Shell-Canada-Energy, 2010a).

Tailings management in oil sands has been addressed in a number of academic publications (Mikula et al., 1998; Chalaturnyk et al., 2002; Soane et al., 2010). One of the latest works that studies the effect of oil sands mine planning on tailings management, in terms of CT production, is published by Kalantari et al. (2013). The authors investigate the linkage between long-term mine planning and CT production in presence of uncertainty. A tailings model including the tailings mass-balance relations are developed to map the tonnage of the ore feed to the final CT tonnage. However, the capacity of tailings facility and the deposition of produced CT are not considered explicitly in the long-term mine planning model.

A review of literature reveals that there are not much academic publications addressing the linkage between tailings management and mine planning. On the other hand, the ERCB forces Alberta oil sands operators, through Directive 074, to publish their tailings management plans (McFadyen, 2008). Hence, the oil sands operators are supposed to report their short-term plan and update long-term plans for treatment of produced tailings. An example of industry publication for tailings management is the annual tailings management published by Shell. Shell has proposed to use AFD in its external tailings facility in Muskeg River Mine. It has presented the engineering design and maps of the facility, the environmental considerations of the site, and a timeline showing the schedule for AFD facility construction and operations over a period of three years (Shell-Canada-Energy, 2010a). More references to the tailings plans provided by other oil sand operators can be found in (Suncor, 2009; CNRL, 2010; Imperial-Oil, 2010; Syncrude-Canada-Ltd., 2010; Shell-Canada-Energy, 2010b; Shell-Canada-Energy, 2011a; Shell-Canada-Energy, 2011b). The current gap between the long-term mine planning modeling and tailings management is one of the subjects addressed in this research.

2.3.3. Mine Planning and Solid Waste Management

The material required for construction of dykes is coming mainly from mining and processing operations, as overburden, interburden, and coarse tailings sand (Fauquier et al., 2009; Ben-Awuah, 2013). In addition, with respect to the regulatory requirements from Directive 074, waste disposal planning must be considered in a close relation to the mine planning system (McFadyen, 2008; Ben-Awuah and Askari-Nasab, 2011). However, there are a number of complexities in modeling and solving an integrated optimization framework. An MILP model for long-term mine planning is known to be an NP-hard problem (Gleixner, 2008). Adding more variables and constraints regarding waste disposal and dyke construction even adds to its complexity. That is one of the reasons why in current practice, the oil sands waste disposal planning is handled as a post-production scheduling optimization (Ben-Awuah, 2013). A team of geologists, geotechnical and mine planning engineers, tailings planners, and operations engineers work on dyke construction plan (Fauquier et al., 2009), yet there is no guarantee that the developed plan meets all the material requirements for dyke construction in all periods and the resulting NPV is maximized.

There are three main methods for dyke construction, as upstream construction, downstream construction, and centerline construction. With some modifications, some more dyke construction methods are developed as well. Depending on the dykes' design, different material types are required for construction. Due to the limited space of leas areas, a common approach is preparing the excavated pit for tailings storage, as in-pit tailings facilities. When the mining-pit is cleared to its bottom level, the in-pit tailings containments will be ready through partitioning the empty pit by constructing a number of internal dykes. The tailings slurry will be sent to the containments and at the same time raises the dyke walls. Vick (1983) and Sego (2010) provide more details on preparation of tailings facilities and dyke construction methods.

Ben-Awuah (2013) proposes an integrated optimization framework for long-term open-pit mine planning in oil sands surface mining. The author considers directional mining as a requirement for in-pit tailings containment, and waste disposal planning to ensure that the optimal mine plan provides required material for dyke construction. The author proposes a mixed integer goal programming model and considers two destinations for the extracted material: the overburden and interburden will be sent for in-pit and external tailings facilities' construction, while the ore will be sent to the processing plant. The tailings coarse sand resulting from oil sands processing will be sent also for dyke construction. The proposed model is a comprehensive mine planning model that covers the solid waste disposal and dyke construction planning. However, it does not include the most important waste in oil sands mining, which is the tailings slurry.

Reclamation planning is the other aspect in oil sands long-term decisions. According to ERCB, the oil sands operators are required to plan for mine closure and reclamation in advance to make sure that the mine site and the tailings ponds will be restored to their original conditions of pre-mining operations (McFadyen, 2008). A review of reclamation plans published by the oil sands operators proves that the material used for capping in closure phase, such as the overburden and tailings coarse sand, are coming from the mining and processing operations (Shell-Canada-Energy, 2011b). This fact shows another potential development in typical mine planning models by inclusion of material requirement for reclamation capping in long-term mine planning. Due to the same reasons mentioned for waste disposal and dyke construction, the reclamation planning is done as a post mine planning process in the current practice. Most of the techniques required for reclamation have been developed by the industry itself (Thompson, 2009). However, the industry will benefit from an integrated mine planning framework that includes reclamation material handling as part of the long-term model, because any shipment of material for capping adds to the costs and will cause the NPV to decrease.

Badiozamani and Askari-Nasab (2014a) propose an integrated model for long-term mine planning, with respect to reclamation material handling and tailings capacity constraints. The concept of directional mining is used in modeling to provide capacity for in-pit tailings facility. The model determines the destination for each extracted parcel (dynamic cut-off) in such a way to maximize the NPV over the mine-life. Mining aggregates are used in the model to follow the selective mining units. The authors reach to integer solutions within 2% optimality gap in less than 10 minutes for the cases with more than 98,000 mining-blocks aggregated to 535 mining-cuts. The resulting schedule generates the maximum NPV, minimizes the material handling cost of reclamation, and the tailings volume produced downstream meets the tailings capacity constraints in each period. The authors take a further step in integrated mine planning (Badiozamani and Askari-Nasab, 2014b), by including the tailings management, in terms of CT production and deposition, in the mine planning optimization framework.

Review of the literature shows there is a missing merger between the four domains of mine planning, tailings management, waste disposal management and reclamation planning. Since the material used in reclamation and dyke construction are mostly provided by the waste material produced in mining operations and oil sands processing, a comprehensive mine planning model covering all these aspects result in a more robust schedule.

2.4. Summary and Conclusions

There are different aspects involved in long-term mine planning for oil sands, such as tailings management, reclamation planning, solid waste management and dyke construction planning. Tailings volume influences the mine planning significantly, as it must be kept within the limited lease area. Dyke construction and reclamation planning are also important to be considered in the same optimization framework, since most of the material used in dyke construction and reclamation phase are the solid waste produced in mining and processing operations. These facts show the necessity to have a comprehensive model to optimize the long-term mine planning with respect to tailings management, dyke construction planning, and reclamation material procurement. The NPV resulting from a global optimization over all related aspects of mine planning in long-run is expected to be higher than the NPV from optimizing each of these aspects separately. This idea motivates the concept of integration. Review of the literature reveals that such an integrated modeling framework is missing.

Operations research techniques have been used extensively in modeling and solving the mine planning problems. In most of the mine planning models, a number of binary decision variables are involved to control the precedence of extraction. This has made the mine planning problem to be modeled as a mixed-integer linear programming model. The model is known to be NP-hard, especially if other aspects such as tailings management and dyke construction are added. The resulting MILP model cannot be solved in a reasonable solution time under the current software and hardware. A number of operations research techniques, such as LP relaxation and Lagrangian relaxation have been used to solve the mine planning model. Yet due to their assumptions, they have failed in providing an optimal integer solution. That is because in both cases, some heuristic algorithms are involved to change the optimal solution to a feasible integer solution, which is not guaranteed to be optimal anymore.

This research addresses the two gaps in the literature of long-term mine planning model, by: (1) proposing a comprehensive integrated long-term mine planning model that includes tailings management and waste disposal planning as the most important environmental concerns related to the oil sand surface mining, and (2) implementation of problem-size reduction techniques such as preprocessing and period aggregation to tackle the curse of dimensionality and find integer solution to the problem within an acceptable optimality gap. A tailings model is developed and used as part of the integrated mine planning model, the concept of block aggregation has been used to generate a minable schedule following the real selective mining units, and the concept of directional mining has been implemented as a practical assumption in oil sands mining to prepare adequate space for in-pit tailings storage.

CHAPTER 3
THEORETICAL FRAMEWORK

3.1. Introduction

In this chapter, the theoretical framework for optimization of an integrated long-term production scheduling for open pit oil sands mining is developed. The goal in this research is to develop a comprehensive optimization framework for mine planning problem, including decisions on material extraction, tailings management, dyke construction, and reclamation planning. A number of concepts are introduced and used in construction of the integrated mine planning model, including: tailings technologies and equations, clustering algorithms and block aggregation, directional mining, and the mixed-integer linear programming model.

The tailings model maps the input ore feed tonnage to the volumes of tailings slurry, potential CT and MFT volumes. These values will be used as the coefficients in the MILP model for controlling the tailings-related capacities. In the block model, the mining-blocks will be aggregated to larger units as mining-cuts to follow the selective mining unit and to reduce the problem size. Then, the tailings volumes and the aggregate units will be used in construction of the MILP model. In order to facilitate the construction of an in-pit tailings facility, horizontal mining directions are also included in the MILP model and the corresponding theoretical frameworks are discussed.

3.2. Tailings Modeling

The Clark hot water extraction process is the dominant bitumen extraction method currently used by oil sands operators in Alberta. The basis for CHWE is discussed in this section. The CT production has been a successful tailings dewatering technology and is being implemented in large-scales in Alberta oil sands industry. Details of CT technology are discussed and the mass-balance relations between the ore feed and the produced tailings are presented under tailings equations.

3.2.1. The Hot Water Extraction Method

The Clark Hot Water Extraction method (Clark and Pasternack, 1932; Clark, 1939) is well introduced and deployed as an efficient method of bitumen extraction in oil sands surface mining. The method is developed by Karl Clark in 1929. Currently, the main oil sands surface mining operators such as Shell Canada, Syncrud Canada, and Suncor Energy use CHWE process to separate bitumen from oil sands.

The CHWE method is based on the following steps: (1) the plant receives the ore feed from the mine site, with an average grade of 10% bitumen in Athabasca bituminous sand. The extracted material passes a crusher for material size reduction. (2) Hot water, with temperature between 50°C to 80°C is added to the crushed material to decrease the viscosity of bitumen. The formed slurry will be sent to a separation cell. (3) The bitumen is recovered through flotation and forms the bitumen froth. As the result of further purifications, the recovery of bitumen can reach to 93% (Guo and Wells, 2010). (4) The remaining slurry -a mixture of water, sand, clay, and fine materials- forms the tailings and is sent to cyclones for further tailings separation and treatment. The cyclone separates the coarse material from water and fines, through centrifuging. Almost all of the active oil sands operators follow the same steps for bitumen extraction from oil sands. Figure 4 illustrates a brief flow process of CHWE method, used by Suncor Energy.

The total volume of the produced slurry at the end points of the process is a summation of volumes of fine material, sand and water captured in the three streams of overflow, underflow, and bitumen froth treatment. The tailings in its slurry form cannot be left in the tailings pond without further processing. A number of environmental issues are caused by the tailings ponds. The tailings water is toxic to aquatic life, nearby plants, migratory birds that land on the ponds, and it may leak into the fresh water tables. In order to minimize the environmental problems associated with oil sands tailings, the operators are responsible to reclaim the mine site and tailings ponds before leaving the site. The requirements of Directive 074 (McFadyen, 2008) force the oil sands operators to recover tailings ponds to their original ecosystem condition. To have that, the tailings slurry must be change to a trafficable mass, so that the pond can be capped and re-vegetated later in closure phase.

The most important technologies that are currently being used in practice for dewatering of the tailings slurry are Composite tailings (CT), Atmospheric fines drying (AFD), and non-saturated tailings (NST) which will be used in near future (Shell-Canada-Energy, 2010b). Selection among different tailings treatment technologies such as CT, NST or AFD depends on the type of tailings facility. Two types of tailings facilities are considerable in oil surface mining practice: in-pit tailings facility and external tailings facility (ETF).

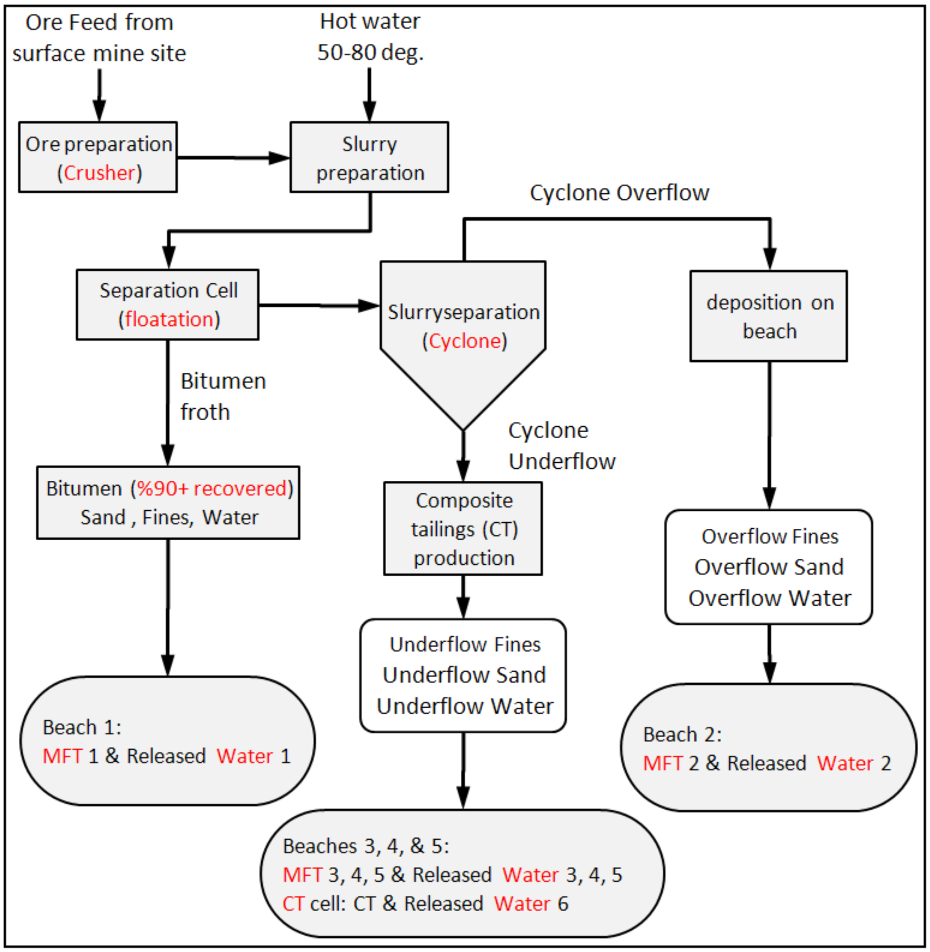

Figure 4: Flow of Hot water extraction method in Suncor, modified after (Badiozamani and Askari-Nasab, 2014b).

3.2.2. External Tailings Facility

In early periods of oil sands mining, the tailings slurry is being sent to the tailings ponds located close to the mine site -inside the lease area- known as ETF. The required dyke walls are constructed outside of the pit to prepare enough space for tailings storage

(Askari-Nasab and Ben-Awuah, 2011a). By starting bitumen extraction process, the produced slurry is sent to the ETF. The solid material in the slurry including the TCS raises the dyke walls while the tailings is discharged over the pond’s beach.

AFD technology is used for dewatering the tailings slurry in ETFs. The AFD includes removing MFT from ETF basin, adding flocculent to it and then deposition of the flocculated MFT on a slight slope. The discharge takes place in redial cells. Environmental factors such as wind, humidity, drainage and radiant heat in addition to the flocculent, facilitate the release of water from MFT (Shell-Canada-Energy, 2010a; Shell-Canada-Energy, 2011a). Figure 5 illustrates a view of proposed AFD facility in Muskeg River Mine, northern Alberta.

Figure 5: Fine drying area location map at MRM, after (Shell-Canada-Energy, 2010a).

3.2.3. In-pit Tailings Facility

Tailings cannot be sent to ETFs for long term. There are two main reasons for that: First, the contracted lease area for each oil sands operator is limited and any tailings facility must be located within the boundaries of the lease area. Obviously, the bitumen reserves under the tailings pond will not be accessible anymore, which is losing recoverable bitumen and is not acceptable. As a second reason, having ETFs will increase the dyke construction costs. That is because a massive volume of dyke material must be moved to build additional long and thick dykes to prepare tailings dams. On the other hand, storage of tailings in an already-excavated pit is less expensive because the surrounding dykes are replaced by pit walls. In this case, only some internal dykes must be constructed in the pit. Further, the in-pit pond will not cover any bitumen reserve that is economically valued to be extracted. In-pit tailings storage starts when a sufficient free space in the pit is available and the required internal dykes are constructed.

Composite tailings technology is the current dominant technology for treatment of tailings in an in-pit facility. CT technology is commercially implemented as a tailings treatment method for the first time by Suncor Energy in the mid 1990s (Guo and Wells, 2010). CT is a mixture of tailings coarse sand, MFT, and gypsum acting as a coagulant aid. It is a non-segregating material that releases water and consolidates more rapidly than MFT. The CT plant process flow published by Shell for MRM project is presented in Figure 6(Shell-Canada-Energy, 2011a).

The NST is the second technology that oil sands operators have started using and is expected to be used more extensively in near future. The final product of NST is a non-segregated tailings deposit, same to the CT process. However, thickened tailings (TT) product stream is used as a fines feedstock in NST, where CT uses MFT recovered from the tailings ponds. In NST process, coarse dewatered sand, TT, and MFT from a fluid tailings cell are mixed with coagulant to prevent segregation of the mixture. To prevent segregation during deposition, the NST is deposited sub-aerially through pumping at a high solids density. after more advancements in NST technology, Shell will start NST production commercially in Jackpine Mine (JPM) and MRM after 2027 and 2019, respectively (Shell-Canada-Energy, 2010b; Shell-Canada-Energy, 2011a). Further references to the published tailings plans can be found in (Syncrude-Canada-Ltd., 2010), (Suncor-Energy-Inc., 2010), (CNRL, 2010), and (Imperial-Oil, 2010).

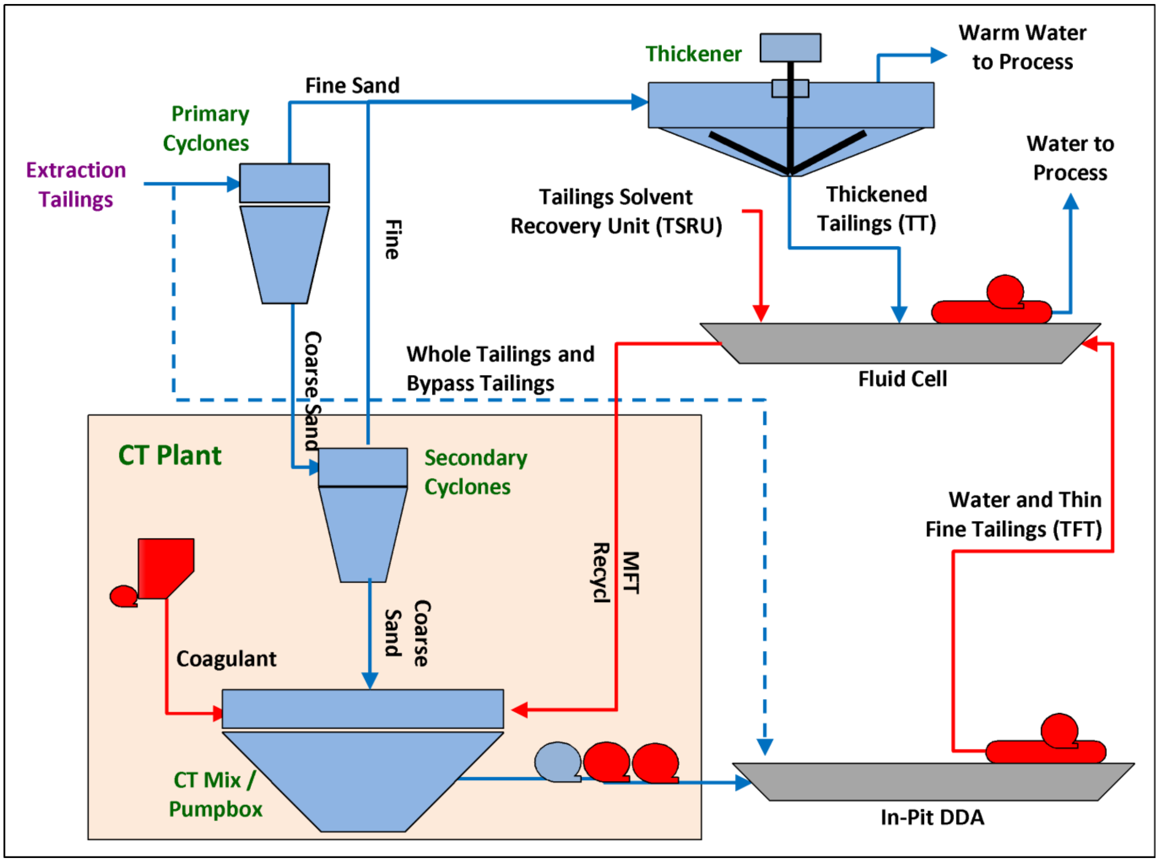

Figure 6: CT plant process flow, modified after (Shell-Canada-Energy, 2011a).

3.2.4. Tailings Equations

The tailings model proposed here is developed based on the CHWE method, being used by Suncor. The input to the bitumen extraction process is the ore feed, including the data about tonnage of the ore and contents of fines, sand and water. The outputs of the process are the volumes of CT, MFT, and released water at the end points of the process. The basis for the mathematical equations is the mass balance relations between the input and the outputs of the CHWE process. The tailings is produced in three main streams: bitumen froth treatment, cyclone overflow and cyclone underflow. The slurry in bitumen froth and over flow streams is sent to beaches one and two and form MFT, while underflow slurry is sent to beaches 3, 4, and 5 as MFT and to CT plant to produce CT (Figure 4).

The total volume of the tailings slurry, produced in all three streams is calculated as in Equation (3.1).

$$V_{Tailings}^{Slurry} = V_{Overflow}^{Slurry} + V_{Underflow}^{Slurry} + V_{Bitumen\ froth}^{Slurry} \tag{3.1}$$

The total volume of fines, sand and water are calculated as in Equations (3.2), (3.3), and (3.4), respectively.

$$V_{Fines} = V_{Fines}^{Overflow} + V_{Fines}^{Underflow} \tag{3.2}$$

$$V_{Sand} = V_{Sand}^{Overflow} + V_{Sand}^{Underflow} \tag{3.3}$$

$$V_{Water} = V_{Water}^{Overflow} + V_{Water}^{Underflow} + V_{Water}^{Bitumenfroth} \tag{3.4}$$

The following notations are used in tailings calculation:

M_{Feed}^{O} : Mass of ore in the feed

B_{Feed} : Bitumen content of the feed (%)

F_{Feed} : Fines content of the feed (%)

W_{Feed} : Water content of the feed (%)

The water content of the ore feed to the processing plant, W_{Feed}, is calculated by Equation (3.5) (Masliyah, 2010).

$$W_{Feed} = 0.75 \times F_{Feed} + 2.3 \tag{3.5}$$

The total tonnage of the overflow slurry is calculated as in Equation (3.6).

$$T_{OverFlow} = T_{OverFLow}^{Fines} + T_{OverFLow}^{Sand} + T_{OverFLow}^{Water} \tag{3.6}$$

Where:

$$T_{OverFlow}^{Fines} = M_{Feed}^{O} \times \left[F_{feed}\left(1 - B_{feed} - W_{feed}\right) - Rj\% \times Rj\%_{F} - F\%_{SET} \times X - \frac{G}{M_{Feed}^{O}} \right] \tag{3.7}$$

$$T_{OverFLow}^{Sand} = M_{Feed}^{O}\left(1 - Sd\%_{UF}\right) \times \left[\left(1 - B_{feed} - W_{feed}\right) \times \left(1 - F_{feed}\right) - Rj\% \times Rj\%_{Sd} - X\right] \tag{3.8}$$

$$T_{OverFlow}^{Water} = M_{Feed}^{O} \times \begin{bmatrix} 1 - B_{feed} - W_{feed} - Rj\% \times \left(Rj\%_{F} + Rj\%_{Sd} \right) \\ -X \times \left(F\%_{SET} + Sd\%_{SET} \right) \end{bmatrix} \times \frac{1 - Sl_{solid\%}}{Sl_{solid\%}} - \frac{I}{M_{Feed}^{O}} \quad (3.9)$$

$$X = Sd\%_{SET} \times R \times \frac{B_{feed} - Rj\% \times Rj\%_{B}}{B\%_{SET}} \quad (3.10)$$

The total tonnage of the underflow slurry is calculated as in Equation (3.11).

$$T_{UnderFlow} = T_{UnderFlow}^{Fines} + T_{UnderFlow}^{Sand} + T_{UnderFlow}^{Water} \quad (3.11)$$

Where:

$$T_{UnderFlow}^{Sand} = Sd\%_{UF} \times M_{Feed}^{O} \begin{bmatrix} \left(1 - B_{feed} - W_{feed}\right)\left(1 - F_{feed}\right) - Rj\% \times Rj\%_{Sd} \\ -\dfrac{Sd\%_{SET} \times R\left(B_{feed} - Rj\% \times Rj\%_{B}\right)}{B\%_{SET}} \end{bmatrix} \quad (3.12)$$

$$T_{UnderFlow}^{Fines} = \frac{UF_{F\%}}{UF_{Sd\%}} \times T_{UnderFlow}^{Sand} \quad (3.13)$$

$$T_{UnderFlow}^{Water} = \frac{UF_{W\%}}{UF_{Sd\%}} \times T_{UnderFlow}^{Sand} \quad (3.14)$$

The tonnages of MFT and released water produced in bitumen froth treatment stream are calculating as in Equations (3.15) and (3.16), respectively.

$$MFT\_1 = M_{Feed}^{O} \times \frac{X}{S\%_{MFT} \times Sd\%_{SET}} \times \left[F\%_{SET} - \frac{Sd\%_{SET} \times F\%_{Beach}}{1 - F\%_{Beach}} \right] \quad (3.15)$$

$$\begin{aligned} Water\_1 = M_{Feed}^{O} \times \frac{X}{Sd\%_{SET}} \times \left[W\%_{SET} - \frac{Sd\%_{SET}}{BDD_{SET}\left(1 - F\%_{Beach}\right)} \right] + \\ \frac{Sd\%_{SET}}{SG_{s}} + \frac{Sd\%_{SET} \times F\%_{Beach}}{SG_{f}\left(1 - F\%_{Beach}\right)} - \left(F\%_{SET} - \frac{Sd\%_{SET} \times F\%_{Beach}}{1 - F\%_{Beach}} \right) \times \frac{1 - S\%_{MFT}}{S\%_{MFT}} \end{aligned} \quad (3.16)$$

The tonnages of MFT and released water produced in Overflow stream are calculating as in Equations (3.17) and (3.18), respectively.

$$MFT\_2 = \frac{1}{S\%_{MFT}} \times \left[T_{OverFlow}^{Fines} - \frac{T_{OverFLow}^{Sand} \times F\%_{Beach}}{1 - F\%_{Beach}} \right] \quad (3.17)$$

$$Water\_2 = T_{OverFlow}^{Water} - \left[\begin{array}{l} \left(T_{OverFLow}^{Sand} \times F\%_{Beach}\right)\times \\ \left(1-F\%_{Beach}\right)\left(\dfrac{1}{BDD_{SET}} - \dfrac{1}{SG_f} - \dfrac{1}{S\%_{MFT}} + 1\right) \\ +T_{OverFLow}^{Sand}\left(\dfrac{1}{BDD_{SET}} + \dfrac{1}{SG_s}\right) + T_{OverFlow}^{Fines}\left(\dfrac{1}{S\%_{MFT}} - 1\right) \end{array} \right] \tag{3.18}$$

The tonnages of MFT and released water produced in underflow stream (in beaches 3 and 4) are calculated as in Equations (3.19), (3.20), (3.21), and (3.22).

$$MFT\_3 = \frac{Fines_{RunOff} \times \left(1-F\%_{Beach}\right) - Sand_{RunOff} \times F\%_{Beach}}{S\%_{MFT} \times \left(1-F\%_{Beach}\right)} \tag{3.19}$$

$$\begin{aligned} Water\_3 = {} & Water_{RunOff} - Sand_{RunOff} \times \left\{ \frac{\dfrac{1}{BDD_{RunOff}} - \dfrac{F\%_{Beach}}{SG_f}}{1-F\%_{Beach}} - \frac{1}{SG_s} \right\} - \\ & \left\{ Fines_{RunOff} - \frac{Sand_{RunOff} \times F\%_{Beach}}{1-F\%_{Beach}} \right\} \times \left(\frac{1}{S\%_{MFT}} - 1 \right) \end{aligned} \tag{3.20}$$

$$MFT\_4 = \left(\frac{G}{H} - \frac{F\%_{Beach}}{1-F\%_{Beach}} \right) \times \frac{\left(1-E_{Cell}\right)\times\left(1-F\%_{Cell}\right)\times V_{Cell} \times CDD}{FC_{Cell} \times E_{Cell} \times S\%_{MFT}} \tag{3.21}$$

$$\begin{aligned} Water\_4 = {} & \frac{\left(1-E_{Cell}\right)\times\left(1-F\%_{Cell}\right)\times V_{Cell} \times CDD}{FC_{Cell} \times E_{Cell}} \times \\ & \left\{ \begin{array}{l} \dfrac{I}{H} + \dfrac{FC_{Cell} \times E_{Cell} \times W_{Make\_up}}{CDD \times V_{Cell} \times \left(1-F\%_{Cell}\right)} - \dfrac{F\%_{Beach} \times \left(\dfrac{1}{BDD_{DT}} - \dfrac{1}{SG_f} \right)}{\left(1-F\%_{Beach}\right)} - \\ \dfrac{1}{BDD_{DT}} + \dfrac{1}{SG_s} + \left(1 - \dfrac{1}{S\%_{MFT}}\right) \times \left(\dfrac{T_{UnderFlow}^{Fines}}{T_{UnderFlow}^{Sand}} - \dfrac{F\%_{Beach}}{1-F\%_{Beach}} \right) \end{array} \right\} \end{aligned} \tag{3.22}$$

Where:

$$Fines_{RunOff} = V_{Cell} \times CDD \times \left\{ \frac{G \times \left(1 + \left(E_{Cell} - 1\right)\left(1-F\%_{Cell}\right)\right)}{FC_{Cell} \times E_{Cell} \times H} - F\%_{Cell} \right\} \tag{3.23}$$

$$Sand_{RunOff} = V_{Cell} \times CDD \times \left(1 - F\%_{Cell}\right)\left\{\frac{1 - FC_{Cell}}{FC_{Cell}}\right\} \tag{3.24}$$

$$\begin{aligned} Water_{RunOff} &= V_{Cell} \times CDD \times \left(1 - F\%_{Cell}\right) \times \left\{\frac{1}{SG_s} + \frac{E_{Cell} \times I}{FC_{Cell} \times E_{Cell} \times H}\right\} + \\ &\frac{V_{Cell} \times CDD \times F\%_{Cell}}{SG_f} + E_{Cell} \times W_{Make\_up} - V_{Cell} \end{aligned} \tag{3.25}$$

The tonnages of MFT and released water produced in underflow stream (in beach5) are calculating as in Equations (3.26) and (3.27), respectively.

$$MFT\_5 = T_{MFT\_5}^{Fines} + T_{MFT\_5}^{Water} \tag{3.26}$$

$$Water\_5 = \left(1 - CT\%_{Tremie}^{Spec}\right) \times \left\{\begin{aligned} &T_{CT}^{Water} + T_{CT}^{Make\ up\ Water} - T_{UnderFlow}^{Sand\ to\ CT} \times \\ &\left[\begin{aligned} &\frac{1}{SCBD} - \frac{1}{SG_s} + \\ &\left(\frac{1}{SCBD} - \frac{1}{SG_f}\right) \times \frac{F\%_{CT}^{Seg}}{1 - F\%_{CT}^{Seg}} \end{aligned}\right] \end{aligned}\right\} - T_{MFT\_5}^{Water} \tag{3.27}$$

Where:

$$T_{UnderFlow}^{Sand\ to\ CT} = T_{UnderFlow}^{Sand} \times \left\{1 - \frac{V_{Cell} \times CDD \times \left(1 - F\%_{Cell}\right)}{T_{UnderFlow}^{Sand} \times FC_{Cell} \times E_{Cell}}\right\} \tag{3.28}$$

$$\begin{aligned} T_{CT}^{Water} &= T_{UnderFlow}^{Water} \times \left(1 - V_{Cell} \times CDD \times \frac{1 - F\%_{Cell}}{FC_{Cell} \times E_{Cell} \times T_{UnderFlow}^{Sand}}\right) + \\ &T_{UnderFlow}^{Sand\ to\ CT} \times \frac{1 - S\%_{MFT}}{S\%_{MFT}} \times \frac{T_{UnderFlow}^{Sand} - T_{UnderFlow}^{Fines} \times SFR}{T_{UnderFlow}^{Sand} \times SFR} \end{aligned} \tag{3.29}$$

$$T_{CT}^{Make\ up\ Water} = MAX\left\{0\ ,\ \frac{T_{UnderFlow}^{Sand\ to\ CT} \times \left(1 + SFR\right) \times \left(1 - S\%_{CT}\right)}{SFR \times S\%_{CT}} - T_{CT}^{Water}\right\} \tag{3.30}$$

$$T_{MFT\_5}^{Fines} = T_{UnderFlow}^{Sand\ to\ CT}\left(1 - CT\%_{Tremie}^{Spec}\right)\left(\frac{1}{SFR} - \frac{F\%_{CT}^{Seg}}{1 - F\%_{CT}^{Seg}}\right) \tag{3.31}$$

$$T_{MFT\_5}^{Water} = MIN\left\{\begin{array}{l} T_{MFT\_5}^{Fines} \times \dfrac{1-S\%_{MFT}}{S\%_{MFT}} \ ,\left(1-CT\%_{Tremie}^{Spec}\right)\times \\ \left(T_{CT}^{Water} + T_{CT}^{Make\ up\ Water} - T_{UnderFlow}^{Sand\ to\ CT} \times \right. \\ \left.\left[\dfrac{1}{SCBD} - \dfrac{1}{SG_s} + \left(\dfrac{1}{SCBD} - \dfrac{1}{SG_f}\right) \times \dfrac{F\%_{CT}^{Seg}}{1-F\%_{CT}^{Seg}}\right]\right) \end{array}\right\} \tag{3.32}$$

Finally, the tonnages of released water produced in CT plant and the tonnage of produced CT are calculating as in Equations (3.33) and (3.34), respectively.

$$Water\_6 = CT\%_{Tremie}^{Spec} \times \left\{T_{UnderFlow}^{Sand\ to\ CT} \times \frac{\left(S\%_{CT}^{Dep} - 1\right)\left(1+SFR\right)}{S\%_{CT}^{Dep} \times SFR} + T_{CT}^{Water} + T_{CT}^{Make\ up\ Water}\right\} \tag{3.33}$$

$$CT = CT\%_{Tremie}^{Spec} \times \left\{T_{UnderFlow}^{Sand\ to\ CT} \times \frac{1+SFR}{SFR} + T_{CT}^{Water} + T_{CT}^{Make\ up\ Water}\right\} \tag{3.34}$$

The total tonnage of released water, MFT, and CT, all resulted from processing of 1000 tonnes of ore feed, are calculated as in Equations (3.35), (3.36), and (3.37), respectively.

$$Water = Water\_1 + Water\_2 + Water\_3 + Water\_4 + Water\_5 + Water\_6 \tag{3.35}$$

$$MFT = MFT\_1 + MFT\_2 + MFT\_3 + MFT\_4 + MFT\_5 \tag{3.36}$$

$$CT = CT\%_{Tremie}^{Spec} \times \left\{T_{UnderFlow}^{Sand\ to\ CT} \times \frac{1+SFR}{SFR} + T_{CT}^{Water} + T_{CT}^{Make\ up\ Water}\right\} \tag{3.37}$$

3.3. Block Aggregation

In any typical block model, the whole mass of the material in the final pit is partitioned through imaginary cubic units known as mining-blocks. The block model includes all the information about each mining-block, such as the spatial coordinates, material tonnage, ore grade, ore tonnage, and waste tonnage. The resulting schedule from solving a mine planning problem in block resolution will determine the destination for each block or portions of the blocks in each period of time. However in real practices of mining operations, there is not selectivity for picking blocks from different areas of a pit. In fact, if the mine planning takes place in block resolution, the optimizer tries to find the best possible schedule by extracting the blocks in such a way that the NPV is maximized. This may end up in extraction of blocks scattered all over a bench in a certain period of time, which is obviously not a feasible solution from a practical point of view.

Due to the costly movements of the mining equipments, some practical limitations are imposed for any position change of the equipment. The general rule is to displace the mining equipment as less as possible to avoid the consequent costs. This means when any equipment such as a shovel starts extraction from an active face in one corner, it keeps extraction and removes the dirt up to the point that the rock type or the ore grade changes significantly. This is when the shovel is dislocated and moved to a new spot for mining. Therefore, mining-blocks are not practical selective mining units. The selective mining unit must be a group of blocks that are aggregated reasonably based on some similarity measures. In this thesis, the aggregate units are called mining-cuts and mining-panels. The details on blocks' clustering and paneling are discussed in the following sections.

3.3.1. Clustering

Clustering is referred to a number of algorithms used to aggregate the data points, such as block model data in this case, in larger groups. The main clustering algorithms include hierarchical clustering (Johnson, 1967), k-means clustering (MacQueen, 1967), and fuzzy c-means clustering (Dunn, 1973).

In hierarchical clustering, it is assumed that every data point is a cluster by itself at the beginning. Therefore, if there are "N" data points, the algorithm starts with "N" clusters. A similarity index measures the closeness of data points (clusters) to each other. In each of algorithm iterations, two of the clusters with the highest value of similarity index will merge and form a new larger cluster. It leaves "N-1" clusters for the next iteration. The algorithm keeps merging the clusters and updating the similarity indices up to the point that all the "N" data points are aggregated under "M" clusters.

In k-means clustering, the algorithm starts with "K" cluster seeds and "N-K" remaining data points. A similarity index is used in k-means algorithm, same to the one in hierarchical clustering, to measure the similarity of each "N-K" data points to each of "K" cluster seeds. At the end of each iteration, all the points are assigned to the seeds, resulting in "K" clusters. In the next iterations, a new set of "K" data points will be selected as cluster seeds and the rest of data points will be assigned to the new seeds. The algorithm continuously changes the seeds to reach to a certain number of iterations and the best result among iterations with the highest overall similarity of clusters will be selected as the clustering result. The fuzzy c-means algorithm is similar to the k-means, with the only difference that in fuzzy case, each of data points can belong to more than one cluster. The rest of the algorithm steps are close to k-means algorithm.

In this research, the hierarchical algorithm is used to aggregate the blocks and create the mining-cuts. Mining-cuts are clusters of blocks within the same bench, grouped based on a similarity index. The similarity index includes four main properties of mining-blocks as (1) the blocks' spatial coordination, (2) the block's ore grade, (3) the block's rock type, and (4) the shape of the mining-cuts located in the lower bench. The formulation used for the similarity index between blocks "i" and "j" is presented in Equation (3.38) (Tabesh and Askari-Nasab, 2011a).

$$S_{ij} = \frac{R_{ij} \times C_{ij}}{\tilde{I}} \tag{3.38}$$

Where:

R_{ij} is the penalty assigned if two blocks are from different rock types, C_{ij} is the penalty assigned to blocks if they are not located above the same cluster in the lower bench, $\tilde{I}$ is the normalized distance value, based on the Euclidean distance between centers of the two blocks, and $\tilde{C}$ is the normalized grade difference between the two blocks. W_D and W_G are the weights considered for the distance and grade differences, respectively. The size of clusters, i.e. the number of blocks within each cluster is controlled by two parameters: the average number of blocks in each cluster, and the maximum number of block in clusters. The values for the parameters of the similarity index and cluster size control will be provided when the case studies are discussed in chapter 4.

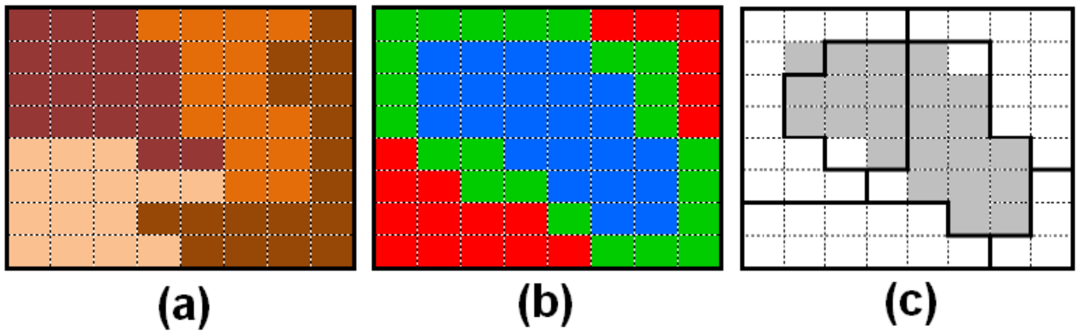

Figure 7: Schematic view of clustering: (a) shows rock types, (b) shows grade distribution, (c) shows the resulting mining cuts.

A schematic view of a simple two-Dimensional clustering example is presented in Figure 7. Four rock types are illustrated in Figure 7(a). The grade distribution is illustrated in Figure 7(b), and Figure 7(c) shows the resulting six mining cuts, separated by the thick border lines. The main ore body is shaded in gray in Figure 7(c). Boarders of the mining cuts follow the shape of ore body, which is resulted from relatively high weight of the grade (W_G) in the similarity index. Since the ore body does not follow any specific pattern and the ore (bitumen) is scatters in the Mac Murray formation, the most important factor in clustering is the spatial location of the blocks. The lower-level cuts, the rock type, and the grade are the next important values in the similarity index in oil sands block aggregation.

3.3.2. Paneling

Mining-panels, also called bench phases, are defined as the intersection of mine phases (pushbacks) and mining benches (Figure 8). Usually, mining-panels are larger units comparing to mining-cuts. The same rationale of clustering blocks to cuts works for larger aggregations in paneling. The practical units for mining operations are the bench phases. When mining starts in a specific elevation in a pushback, it proceeds until the whole material of the pushback in that bench is extracted. Then, according to the number of leads that determines how mining proceeds to the next pushbacks, the equipment may be relocated to start mining of a new bench phase.

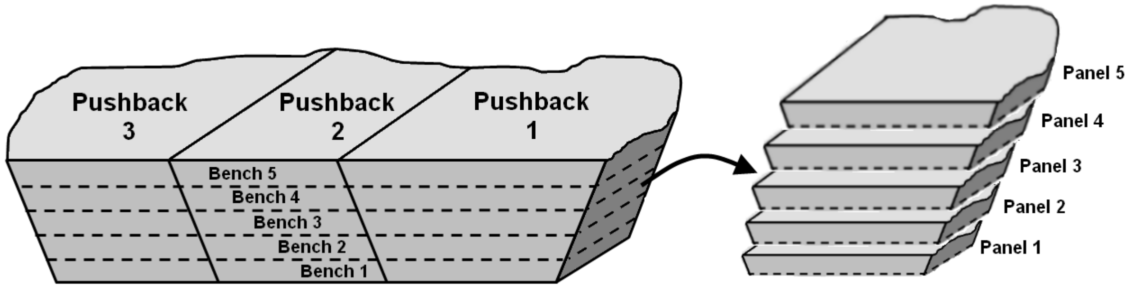

Figure 8: Schematic view of paneling with 3 pushbacks and 5 benches.

Clustering and paneling are done, mainly to follow the practical selective mining units. Block aggregation will also reduce the problem size by eliminating a massive number of integer variables corresponding to mining-blocks and replace them by smaller number of variables associated with aggregate units. However, there is an undesirable consequence associated with any block aggregation: the NPV will be decreased due to mixing high grade and low grade material when larger units are extracted together as mining-cuts or mining-panels. This shortfall can be avoided to some extents by considering different resolutions for mining operations and processing of the material. Mining-panels can be used as the units for mining operations, while mining-cuts can be used for determining the destination of the extracted material. In this way, there is more selectivity in deciding between ore material that must be sent to the processing plant and the low grade and waste material that will be sent to the stockpiles and waste dumps, respectively. The concept of having different units in scheduling has been used in the latest edition of the formulation, presented in the following sections in this chapter.

3.4. The MILP Models

Operations research techniques have been used since 1960s to find the optimal order of extraction of the material and the destination of the extracted material in such a way that maximizes the NPV over the mine-life. The NPV maximization is subject to a number of constraints, such as mining and processing capacities in each planning period, procurement of material required in dyke construction, the capacity of tailings facilities that accommodates the tailings slurry, and the precedence order of extraction between mining units. Some of OR methods used are linear programming, integer programming, mixed-integer linear programming (Johnson, 1969) and dynamic programming (Tan and

Ramani, 1992). To control the precedence order of extraction for mining blocks, the common approach is to define binary variables in the linear programming model, which changes the formulation to a mixed-integer linear programming (MILP) model that is an NP-hard problem for large-scale (Gleixner, 2008). The other technique used in mine planning is the goal programming, when more than one objective function must be optimized such as NPV-maximization and waste-management cost minimization (Ben-Awuah, 2013). In this case, the multiple objective functions can be easily combined as a new set of objective function formulation and change the problem to an MILP problem. Due to the large number of integer variables corresponding to mining blocks over many time periods, it takes considerably a long time for the current solvers to solve the MILP problem.

A number of techniques have been used to overcome the dimensionality of the problem. In linear programming (LP) relaxation, a reduced version of the problem, which does not consider the integer nature of the binary variables is solved and provides an upper bound for maximization problem (Tan and Ramani, 1992; Bienstock and Zuckerberg, 2010; Alvarez et al., 2011; Chicoisne et al., 2012; Epstein et al., 2012). In many cases, however, the LP relaxation does not deliver a feasible solution for the original integer problem. Therefore, the solution must be modified further using some heuristic algorithms to become feasible. The Lagrangian relaxation (LR) (Jünger et al., 2010) is the other technique implemented extensively in mine planning problems (Dagdelen and Johnson, 1986; Akaike and Dagdelen, 1999; Kawahata, 2006; Gaupp, 2008; Cullenbine et al., 2011). In LR, the constraints are divided into hard constraints versus soft co constraints. The assumption is that the problem can be solved easily, e.g. as a knapsack problem, in presence of only soft constraints. In order to adjust the relaxation of each constraint, a penalty function is added to the objective function that controls any violation from the corresponding constraint. When LR is chosen as a solution method, the penalty multipliers for the objective functions must be determined and tuned. The sub-gradient method (Fisher, 1981; Fisher, 1985) is one of the algorithms used in determining the value of penalty multipliers. However, there is a limitation involved in using the sub-gradient algorithm: it is not an exact method, since a heuristic sub-model is used in the algorithm and therefore, there is no guarantee to find the optimal penalty values. As a result, the solution may or may not be feasible for the original problem and may need further heuristic modifications. In conclusion, the LP relaxation and LR methods need supplementary heuristic algorithms to adjust the solutions and both fail in guaranteeing an optimal feasible solution to the MILP problem.

A review of the applied optimization methods in mine planning optimization reveals that the MILP is a powerful operations research technique that has been used extensively to optimize the mine production schedule. However for large-scale mine planning problems, the resulting MILP is NP-hard and heuristic algorithms must be used to reduce the problem size, either directly as in block aggregation, or in LP relaxation and LR algorithms. Knowing that heuristic methods do not guarantee the optimality of the solution, the goal in this research is to solve the MILP model with a minimum use of heuristics (only in block aggregation), and implement other available problem-size reduction techniques, such as preprocessing (through application of floating cones) and period aggregation, to overcome the dimensionality of the MILP problem.

Three versions of the MILP model are developed in this research. The first version (M1) is the simplest one, by including material procurement for reclamation and tailings capacity constraints in the scheduling model (Badiozamani and Askari-Nasab, 2014a). In the second version (M2), the deposition of processed CT as the main tailings product is added to the model (Badiozamani and Askari-Nasab, 2014b). Finally in the most comprehensive version (M3), dyke construction planning is added to the previous model to present an integrated optimization model for mine planning, tailings management, and dyke construction planning.

All the three versions of the model share the same sets, indices, and parameters presented in list of nomenclature. The structure and the specific decision variables of each model is presented as follows.

3.4.1. M1 - Long-Term Mine Planning with Reclamation

In this version, the procurement of material for capping purpose in reclamation phase is considered in the mine planning framework. The original objective function of the mine scheduling optimization problem is maximizing the NPV. In this case, a new term is added to the objective function to minimize the material handling cost associated with capping. Also, a number of constraints are included in the model to make sure that the capacity of tailings facilities and the allowable ranges for tailings contents such as sand, water, and fine material are met. The other specific constraints are the ones that control the availability of reclamation material, i.e. the TCS and OI required for capping. The units for mining and processing are the mining-cuts. The specific features of M1 (Badiozamani and Askari-Nasab, 2014a) are bolded in the following structure:

Maximize: *NPV* – ***Reclamation costs***

Subject to:

- *Mining capacity constraints*
- *Processing capacity constraints*
- ***OI and TCS requirements for reclamation***
- *Tailings, fines, sand and water capacity constraints*
- *Ore and* ***reclamation material*** *blending constraints*
- *Mass balance constraints*
- *Mining precedence*
- *Add-up relations for decision variables*

The following decision variables are defined for M1:

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

$w_k^{u,t} \in [0,1]$ A continuous variable representing the portion of OI material from mining-cut k to be extracted and used for reclamation at destination u in period t.

$v_k^{u,t} \in [0,1]$ A continuous variable representing the portion of TCS material from mining-cut k to be extracted and used for reclamation at destination u in period t.

$y_p^{a,t} \in [0,1]$ A continuous variable representing the portion of mining-panel p to be mined in period t from location a, which includes ore, OI material, TCS and waste.

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

$c_j^t \in [0,1]$ A binary integer variable controlling the precedence of mining phases. c_j^t is equal to one if the extraction of phase j has started by or in period t, otherwise it is zero.

3.4.2. M2 - Long-Term Mine Planning with Composite Tailings Deposition

In this version, instead of reclamation planning, the tailings management has been added in more details to the MILP model by considering the production of CT and MFT, and deposition of the produced CT in CT cells. In this case, a new term is added to the NPV maximization, which minimizes the costs associated with CT deposition. Also, a number of constraints are added to the model to keep the production of CT and MFT within the capacity ranges. All the decision variables and constraints referring to reclamation planning are ignored in M2. Mining-panels are used as the units for mining operations, while mining-cuts are used for processing. The specific features of M2 (Badiozamani and Askari-Nasab, 2014b) are bolded in the following structure:

Maximize: *NPV* – ***CT deposition costs***

Subject to:

- *Mining capacity constraints*

- *Processing capacity constraints*
- *Tailings, fines, sand and water capacity constraints*
- ***CT and MFT capacity constraints***
- *Ore blending constraints*
- *Mass balance constraints for mining **and produced CT***
- *Mining precedence*
- ***CT deposition precedence***
- *Add-up relations for decision variables*

The following decision variables are defined for M2:

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

$y_p^{a,t} \in [0,1]$ A continuous variable representing the portion of mining-panel p to be mined in period t from location a, which includes ore, OI material, tailings sand and waste.

$z_c^t \in [0,1]$ A continuous variable representing the portion of CT cell c to be filled with CT in period t.

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

$c_j^t \in [0,1]$ A binary integer variable controlling the precedence of mining phases. c_j^t is equal to one if the extraction of phase j has started by or in period t, otherwise it is zero.

$a_c^t \in \{0,1\}$ A binary integer variable controlling the precedence of filling of CT cells. a_c^t is equal to one if the filling of CT cell c has started by or in period t, otherwise it is zero.

3.4.3. M3 - Long-Term Mine Planning with Dyke Construction

This final version includes both tailings management, in terms of CT deposition, and waste management in terms of dyke construction planning, within the framework of long-term mine planning optimization model. The objective function includes three parts as: (1) NPV maximization, (2) Dyke construction costs' minimization, and (3) CT deposition costs minimization. Same to the M2, in this case mining-panels are used as the units for mining operations, while mining-cuts are used for processing. The specific features of M3 are bolded in the following structure:

Maximize: *NPV* ***– Dyke construction costs*** *- CT deposition costs*

Subject to:

- *Mining capacity constraints*
- *Processing capacity constraints*
- ***OI and TCS requirements for dyke construction***
- *Tailings, fines, sand and water capacity constraints*
- *CT and MFT capacity constraints*
- *Ore blending constraints*
- *Mass balance constraints for mining, produced CT,* ***and dyke material***
- *Mining precedence*
- *CT deposition precedence*
- ***Dyke construction precedence***
- *Add-up relations for decision variables*

The following decision variables are defined for M3:

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

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

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

$y_p^{a,t} \in [0,1]$ A continuous variable representing the portion of mining-panel p to be mined in period t from location a, which includes ore, OI material, tailings sand and waste.

$z_c^t \in [0,1]$ A continuous variable representing the portion of CT cell c to be filled with CT in period t.

$u_d^t \in [0,1]$ A continuous variable representing the portion of dyke unit d to be constructed in period t.

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

$c_j^t \in \{0,1\}$ A binary integer variable controlling the precedence of mining phases. c_j^t is equal to one if the extraction of phase j has started by or in period t, otherwise it is zero.

$a_c^t \in \{0,1\}$ A binary integer variable controlling the precedence of filling of CT cells. a_c^t is equal to one if the filling of CT cell c has started by or in period t, otherwise it is zero.

$q_d^t \in \{0,1\}$ A binary integer variable controlling the precedence of Constructing dyke units. q_d^t is equal to one if the construction of dyke unit d has started by or in period t, otherwise it is zero.

The detailed structure of the M3 is as follows:

3.4.4. The Objective Function

In general, the objective function is set to optimize one or a number of objectives. Some objective examples are: maximization of reserve exploitation, minimization of deviations from production targets, maximization of work force employment, and so on. The objective function may also be different for various time horizons (short-term, medium-term and long-term) in a mining project. However, the industry standard measure for long-term oil sands mine planning is the discounted cash flow, known as the NPV, which ranks different long-term operational scenarios in terms of the dollar value they generate.

In this model, the objective function maximizes the net present value of the profit gained from processing of each mining-panel. The revenue from each mining-panel consists of two terms: the revenue from selling each tonne of bitumen, and a summation of operational costs. In a larger picture, some capital costs are involved in the model as well, such as the capital investment for buying the mining machinery (shovels, trucks, dozers, …), the capital costs for setting up the processing plants (crushers, conveyors, …) and hot water extraction plant (boilers, separation cells, piping, …). However, these capital costs are not involved in the objective function. That is because the capital costs are considered as the investments that facilitate the start and continuation of the mining and processing operations and will happen under any operational scenario. The operational costs include the material extraction costs, the extra costs for mining ore material, and the cost of selling the ore. There is another operational cost involved in material extraction and preparation as the extra costs of mining and preparing material for dyke construction. The last operational cost function is the cost of CT deposition in the CT cells.

The economic value of mining panels is calculated through Equation (3.39):

$$d_p^{a,u,t} = \sum_{k \in p_a} \left(r_k^{u,t} - n_k^{u,t} - m_k^{u,t} \right) - q_p^{a,t} \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U},\ p \in \mathbf{P},\ a \in \mathbf{A} \qquad (3.39)$$

Where:

$$r_k^{u,t} = \sum_{e=1}^{E} o_k \times g_k^e \times r^{u,e} \times \left(p^{e,t} - cs^{e,t} \right) - \sum_{e=1}^{E} o_k \times cp^{u,e,t} \qquad \forall t \in \mathbf{T}, u \in \mathbf{U}, k \in \mathbf{K} \qquad (3.40)$$

$$q_p^{a,t} = \sum_{k \in p} \left(o_k + d_k + w_k \right) \times cm^{a,t} \qquad \forall t \in \mathbf{T}, p \in \mathbf{P}, a \in \mathbf{A} \qquad (3.41)$$

$$n_k^{u,t} = d_k \times cl^{u,t} \qquad \forall t \in \mathbf{T}, u \in \mathbf{U}, k \in \mathbf{K} \qquad (3.42)$$

$$m_k^{u,t} = l_k \times cu^{u,t} \qquad \forall t \in \mathbf{T}, u \in \mathbf{U}, k \in \mathbf{K} \qquad (3.43)$$

And the cost of CT deposition is calculated as in Equation (3.44):

$$i_c^t = h_c \times ct^{c,t} \qquad \forall t \in \mathbf{T}, c \in \mathbf{C} \qquad (3.44)$$

The first objective is to maximize the discounted revenue from each mining panel, as:

$$Max \sum_{t=1}^{T} \sum_{u=1}^{U} \sum_{a=1}^{A} \sum_{j=1}^{J} \sum_{\substack{p \in B_j \\ k \in B_p}} \left(r_k^{u,t} \times x_k^{u,t} - q_p^t \times y_p^{a,t} \right) \qquad (3.45)$$

The second objective is to minimize the discounted costs of mining and preparation of material for dyke construction, including OI and TCS, as:

$$Min \sum_{t=1}^{T} \sum_{u=1}^{U} \sum_{a=1}^{A} \sum_{j=1}^{J} \sum_{\substack{p \in B_j \\ k \in B_p}} \left(n_k^{u,t} \times w_k^{u,t} + m_k^{u,t} \times v_k^{u,t} \right) \qquad (3.46)$$

And finally, the third objective is to minimize the discounted costs associated with deposition of CT, as:

$$Min\sum_{t=1}^{T}\sum_{c=1}^{C} i_c^t \times z_c^t \tag{3.47}$$

The three objective functions presented in Equations (3.45), (3.46), and (3.47) can be combined into a single objective function, as presented in Equation (3.48):

$$Max\sum_{t=1}^{T}\left(\sum_{u=1}^{U}\sum_{a=1}^{A}\sum_{j=1}^{J}\sum_{\substack{p\in B_j\\ k\in B_p}}\left[r_k^{u,t}\times x_k^{u,t} - q_p^t \times y_p^{a,t} - \left(n_k^{u,t}\times w_k^{u,t} + m_k^{u,t}\times v_k^{u,t}\right)\right] - \sum_{c=1}^{C} i_c^t \times z_c^t\right) \tag{3.48}$$

3.4.5. Mining and Processing Capacity Constraints

The tonnage of the material is the summation of the ore tonnage (including TCS), waste tonnage, and the OI dyke material. However, the total tonnage $\left(o_k + w_k + d_k\right)$ may not be extracted all together in a specific period. The fractional extraction has been made possible through decision variables $y_p^{a,t}$. In the most general version of the model, there are a total number of **A** mine sites. The mining capacity constraints ensure that the total tonnage of all material extracted in each period will not exceed the minimum required and the maximum capacity of each mine site. There are $\mathbf{A}\times\mathbf{T}$ Mining capacity constraints, presented in Equation (3.49).

$$T_{Ml}^{a,t} \le \sum_{j=1}^{J}\left(\sum_{p\in B_j}\sum_{k\in B_p}\left(o_k + w_k + d_k\right)\times y_p^{a,t}\right) \le T_{Mu}^{a,t} \qquad \forall t\in\mathbf{T}, \forall a\in\mathbf{A} \tag{3.49}$$

$$T_{Pl}^{u,t} \le \sum_{j=1}^{J}\left(\sum_{k\in B_j}\left(o_k \times x_k^{u,t}\right)\right) \le T_{Pu}^{u,t} \qquad \forall t\in\mathbf{T},\ u\in\mathbf{U} \tag{3.50}$$

The extracted ore will be sent to the processing plants. In a general case, there is U number of destinations, including processing plants among them. In this case, the decision variable $x_k^{u,t}$ determines what portion of the mineralized tonnage from the mining-cut "k" must be sent to each processing plant. Therefore, the ore tonnage of mining-cut "k" sent to the processing plant "u" in period "t" is equal to $\left(o_k \times x_k^{u,t}\right)$. The processing capacity constraints ensure that the total tonnage of ore material from all the mining-cuts, extracted in period "t" and being sent to processing plant "u" will not exceed the minimum requirement and maximum capacity of the processing plant. There are $\mathbf{U} \times \mathbf{T}$ processing capacity constraints, presented in Equation (3.50).

3.4.6. Dyke Construction Material Requirement

Two types of material are used in construction of dyke walls: OI and TCS. In this case, the dyke construction site is assumed to be one destination, beside the processing plant. Same to the mining and processing plants, the fractional selection from the dyke material is possible through decision variables $w_k^{u,t}$ and $v_k^{u,t}$, for OI and TCS, respectively. The total tonnages of OI and TCS being sent for dyke construction in period "t" are equal to $\left(d_k \times w_k^{u,t}\right)$ and $\left(l_k \times v_k^{u,t}\right)$. Equations (3.51) and (3.52) ensure that the material sent for dyke construction are within the range of minimum and maximum requirements.

$$T_{Cl}^{u,t} \le \sum_{j=1}^{J}\left(\sum_{k \in B_j}\left(d_k \times w_k^{u,t}\right)\right) \le T_{Cu}^{u,t} \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U} \qquad (3.51)$$

$$T_{Nl}^{u,t} \le \sum_{j=1}^{J}\left(\sum_{k \in B_j}\left(l_k \times v_k^{u,t}\right)\right) \le T_{Nu}^{u,t} \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U} \qquad (3.52)$$

Equation (3.53) ensures that the summation of material tonnage extracted either as ore ($o_k \times x_k^{u,t}$) or OI for dyke construction ($d_k \times w_k^{u,t}$) from all the mining-cuts belonging to a specific mining-panel is not greater than the total tonnage of that mining-panel.

$$\sum_{u=1}^{U}\sum_{k \in B_p}\left(o_k \times x_k^{u,t} + d_k \times w_k^{u,t}\right) \le \sum_{a=1}^{A}\sum_{k \in B_p}\left(o_k + d_k\right) \times y_p^{a,t} \qquad \forall t \in \mathbf{T},\ p \in \mathbf{P} \qquad (3.53)$$

Since the TCS is a part of the ore resulting from bitumen processing, the total tonnage of produced TCS from processing mining-cut "k" cannot exceed the total ore tonnage extracted from that mining-cut. This relation is guaranteed by Equation (3.54).

$$\sum_{u=1}^{U}\left(l_k \times v_k^{u,t}\right) \le \sum_{u=1}^{U}\left(o_k \times x_k^{u,t}\right) \qquad \forall t \in \mathbf{T},\ k \in \mathbf{K} \tag{3.54}$$

A new set of constraints are essential to control the mass balance relation between the materials extracted as OI and TCS for dyke construction, and the actual consumption of material for dyke construction. Integer decision variable u_d^t is defined to control the construction of dyke lifts that shape the dyke walls. The term $\left(k_d \times u_d^t\right)$ calculates the actual tonnage of dyke cell "d" that is constructed in period "t". Equation (3.55) ensures that the mass balance is hold between the produced material in right hand side, and the used material in left hand side for each of dike units in each period.

$$\sum_{d=1}^{D}\left(k_d \times u_d^t\right) \le \sum_{u=1}^{U}\sum_{j=1}^{J}\left(\sum_{k\in B_j}\left(d_k \times w_k^{u,t} + l_k \times v_k^{u,t}\right)\right) \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U} \tag{3.55}$$

3.4.7. Blending Constraints

The ore feed must follow a pre-determined criteria to be accepted as input to the processing plant. The most important criteria in bitumen processing plants are the head grade of bitumen and fines in the ore feed. Blending constraints control the average grades and guarantee that all the material entering the CHWE process has a minimum acceptable grade of bitumen ($\underline{g}^{u,t,e}$)and a maximum acceptable grade of fines ($\overline{f}^{u,t,c}$). The blending constraints for bitumen as the only element of interest in oil sands mining, and fine material are presented in Equations (3.56) and (3.57), respectively.

$$\underline{g}^{u,t,e} \le \sum_{j=1}^{J}\left(\sum_{k\in B_j} g_k^e \times o_k \times x_k^{u,t} \Big/ \sum_{k\in B_j} o_k \times x_k^{u,t}\right) \le \overline{g}^{u,t,e} \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U}, e \in \mathbf{E} \tag{3.56}$$

$$\underline{f}^{u,t,o} \leq \sum_{j=1}^{J}\left(\sum_{k\in B_j} f_k^o \times o_k \times x_k^{u,t} \Big/ \sum_{k\in B_j} o_k \times x_k^{u,t}\right) \leq \overline{f}^{u,t,o} \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U} \tag{3.57}$$

The average grade of ore is calculated by dividing the bitumen tonnage ($g_k^e \times o_k \times x_k^{u,t}$) to the ore tonnage ($o_k \times x_k^{u,t}$). The same formulation is applied for calculation of average grade of fines in ore material by dividing fines tonnage ($f_k^o \times o_k \times x_k^{u,t}$) to the ore tonnage.

The third set of blending constraints controls the head grade of fines in OI dyke material. These constraints ensure that the fines in the OI dyke material will not violate the limits of $\underline{f}^{u,t,c}$ and $\overline{f}^{u,t,c}$, as it is essential for stability of dyke walls. Equation (3.58) shows blending constraints for OI dyke material.

$$\underline{f}^{u,t,c} \leq \sum_{j=1}^{J}\left(\sum_{k\in B_j} f_k^c \times d_k \times w_k^{u,t} \Big/ \sum_{k\in B_j} d_k \times w_k^{u,t}\right) \leq \overline{f}^{u,t,c} \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U} \tag{3.58}$$

For a better linear appearance of the formulation, Equation (3.56) can be expanded to two equations of (3.59) and (3.60).

$$\underline{g}^{u,t,e} \sum_{j=1}^{J}\sum_{k\in B_j}\left(o_k \times x_k^{u,t}\right) \leq \sum_{j=1}^{J}\sum_{k\in B_j}\left(g_k^e \times o_k \times x_k^{u,t}\right) \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U}, e \in \mathbf{E} \tag{3.59}$$

$$\sum_{j=1}^{J}\sum_{k\in B_j}\left(g_k^e \times o_k \times x_k^{u,t}\right) \leq \overline{g}^{u,t,e} \sum_{j=1}^{J}\sum_{k\in B_j}\left(o_k \times x_k^{u,t}\right) \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U}, e \in \mathbf{E} \tag{3.60}$$

Equations (3.57) and (3.58) can be expanded in a similar way.

3.4.8. Tailings Capacity Constraints

A number of constraints control the production of tailings slurry, tailings components, and tailings products. The volume of the whole tailings slurry is controlled by Equation (3.61), where $\left(t_k \times x_k^{u,t}\right)$ measures the total volume of tailings slurry produced from partial extraction of mining-cut “k” in period “t”. The total volume of tailings slurry (t_k)

potentially can be produced from processing of ore material in mining-cut “k” has been already calculated in the tailings model. In addition to the volume of slurry, tailings contents –fines, sand, and water - are also important. That is because by regulations, oil sands operators are supposed to control the fines contents of the slurry and must have control on sand since it will be used for dyke construction and capping. Same to the total tailings equation, the volume of produced fines, sand, and water downstream is calculated by $\left(f_k \times x_k^{u,t}\right)$, $\left(s_k \times x_k^{u,t}\right)$, and $\left(r_k \times x_k^{u,t}\right)$, where the value of multipliers f_k, s_k, and r_k are already calculated from the tailings model. Equations (3.62), (3.63), and (3.64) ensure that the volume of tailings content will not exceed the capacity range in each period.

$$T_{Tl}^{u,t} \leq \sum_{j=1}^{J}\left(\sum_{k\in B_j}\left(t_k \times x_k^{u,t}\right)\right) \leq T_{Tu}^{u,t} \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U} \tag{3.61}$$

$$T_{Fl}^{u,t} \leq \sum_{j=1}^{J}\left(\sum_{k\in B_j}\left(f_k \times x_k^{u,t}\right)\right) \leq T_{Fu}^{u,t} \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U} \tag{3.62}$$

$$T_{Sl}^{u,t} \leq \sum_{j=1}^{J}\left(\sum_{k\in B_j}\left(s_k \times x_k^{u,t}\right)\right) \leq T_{Su}^{u,t} \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U} \tag{3.63}$$

$$T_{Wl}^{u,t} \leq \sum_{j=1}^{J}\left(\sum_{k\in B_j}\left(r_k \times x_k^{u,t}\right)\right) \leq T_{Wu}^{u,t} \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U} \tag{3.64}$$

Tailings slurry will be dewatered at the end points and forms the MFT and CT. The volumes of the potential MFT and CT produced downstream from processing of mining-cut “k” are already calculated as h_k and p_k, and are used to measure the total volumes resulting from processing of portion $x_k^{u,t}$, as in Equations (3.65) and (3.66).

$$T_{Xl}^{u,t} \leq \sum_{j=1}^{J}\left(\sum_{k\in B_j}\left(h_k \times x_k^{u,t}\right)\right) \leq T_{Xu}^{u,t} \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U} \tag{3.65}$$

$$T_{Yl}^{u,t} \le \sum_{j=1}^{J}\left(\sum_{k\in B_j}\left(p_k \times x_k^{u,t}\right)\right) \le T_{Yu}^{u,t} \qquad \forall t \in \mathbf{T},\ u \in \mathbf{U} \tag{3.66}$$

The last tailings-related constraint is the mass balance relation between the volumes of produced CT and deposited CT in CT cells. In Equation (3.67), the left hand side adds up the whole volume of deposited CT in CT cells in period t. This relation ensures that the deposited CT cannot be more than the whole produced CT in right hand side.

$$\sum_{c=1}^{C}\left(h_c \times z_c^t\right) \le \sum_{j=1}^{J}\sum_{k\in B_j}\sum_{u=1}^{U}\left(p_k \times x_k^{u,t}\right) \qquad \forall t \in \mathbf{T} \tag{3.67}$$

3.4.9. Decision Variables' Add-ups

The decision variables used for partial extraction of ore, OI dyke material, and TCS dyke material are all portions, non-negative continuous values bounded by one. Since they are fractions, they must add up to one for every mining cut over all time periods. These relations are defined in Equations (3.68), (3.69), and (3.70).

$$\sum_{u=1}^{U}\sum_{t=1}^{T} x_k^{u,t} \le 1 \qquad \forall k \in \mathbf{K} \tag{3.68}$$

$$\sum_{u=1}^{U}\sum_{t=1}^{T} w_k^{u,t} \le 1 \qquad \forall k \in \mathbf{K} \tag{3.69}$$

$$\sum_{u=1}^{U}\sum_{t=1}^{T} v_k^{u,t} \le 1 \qquad \forall k \in \mathbf{K} \tag{3.70}$$

The same relation holds for the other two continuous variables of z_c^t and u_d^t, as they are portions of CT cells and dyke units to be filled out over time periods and by definition, must add up to one if they are completely filled out CT or dyke material. This is presented in Equations (3.71) and (3.72).

$$\sum_{t=1}^{T} z_c^t \le 1 \qquad \forall c \in \mathbf{C} \qquad (3.71)$$

$$\sum_{t=1}^{T} u_d^t \le 1 \qquad \forall d \in \mathbf{D} \qquad (3.72)$$

Finally, the reserve constraints presented by Equation (3.73) ensure that the portions of mining-panels extracted over the mine-life add up to one. Equation (3.73) can be expressed as an equality constraint, if the mine planner assumes that the whole mining pit, including all of the mining-panels must be extracted completely by the end of mine-life.

$$\sum_{t=1}^{T} y_p^{a,t} \le 1 \qquad \forall p \in \mathbf{P}, a \in \mathbf{A} \qquad (3.73)$$

3.4.10. Mining Precedence Constraints

The extraction of mining-panels must follow the precedence order, based on the spatial location of the mining-panels. Two precedence sets can be defined for extraction of each panel, as (1) the vertical precedence, and (2) the horizontal precedence. The notion of vertical and horizontal precedence is elaborated more under the title of directional mining. Briefly, prior to extraction of a specific mining-panel, all the panels on top must already have been extracted so that the panel is accessible (vertical precedence). By definition, $N_p(L)$ represents the set of immediate mining panels that are on top of mining-panel “p”. Equation (3.74) ensures that the vertical precedence is met. The other precedence can be defined to guide the extraction operations follow a certain direction (horizontal precedence). By definition, $O_p(L)$ represents the set of immediate mining-panels in a specified horizontal mining direction that must be extracted prior to extraction of mining-panel p at a specified level. The horizontal precedence is presented in Equation (3.75).

$$b_p^t - \sum_{a=1}^{A}\sum_{i=1}^{t} y_s^{a,i} \leq 0 \qquad \forall t \in \mathbf{T},\ p \in \mathbf{P},\ s \in N_p(L) \tag{3.74}$$

$$b_p^t - \sum_{a=1}^{A}\sum_{i=1}^{t} y_r^{a,i} \leq 0 \qquad \forall t \in \mathbf{T},\ p \in \mathbf{P},\ r \in O_p(L) \tag{3.75}$$

$$\sum_{a=1}^{A}\sum_{i=1}^{t} y_p^{a,i} - b_p^t \leq 0 \qquad \forall t \in \mathbf{T},\ p \in \mathbf{P} \tag{3.76}$$

$$b_p^t - b_p^{t+1} \leq 0 \qquad \forall t \in \{1,...,T-1\},\quad p \in \mathbf{P} \tag{3.77}$$

Equation (3.76) relates the continuous decision variable $y_p^{a,i}$, with the integer variable b_p^t, while Equation (3.77) states that when extraction of a panel starts in a specific period, then that panel is accessible and available for extraction in all the periods after.

The ultimate mining pit is partitioned by a number of nested pits known as pushbacks. Pushbacks are the final pit limits resulting from increments in revenue factors, related to the selling price of ore between 0.0 and 2.0. The pushbacks are the backbones in long-term mine planning because they are considered as the phases in mining operations. In the case of oil sands mining, it is essential to follow a specific order for extraction from pushbacks to make sure that enough space will become available for in-pit tailings storage. This emerges a new precedence concept as pushback precedence. Equations (3.78) and (3.79) ensure that mining operation can be started in any specific pushback only after the immediate predecessor pushbacks in a certain horizontal direction to that pushback are already cleared. The constraints presented in Equation (3.80) work in the same way as Equation (3.77), here for pushbacks.

$$H \times c_j^t - \sum_{a=1}^{A}\sum_{i=1}^{t} y_h^{a,i} \leq 0 \qquad \forall t \in \mathbf{T},\ j \in \mathbf{J},\ h \in B_j(H) \tag{3.78}$$

$$\sum_{a=1}^{A}\sum_{i=1}^{t} y_h^{a,i} - H \times c_j^t \leq 0 \qquad \forall t \in \mathbf{T},\ j \in \mathbf{J},\ h \in B_{j+1}(H) \tag{3.79}$$

$$c_j^t - c_j^{t+1} \le 0 \qquad \forall t \in \{1,...,T-1\},\ j \in \mathbf{J} \qquad (3.80)$$

3.4.11. CT Cells, Dyke Units, and Mining-Panels Precedence Constraints

In mining operations, the precedence is defined to control the extraction of mining units, here the mining-panels. In CT deposition and dyke construction, the CT or the dyke material will be deposited to fill a number of imaginary spatial units. These units are called CT cells in CT deposition, and dyke units in dyke construction. The precedence constraints in this case control the spatial order in deposition of CT and construction of dykes. Equation (3.81) controls precedence order in CT deposition. Equation (3.82) relates the continuous variable z_c^i, representing the portion of CT cell "c" to be filled up by period "t", with the integer variable a_c^t that controls the precedence. Equation (3.83) ensures that when deposition in a CT cell starts in certain period "t", the CT can be deposited in that cell for all the next periods greater than "t".

$$a_c^t - \sum_{i=1}^{t} z_r^i \le 0 \qquad \forall t \in \mathbf{T},\ c \in \mathbf{C},\ r \in Q_c(R) \qquad (3.81)$$

$$\sum_{i=1}^{t} z_c^i - a_c^t \le 0 \qquad \forall t \in \mathbf{T},\ c \in \mathbf{C} \qquad (3.82)$$

$$a_c^t - a_c^{t+1} \le 0 \qquad \forall t \in \{1,...,T-1\},\quad c \in \mathbf{C} \qquad (3.83)$$

Following the same concept of precedence relation between CT cells, Equations (3.84), (3.85), and (3.86) control the precedence between dyke units in dyke construction.

$$q_d^t - \sum_{i=1}^{t} u_m^i \le 0 \qquad \forall t \in \mathbf{T},\ d \in \mathbf{D},\ m \in S_d(G) \qquad (3.84)$$

$$\sum_{i=1}^{t} u_d^i - q_d^t \le 0 \qquad \forall t \in \mathbf{T},\ d \in \mathbf{D} \qquad (3.85)$$

$$q_d^t - q_d^{t+1} \le 0 \qquad \forall t \in \{1,...,T-1\}, \quad d \in \mathbf{D} \qquad (3.86)$$

The next constraint controls the precedence between dyke construction and mining-panels extraction. It ensures that any starter dyke (the first dyke unit at the bottom) can only be constructed when the mining pit in that specific coordination has been extracted and the dyke footprint is already cleared. Equation (3.87) shows this set of constraints. It lets any dyke unit construction (q_d^t) to be started only after all the predecessor mining-panels, members of $X_d(P)$, are completely extracted.

$$q_d^t - \sum_{a=1}^{A}\sum_{i=1}^{t} y_f^{a,i} \le 0 \qquad \forall t \in \mathbf{T},\, d \in \mathbf{D},\, f \in X_d(P) \qquad (3.87)$$

The last constraint defines the precedence relation between dyke construction and CT deposition. In fact, CT cells are constructed by dykes. CT can be deposited in CT cells only after the required space of the CT cell has been already prepared by raising the dyke walls to the required height. The dyke walls are constructed to provide adequate room for CT deposition through partitioning the already-excavated mining pit. Equation (3.88) ensures that the deposition of CT in CT cell “c” can only start when all the dyke units required for raising the dyke walls corresponding to CT cell “c” - members of $T_c(D)$ - are already constructed.

$$a_c^t - \sum_{i=1}^{t} u_n^i \le 0 \qquad \forall t \in \mathbf{T},\, c \in \mathbf{C},\, n \in T_c(D) \qquad (3.88)$$

3.5. Directional Mining

Two types of mining precedence can be defined between mining panels, the vertical precedence and the horizontal precedence. The precedence relation between mining-panels is defined based on the precedence relation between mining-blocks. The most general format is to consider nine blocks on top of each block, resulting in nine vertical precedence relations for each mining-block. The vertical precedence is illustrated in Figure 9(a).

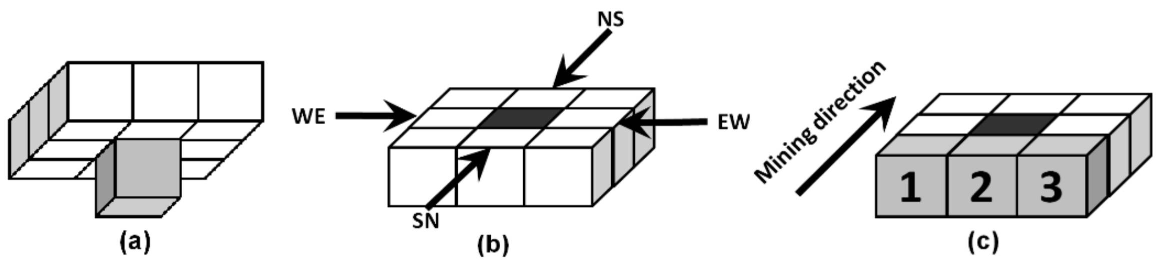

Figure 9: Block precedence in (a): vertical direction, and (b) and (c): horizontal direction, after (Badiozamani and Askari-Nasab, 2014a).

In the case of oil sands surface mining, a new set of precedence is essential to be defined as the horizontal precedence, which forces the mining operations to start from a certain corner and progress in a specific direction. In this case, the horizontal precedence between mining-blocks builds the horizontal precedence between mining-panels too. An infinite number of horizontal directions can be considered. However, there are eight main horizontal directions, including four non-diagonal directions of N-S, S-N, E-W, and W-E, and four diagonal directions of NE-SW, SW-NE, NW-SE, and SE-NW. Figure 9(b) illustrates the main four non-diagonal directions. Figure 9(c) shows schematic block precedence in S-N direction. Blocks one, two, and three must be extracted to access the shaded block behind them.

All the vertical and horizontal relations between mining-blocks belonging to each pair of mining-cuts are investigated in determining the precedence relations between the mining-cuts. If there is only one precedence order between one mining-block from the first mining-cut and one from the second mining-cut, then the two mining-cuts will be considered as predecessor and successor to each other when considering the order of extraction.

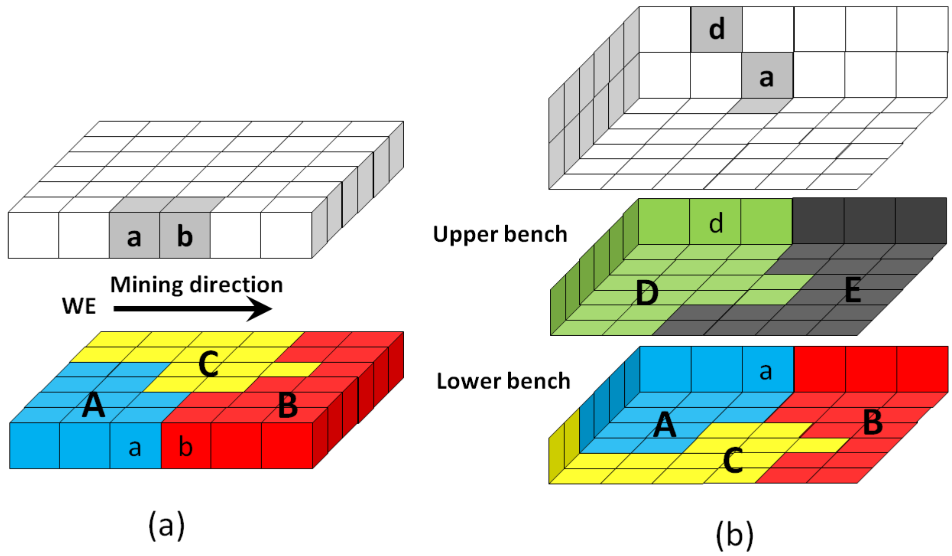

Figure 10: Schematic precedence order between mining cuts: (a) horizontal precedence and (b): vertical precedence, modified after (Badiozamani and Askari-Nasab, 2014a).

Figure 10(a) illustrates a schematic view of horizontal precedence between mining-cuts. At the top, the two mining-blocks of “a” and “b” are located beside each other. Assuming a W-E mining direction, block “a” must be extracted first to provide access to block “b”. At the bottom, the block model is presented in cut-level resolution. The same bench on top is clustered into three mining-cuts of “A”, “B”, and “C”. The blocks “a” and “b” belong to the mining-cuts “A” and “B”, respectively. Since mining-block “a” proceeds “b”, the mining-cut “A” that includes “a” is the predecessor of the mining-cut “B” that includes “b”, in the W-E direction. Figure 10(b) shows the vertical precedence between mining-cuts. In this case, mining-block “d” proceeds “a” vertically. Since “d” belongs to mining-cut “D” in the upper bench and “a” belongs to mining-cut “A” in the lower bench, mining-cut “D” is the vertical precedence to mining-cut “A”.

The precedence order is extendable from cut level to panel level with the same logic. The binary decision variable $b_p^t \in \{0,1\}$ is used to control the precedence order between mining-panels. Equations (3.75), (3.76), and (3.77) control the horizontal precedence order among mining-panels, while Equations (3.74), (3.76), and (3.77) control the vertical precedence order.

Pushbacks are used as the phases in mining operations. In oil sands mining, pushbacks are designed in a way that by complete extraction of each pushback, required width for dyke construction becomes available for in-pit tailings storage. Therefore, it is essential to consider the mining direction when deciding on the order of extraction for pushbacks. The pushback precedence can be defined in a number of ways. A simple method used in this research is the one introduced by (Ben-Awuah, 2013), shown schematically in Figure 11.

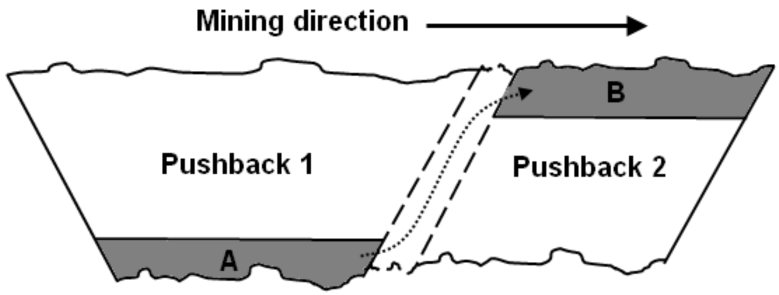

Figure 11: Pushback precedence and directional mining.

With considering the mining direction shown in Figure 11, the proposed pushback precedence implies that pushback one must be extracted completely prior to start extraction of pushback two. The mining-blocks belonging to the very bottom bench of pushback one are making the mining-panel "A". All of these blocks are assumed to be the predecessors for all of the blocks at the top bench of pushback two, which make mining-panel "B". In other words, due to the directional mining assumption, one more precedence relation is added to the panels' precedence list to control the extraction priority between pushbacks. The binary integer variable $c_j^t \in \{0,1\}$ controls the pushback precedence in Equations (3.78), (3.79), and (3.80).

The same concept of directional mining applies in construction of dyke walls and deposition of CT in the in-pit tailings facility. While constraints presented in (3.81) to (3.86) control the precedence order in CT cells construction and CT deposition, Equations (3.88) represents a set of constraints that define the relation between dyke construction and CT deposition. The set $T_c(D)$ includes the dyke units that must be constructed prior to CT deposition in CT cell "c". The members of $T_c(D)$ are determined based on the direction of tailings facility progress. This is illustrated schematically in Figure 12.

In this example, the excavated pit is partitioned to two CT containments, after construction of dykes A and B. Dyke units D1, D2, and D3 will gradually raise the Dyke A, and D4, D5, and D6 will raise Dyke B. For the sake of simplicity in modeling, it is assumed that the CT will be deposited in a number of lifts. After raising the dyke walls to a proper height, the CT lifts can be stored in the provided space behind the dykes.

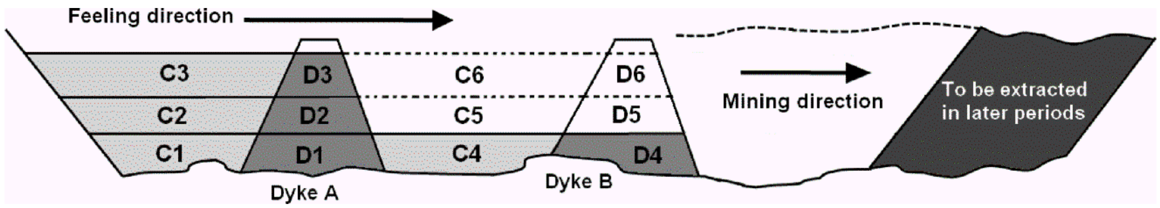

Figure 12: Schematic cross section of a sample pit, showing the precedence order of dyke construction and CT deposition.

In this example, the precedence list for CT deposition and dyke construction is presented in Table 1.

Table 1: Precedence list for directional dyke construction and CT deposition.

Dyke unit	Predecessor dyke unit	Dyke unit	Predecessor dyke unit	CT cell	Predecessor dyke unit & CT cells	CT cell	Predecessor dyke unit & CT cells
D1	-	D4	D3	C1	D1	C4	D4 , C3
D2	D1	D5	D4	C2	D2 , C1	C5	D5 , C4
D3	D2	D6	D5	C3	D3 , C2	C6	D6 , C5

3.6. Preprocessing (Floating Cones)

The mathematical model presented in the previous section includes a massive number of integer and continuous variables, and relatively a large number of constraints. If the problem size can be reduced through some modeling techniques or model refinements, the solution time will be decreased significantly. Preprocessing is one of the techniques that can be applied to eliminate a significant number of binary variables by fixing their values to either zero or one before solving the problem. The preprocessing technique presented and used in this research is based on the comparison between mining and processing capacities on one hand, and the accumulated tonnage of predecessor and successor mining-panels corresponding to each mining-panel on the other hand.

This technique of preprocessing has been used for the first time by Bley et al. (2010). The idea behind it is that some of the benches will not be accessible in certain periods due to the limited capacity of mining. As an example, let's assume that the total tonnage of the whole material lying on top of mining-panel p that must be extracted before extraction of this panel equals to A_p, and the accumulated mining capacity up to period t^* is $M_{t^*}^{uc}$. Now if $A_p > M_{t^*}^{uc}$, it means that the mining-panel p cannot be extracted in the periods one to t^*, as the material on top of it is not cleared yet by period t^*. As a result, the value of the binary variable $b_p^t \in \{0,1\}$, the continuous variable $y_p^{a,t} \in [0,1]$, and variables associated with the mining-cuts contained in the mining-panel p, ($x_k^{u,t} \in [0,1]$, $w_k^{u,t} \in [0,1]$, and $v_k^{u,t} \in [0,1]$) will be fixed to zero for all the time periods from one to t^*. This is referred to as "the upper cone" variable reduction.

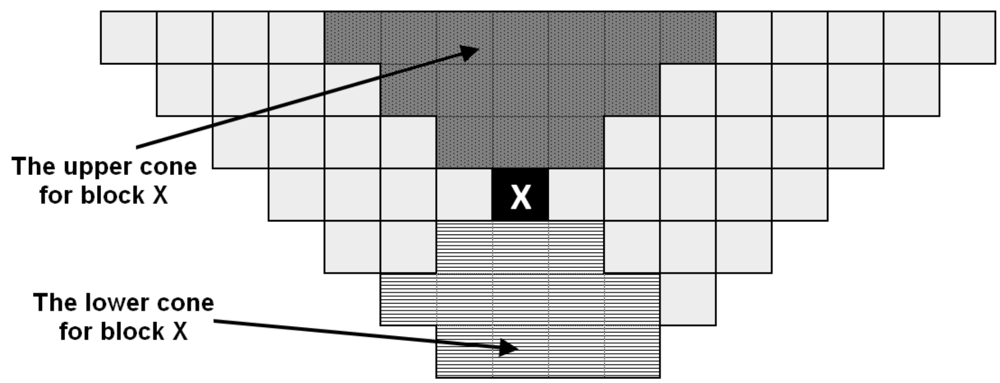

Figure 13: 2-dimensional upper & lower cones for preprocessing, modified after (Badiozamani and Askari-Nasab, 2014b)

The same concept can be implemented for "lower cone" variable reduction (Tabesh and Askari-Nasab, 2011b). In this case, let's assume that the total tonnage of material in the lower cone of mining-panel p, which includes the successor panels of mining-panel p, is B_p, and the accumulated mining capacity from period t^* until the end of mine-life is $M_{t^*}^{lc}$. Also it is assumed that all the material within the final pit must be extracted by the end of mine-life. Now if $B_p > M_{t^*}^{lc}$, it means that the mining-panel p must have been extracted by period t^*. As a result, the value of the binary variable $b_p^t \in \{0,1\}$, the continuous variable $y_p^{a,t} \in [0,1]$, and variables associated with the mining-cuts contained in mining-panel p, ($x_k^{u,t} \in [0,1]$, $w_k^{u,t} \in [0,1]$, and $v_k^{u,t} \in [0,1]$) will be fixed to one for all the time periods from t^* to the end of mine-life.

In the above, the variable values are fixed to zero or one based on the mining capacity. The same logic can be used for processing capacity as well. After doing the preprocessing, some of the constraints in the model will contain only zero values. Preprocessing finishes by deleting zero-constraints from the model. Figure 13 illustrates a 2-dimensional schematic of upper and lower cones.

3.7. Summary and Conclusions

To optimize a comprehensive mine planning model in long-term, different aspects of oil sands mining must be visited within an integrated framework. The overall objective is to maximize the discounted net value of the operations. This optimization is constrained by scarce resources for mining the oil sands material and processing it for bitumen extraction. There other important factor that limits the operation is finding space for storage of the produced tailings slurry resulting from oil sands processing. The by-products of mining and processing oil sands are the main sources of material used in dyke construction for preparation of tailings storage facility. The interconnectivity in flow of material in oil sands surface mining emerges the concept of integrated mine planning model, with respect to solid waste disposal and tailings management.

In this chapter, the theoretical basis of the research was developed. A tailings model, including the mass balance formulations was presented, followed by the concept of block aggregation. An MILP model has been proposed to solve the integrated mine planning model. The details of the MILP model, including different objective functions and a number of constraint sets were discussed in details. The concept of directional mining and its application in oil sands mining waste disposal, and tailings deposition was presented and discussed. Finally, the preprocessing technique through application of floating cones used for problem size reduction was introduced. The proposed theoretical framework provides the required basis for implementation of an integrated mine planning model.

CHAPTER 4
APPLICATION OF METHODOLOGY AND DISCUSSION OF RESULTS

4.1. Introduction

After establishing the research theoretical framework in Chapter 3, the proposed mixed-integer linear programming (MILP) model for the integrated mine production scheduling problem is implemented in this chapter through 13 experiments under three case studies of an oil sands deposit (Table 2). The experiments in each case study are designed to show how different features of the proposed model contribute to generating an integrated production schedule and determine what should be selected among different decision options, such as the mining direction, mining unit resolution and period aggregation to generate a practical schedule with higher net present value (NPV).

To analyze the dataset that will be used in the case studies, the first step was to develop a Whittle project. The block model is divided into two pits, separated by a river. For each pit, the optimal nested pits are determined using the LG algorithm, under different revenue factors. Also, six scenarios are analyzed in the Whittle, corresponding to different mining directions to narrow down the options for directional mining in MILP experiments. A scenario analysis in Whittle has resulted in choosing two mining directions for further studies in Case study 1.

The first case study is implemented to determine the best mining direction and mine planning resolution through the design and implementation of six experiments. The first objective in Case study 1 is to test the two mining directions (pre-determined in the Whittle scenario analysis) and select the one that generates a higher NPV for further experiments. This has been done in experiments A1 and A2. The next objective is to verify the effect of the mining unit resolution on the NPV. A number of mining-cut and mining-panel resolutions are tested in experiments A3 to A6 to achieve this purpose. The data used in Case study 1 contains the block model data of pit one. The experiments are run over 10 periods.

Table 2: Design of experiments.

Case study	Expr.	# Periods	Direction	# Panels	# Cuts	Experiment purpose
Case study 1 (Direction & Resolution)	A1	10	SN	31	962	Mining direction
	A2	10	WE	25	942	Mining direction
	A3	10	WE	25	942	Mining-cut resolution
	A4	10	WE	25	570	Mining-cut resolution
	A5	10	WE	25	428	Mining-cut resolution
	A6	10	WE	70	972	Mining-panel resolution
Case study 2 (Integration)	B1	10	WE	70	972	Dyke construction
	B2	10	WE	70	972	CT deposition
Case study 3 (Large-scale)	C1	30	WE	214	5,560	Solving directly
	C2	10	WE	214	5,560	Initial solution (cut X)
	C3	30	WE	214	5,560	Period aggregation (cut X)
	C4	10	WE	214	2,456	initial solution (cut 3X)
	C5	30	WE	214	2,456	Period aggregation (cut 3X)

The purpose of the second case study is to show how the proposed MILP model handles the integrated features, dyke construction and tailings planning, in terms of composite tailings CT deposition. This is a very important case study, as it aims to study the main contributions of this research. Two experiments B1 and B2 are designed for this purpose. The model is solved for the better mining direction determined in Case study 1 and in a higher mining-panel resolution (i.e., with smaller pushbacks), as suggested by the results of the first case study. The results show that it is valid and feasible to integrate waste management in terms of dyke construction and CT deposition within the framework of mine planning. Such an integration generates less NPV compared to a basic mine plan. In this case, the first pit is selected as the dataset and the problem is again solved over 10 periods.

The third case study is designed and implemented to show how the proposed integrated mine planning model performs, with all of its features and assumptions, on a real large-scale oil sands dataset. Case study 3 includes pits one and two, and is run over 30 periods. The findings presented in previous case study conclusions, in terms of mining direction and mining-unit resolution, are applied in the first experiment (C1). To improve the CPU-time efficiency, a variable reduction technique called "period aggregation" has been implemented in Case study 3. The second experiment (C2) solves the problem over 10 aggregated periods. The solution of C2 is used as an initial solution for solving the problem over 30 periods in experiment C3. Finally, experiment C5 is designed to study the effect of the mining-cut resolution on the solution on a large scale, which uses the results of C4 as an initial solution. C4 is run over 10 aggregated periods. All of the experiments are run to the optimality (0% MIP gap). The implementation of period aggregation has reduced the CPU time significantly from 30 hours in C1 to around 90 minutes in C3, without considerable reduction in NPV (less than 1%).

The following sections elaborate the specifications of each case study, the design of the experiments, and a discussion on the numerical results from each case study, followed by conclusions. The chapter also includes an overall conclusion.

4.2. Analyzing Scenarios in Whittle

Whittle (Gemcom, 2012) is one of the software programs used extensively in the mining industry for making decisions about ultimate pit limits and production scheduling. It uses a 3-dimensional LG algorithm (Lerchs and Grossmann, 1965) for ultimate pit limit optimization. As an input for pit limit optimization, Whittle requires a block model, including mining-blocks' coordinates, rock types, and the grade of different elements of interest. The other input parameter is the slope limit that must be considered for each rock type to generate a safe pit wall profile. The other mining-related parameters are the reference mining cost, mining recovery fraction, mining dilution fraction, and mining cost adjustment factors for each rock type. The processing-related parameters are processing cost, the recovery, and the selling price for each element. Whittle is enabled to optimize the pit limits in certain directions through defining expressions and selling price adjustments, specific for each direction. Finally, it produces nested pit shells corresponding to increments in the value of the ore revenue factor.

The oil sands deposit considered in the Whittle analysis and used in case studies is located in the Fort McMurray region in the province of Alberta, Canada. The samples from 210 drillholes have been used in geological studies of the site. The final pits cover a total area of about 704 ha and include five main soil layers (rock types): (1) Muskeg/Peat, which is the top soil and contains the seeds and roots of native plants, (2 and 3) Pleistocene Unit and Clearwater Formation, which are considered waste rocks and can be used for dykes and road construction, (4) McMurray Formation, which contains the bitumen and gas reserves in the oil sands area, and (5) Devonian Carbonates, which lies beneath the McMurray formation and determines the vertical end of the oil sands deposit (Masliyah, 2010).

The McMurray formation is made up of three rock types as Upper McMurray (UKM), Middle McMurray (MKM) and Lower McMurray (LKM). The UKM and MKM contain micaceous, fine-to-medium-grained sand, silt and clay, with rare siderite as cement. The LKM contains gravel, coarse sand, silt and clay with siderite as cement. The three rock types contain coarse sand, fine sand, water and bitumen that exists across the formation rock types in various grades. The thickness of the McMurray formation ranges between 0 – 130m from Devonian highs to bitumount basins (Hein et al., 2000).

Table 3: Specifications of the block model used in Whittle for scenario analysis.

	Pit 1	Pit 2	Total
# mining-blocks in direction X (block size in X direction: 50 m):			210
# mining-blocks in direction Y (block size in Y direction: 50 m):			150
# mining-blocks in direction Z (block size in Z direction: 15 m):			17
Devonian (Mt)	4,526	11,072	15,598
McMurray Formation (Mt)	642	4,308	4,950
Over Burden (Mt)	446	1,893	2,339
Bitumen Content in MMF (Mt)	54	292	346
Average Bitumen Grade in MMF (%)	8%	7%	7%
Fines Content in MMF (Mt)	86	754	840
Average Fine Grade in MMF (%)	13%	18%	17%
Water Content in MMF (Mt)	26	158	184

Geological modeling is out of the scope of this research. The result of a geological modeling, using an inverse distance squared interpolation scheme (ArcGIS, 2013) to estimate the material grade, has been used as an input for the

Whittle analysis and the MILP experiments. The proposed MILP model considers deterministic values for the grade and the geological model. This means that the production schedule needs to be re-optimized when new data are available as the result of more sampling, or as the mining operations progress, to address the sensitivity of the optimal schedule to the grade estimates.

The specifications of the block model used in the case studies of this research are provided in Table 3. The original mining-blocks were 25m by 25m by 5m. The block model is re-blocked into larger mining-blocks with dimensions of 50m by 50m by 15m, to align the scheduling resolution with the practical selective mining units. Re-blocking also reduces the number of decision variables in the LG algorithm. However, while re-blocking reduces the problem size, it also decreases the resolution of the block model. In general, reducing the resolution is expected to reduce the NPV as the selectivity in mining and processing blocks is reduced. However, this is negligible in the case of oil sands mining, and will be discussed further in Case study 1. The studied case includes a river that flows from the northwest to the southeast corner of the mining area, dividing the mine into two separate pits. There are three rock types in the mine: the Devonian strata, the main McMurray formation (MMF) that includes the bitumen, and the over burden. The three material types that have specific grades in each mining-block are bitumen, fine material, and water. The total material tonnage of the block model, before determining the pit limits, is 22,887 Mt.

The parameters used in pit limit optimization are presented in Table 4. There are 86 revenue factors involved in generating the nested pit shells, which are defined from 0.3 to 2.0 with increments of 0.02. The minimum mining width is set to 150m, which is equal to the width of three mining-blocks of 50m. As a result, the only revenue factors that will be considered for pit shell generation are those that generate a new pit with a minimum of 150m enlargement compared to the previous pit shell. Table 4 also provides the interest rate and the mining and processing capacities used in production scheduling.

Table 4: Parameters for pit-limit optimization and production scheduling in Whittle.

Parameters	Value	Parameters	Value
Mining Recovery Fraction	95%	Mining Width (m)	150
Reference Mining Cost ($/t)	4.6	Mining Limit (Mt)	350
Mining Cost Adjustment Factors	1.0	Mill Limit (Mt)	86
Processing Cost ($/t)	5.03	Mining Dilution Fraction	1.0
Selling Price ($/Bit %m)	4.5	Revenue Factors (0.02 increments)	0.3 – 2.0
Interest rate	10%	Ore selection method	Cash flow

In order to test the effect of mining direction on the production's NPV and determine the better directions for further analysis in the MILP, a pre-feasibility study is carried out to test six mining directions, including the four main orthogonal and two diagonal directions, south-north and opposite (S-N & N-S), west-east and opposite (W-E & E-W), and northwest to southeast and its orthogonal (NW-SE & SW-NE). The production scheduling is done with three different algorithms in Whittle: (1) Milawa balanced, (without lead), which tends to balance the ore feed to the processing plant and generate a uniform processing rate, (2) Milawa balanced (with ten leads), and (3) the fixed lead of ten. The lead number determines the minimum number of benches that must be extracted from one pushback prior to the start of extraction from the next pushback. The lead number controls the depth of mining as the operation advances in a certain direction. Since there is a maximum of ten benches in the mining pits, a lead of 10 is considered to make sure that each pushback is fully extracted to its bottom before extracting from the next pushback. The other possible algorithm for scheduling in Whittle is Milawa NPV, which maximizes the NPV of the production schedule. However, it has not been considered as an algorithm because its generated schedule is not usually a practical schedule. It mainly tends to access the ore in earlier periods to increase the discounted cash flow, regardless of the practical considerations such as a uniform ore feed to the processing plant or a contiguous pattern for mining operations.

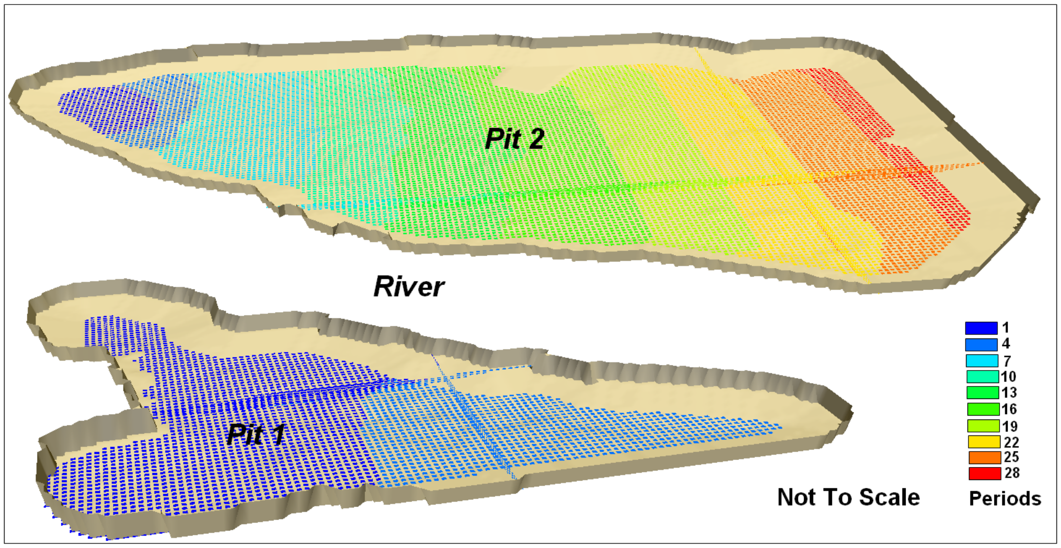

Figure 14. A 3-dimensional view of mining pits and the Milawa schedule in the W-E direction.

A 3-dimensional view of the case study, showing the two mining pits and the result of the Whittle production schedule in the W-E direction (Milawa with 10 leads), is illustrated in Figure 14. The figure is not to scale and is provided to illustrate a 3-dimensional view of the mining pits with a sample schedule in plan views and cross sectional views. The results of running all three algorithms on the data for the six directions are summarized in Table 5.

Table 5: Comparing the schedule results generated by Whittle for six directions.

Direction	W - E	E - W	N - S	S - N	NW - SE	SW - NE
Rock (Mt)	7,969	7,971	7,967	7,968	7,970	7,968
Ore (Mt)	2,144	2,144	2,144	2,144	2,144	2,144
Rejected Waste (Interburden) (Mt)	2,013	2,014	2,012	2,013	2,014	2,013
Other Waste (OB and Devonian) (Mt)	3,726	3,727	3,725	3,725	3,727	3,725
Bitumen (Mt)	237	237	237	237	237	237
Fine (Mt)	322	322	322	322	322	322
Water (Mt)	73	73	73	73	73	73
NPV-Millawa balanced (M$)	12,615	11,502	8,060	11,695	9,412	11,744
Improvement comparing to the worst	57%	43%	-	45%	17%	46%
NPV-Millawa fix lead (M$)	14,645	12,739	8,484	13,714	10,326	13,950
Improvement comparing to the worst	73%	50%	-	62%	22%	64%
NPV-Fixed lead (M$)	13,793	12,323	8,525	14,050	10,088	13,620
Improvement comparing to the worst	62%	45%	-	65%	18%	60%
Mine life (year)	28	29	32	28	30	28

The table starts with the rock tonnage, which is the tonnage of the total extracted material, either as ore or waste. Since the final pit is optimized separately based on the discounted value of the extracted material in each direction, the total rock tonnages are not equal. However, they are in the same range with a maximum tolerance of 0.05%. Table 5 is continued with the tonnages of extracted ore (ore tonnage), extracted low-grade mineralized material (rejected waste), and the extracted waste from unmineralized material (other waste). The tonnages of produced bitumen, water, and fine material are also reported.

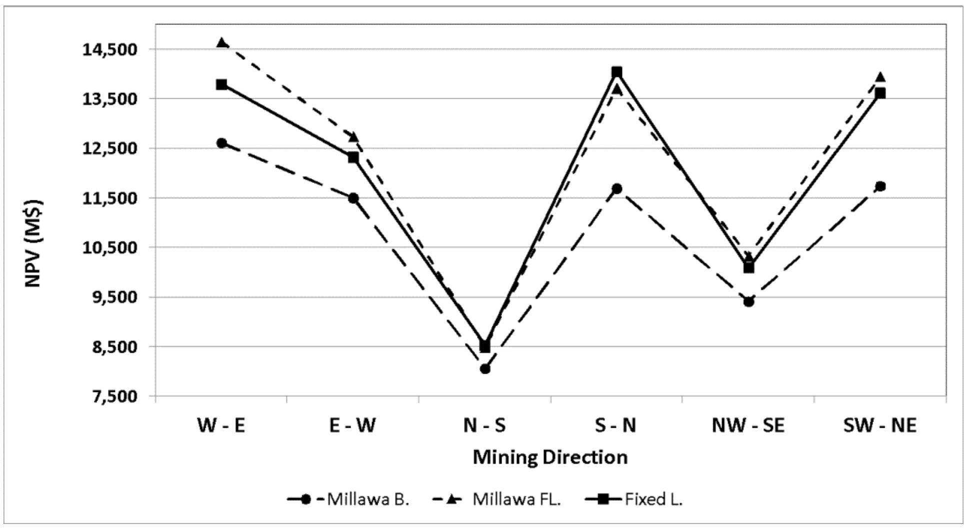

Figure 15: Comparing the Whittle-generated NPVs in different directions.

The NPVs for six directions, generated from three algorithms, are compared in Figure 15. Both Milawa-balanced algorithms have generated the highest NPV in the W-E direction, while the fixed lead algorithm generates the highest NPV in the S-N direction. Therefore, the two directions (W-E and S-N) will be considered for further analysis in the next case studies, using the MILP model.

4.3. Case Study 1: Mining Direction and Mine Plan Resolution

Pit one from the block model is selected for experiments in the first case study. It includes 16,878 mining-blocks of 50m by 50m by 15m. There are nine benches, each with a bench height of 15m. The rock types present in the area are Pleistocene, Clearwater, Upper McMurray, Middle McMurray, and Lower McMurray formations. Pit one contains a total of 1,237 Mt of material, including

374 Mt of mineralized material, 597 Mt of OI material, and 278 Mt of TCS. The production is to be scheduled over 10 periods, equivalent to 10 years. The MILP model is implemented on a Dual quad-core Dell Precision T7500 computer at 2.8 GHz, with 24GB of RAM. The specifications of the first case study and the parameters to be used for the MILP implementation are summarized in Table 6. The ore cut-off grade is set equal to the regulatory cut-off, which is 7% for oil sands. The average values for the upper bound on the fine grade in ore feed (18%) and OI dyke material (30%) are tuned based on the practical blending constraints.

Table 6: MILP Input parameters for Case study 1.

Input parameters	Value	Input parameters	Value
Recovered barrel of bitumen per tonne of Bit.	0.65	Extra OI dyke mining cost ($/t)	0.92
Ore Price ($/t of Bitumen)	450	Extra TCS dyke mining cost ($/t)	1.38
Mining Cost ($/t)	4.60	CT deposition cost ($/m3)	0.50
Processing Cost ($/t)	5.03	Ore cut-off grade	7%
Total material (Mt)	1,237	Upper bound on fine grade in ore	18%
Mineralized material (Mt)	374	Upper bound on fine grade in OI	30%
OI material (Mt)	597	Interest rate	10%
TCS material (Mt)	278	Recovery	90%

Figure 16 illustrates the bitumen grade distribution in the sixth bench (elevation 90m from the bottom of the pit). The dark color represents high grade material with a bitumen grade of more than 7%. These portions are assumed as the mineralized material. The specifications of each experiment for Case study 1 and the important parameters are summarized in Table 7.

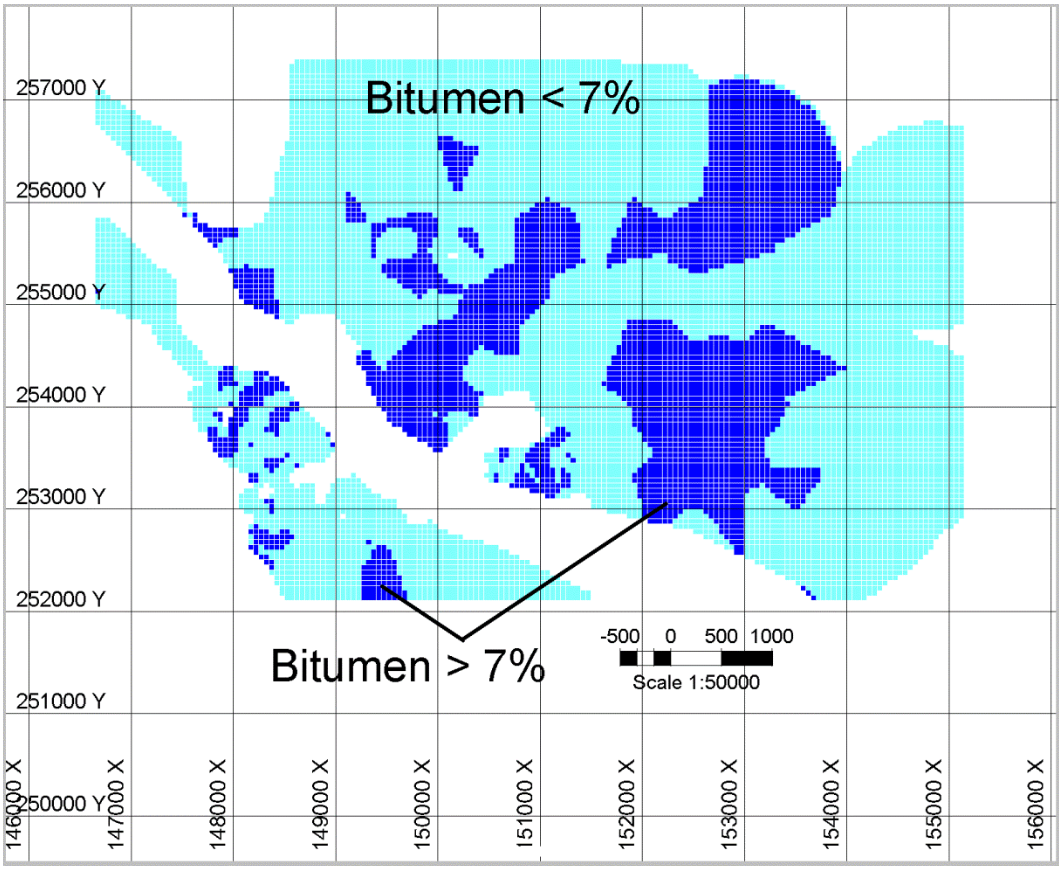

Figure 16: Bitumen grade distribution in Pits one and two.

Table 7: Experiments' specifications and parameters: Case study 1.

Expr.	# of Periods	Mining direction	# of panels	Mining cap. (Mt)	# of cuts	Ave. # of blocks in cuts	Max # of blocks in cuts	Experiment purpose
A1	10	SN	31	180	962	20	25	Direction
A2	10	WE	25	180	942	20	25	Direction
A3	10	WE	25	200	942	20	25	cut size
A4	10	WE	25	200	570	30	50	cut size
A5	10	WE	25	200	428	40	75	cut size
A6	10	WE	70	200	972	20	25	panel size

4.3.1. Discussion: Mining Direction

The first purpose of this case study is to present how the developed MILP model can handle a certain directional mining constraint and how the NPV changes as a result of any change in the mining direction. To achieve this goal, two directions of W-E and S-N that have generated the highest NPV values with the Milawa algorithm are tested in experiments A1 and A2 (Table 7). For each of these two experiments, the nested pit shells are formed in Whittle in the given direction. For the W-E direction, three pushbacks are selected from nine generated pit shells in such a way that they balance the total tonnage of material contained in each pushback. As a result, 25 mining-panels in nine benches are generated. For the S-N direction, four pushbacks are selected from 12 generated pit shells, resulting in 31 mining-panels in nine benches.

For both cases, the mining and processing capacities have been 180Mt and 35 Mt per period, respectively. Same clustering parameters are used to make the mining-cuts. However, since the pushback designs and mining-panels for the two cases are different, the numbers of mining-cuts are also different. The total tonnage of extracted material in the two cases is very close (1,235 Mt and 1,237 Mt). However, the tonnage of the processed oil sands is slightly larger in W-E direction (313 Mt), resulting in 37 Mt of recovered bitumen, compared to processed oil sands in S-N direction (303 Mt) that has produced 36 Mt of bitumen. Both cases are run to the optimality (0% gap). Mining in the W-E direction has generated a higher NPV of $3,890M, which is 5% greater than the generated NPV in S-N direction ($3,693M). The results are compared in Table 8.

Table 8: Comparing the parameters and results of experiments A1 and A2.

Expr.	Mining Direction	Num periods	Interest rate	Num blocks	Num cuts	Num panels	Mining Cap. (Mt)	Processing Cap. (Mt)
(A1)	SN	10	10%	16,854	962	31	180	35
(A2)	WE	10	10%	16,878	942	25	180	35
Experiment	**Total (Mt)**	**Mineralized (Mt)**	**Processed Ore (Mt)**	**Recovered Bit. (Mt)**	**Gap**	**Run time (s)**	**NPV (M$)**	**NPV Improvement**
(A1)	1,235	374	303	36	0.0%	17	3,693	-
(A2)	1,237	374	313	37	0.0%	27	3,890	5%

Figure 17 and Figure 18 illustrate how the mining operation advances in the S-N and W-E directions, respectively. The numbers on the figures show the period number in which the portion is scheduled to be extracted.

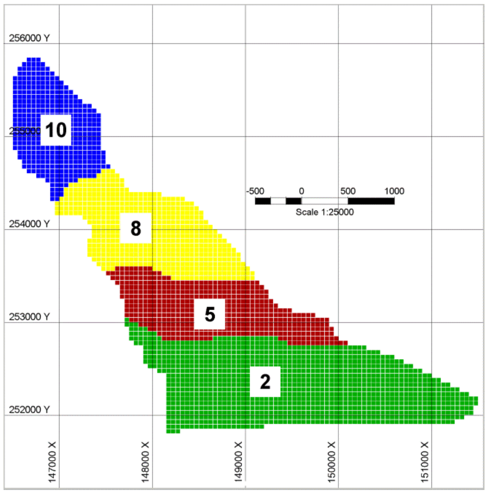

Figure 17: Production progress in S-N direction (A1).

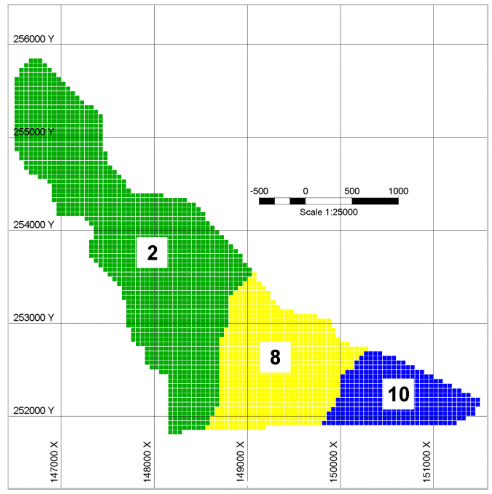

Figure 18: Production progress in W-E direction (A2).

4.3.2. Discussion: Mine Plan Resolution

The next goal in this case study is to investigate the effect of mining unit resolution on the NPV. Before the MILP implementation starts, the mining-blocks are aggregated into larger units as mining-cuts. The similarity index controls the shape and homogeneity of the mining-cuts through four values corresponding to the weights of distance, grade, rock type, and cluster shape in the lower bench. For all the case studies in this thesis, these weights are set to 10 for distance, 0.1 for grade, 0.8 for rock type, and 0.2 for the beneath cluster. This means that the most important factor in aggregating the mining-blocks is the distance between them. The size of the mining-cuts is controlled by two parameters: the average and the maximum number of mining-blocks contained in each mining-cut.

Figure 19 and Figure 20 provide the grade distributions for two sample mining-cuts, including 23 and 22 mining-blocks respectively. Both mining-cuts are selected from bench number six. The mining-cut presented in Figure 19 includes low-grade and high-grade material, which is considered as interburden and can be used for dyke construction. The average grade is 4% with a standard deviation of 0.7%, which is around 18% of the mean. This shows that the material grade does not change significantly in interburden material. The standard deviation in oil sands material is even less than this, equal to 0.8%, which is just 9% of the average grade (Figure 20). These values show that the bitumen grade is not fluctuating significantly among the mining-blocks contained in mining-cuts, and justifies the low weight of grade in similarity index.

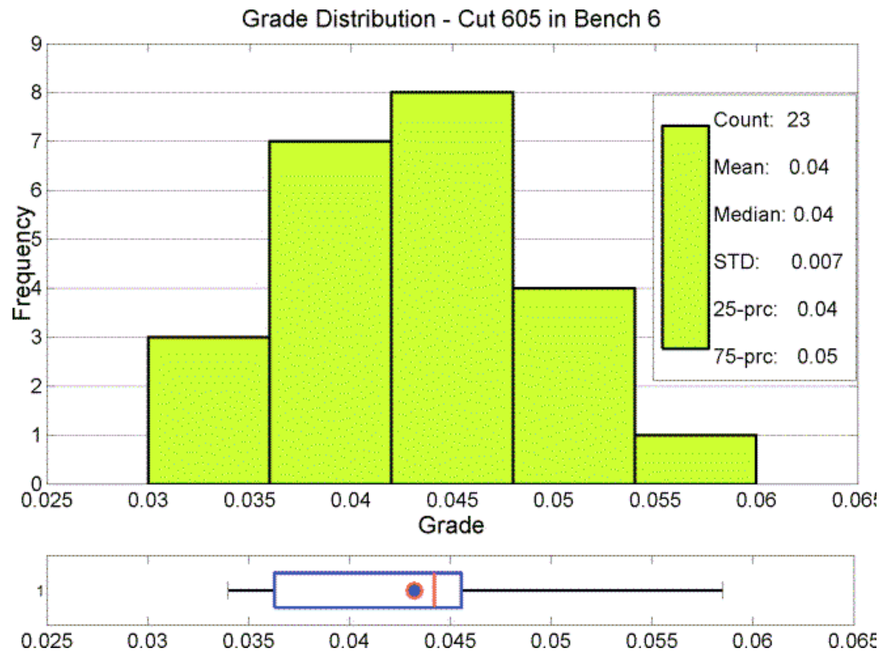

Figure 19: Grade distribution for a sample mining-cut with 23 blocks, including ore and waste material.

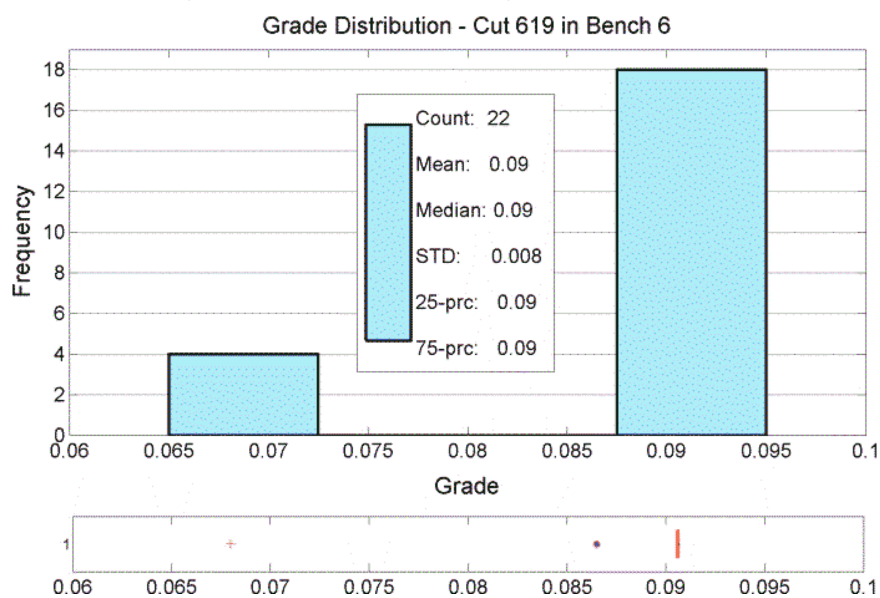

Figure 20: Grade distribution for a sample mining-cut with 22 blocks, including ore material.

Figure 21 shows the rock unity index of mining-cuts in bench 6 for two different cut resolutions. Tabesh and Askari-Nasab (2013) define rock unity as “the largest portion of each cluster that is from one rock type”. As an example, if there are tree rock types present in a certain cluster as A, B and C each with a share of 65%, 20% and 15%, then the rick unity of the cluster is assumed to be 65% (corresponding to rock type A), which is the largest portion among three rock types. As illustrated in Figure 21, the rock unity is fluctuating between 48% and 100% with a mean of 79% for the case where each mining-cut contains 75 mining-blocks on average (the blue line). When the mining-cut resolution is increased, in the second case each mining-cut contains 25 mining-blocks. The mining-cuts are smaller compared to the previous case, but the rock unity does not change significantly. It fluctuates in the same range with a mean of 82% (the red line) and the same standard deviation as the lower resolution, equal to 16%. This shows that the rock unity index is not sensitive to the size of mining-cuts.

The inverse distance squared interpolation scheme, similar to the simple Kriging, generates a smooth map of grade distribution. That means the estimated values do not reproduce the histogram of the data because of a reduced variance as the consequence of the smoothing effect. The smoothing effect is more severe in inverse distance method, as the redundancy between the data points (in terms of variograms) is not considered. As a result, high values will be underestimated and low values will be overestimated, making the estimated histogram narrower than the sample histogram (Rezaee et al., 2012). Due to the nature of the inverse distance scheme used in grade estimation, the blocks’ grade estimates are smooth, resulting in a smooth grade distribution over the mining-blocks contained in each mining-cut. Therefore, the grade is not a crucial factor in the aggregation of mining-blocks.

From comparing the rock unities and grade distributions, it can be concluded that the most important element in the clustering similarity index is the distance between mining-blocks. For numerical comparison, Table 9 shows the statistics for some of the mining-cuts selected randomly from bench 6.

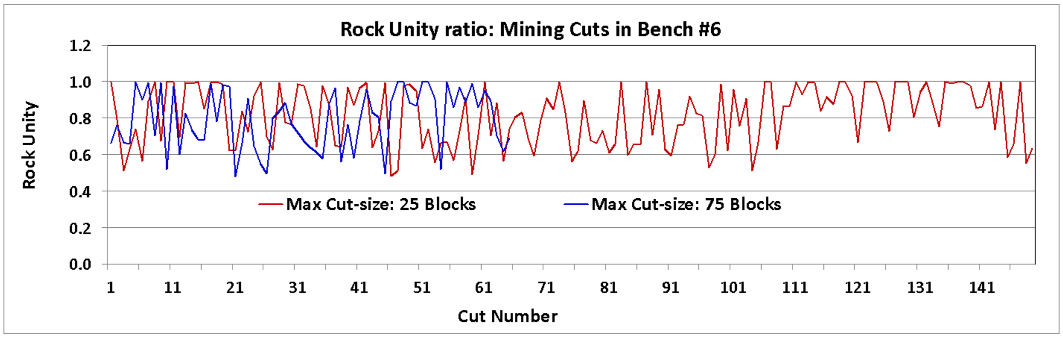

Figure 21: Rock unity index of mining-cuts for two cut resolutions.

Table 9: summary of statistics for sample mining-cuts in bench 6.

Cut ID	233	236	239	257	260	269	272	287	296	Ave.	Stdev.
# Blocks	26	45	45	49	38	31	40	47	43	40	11
Min grade	0.0%	0.0%	0.0%	0.0%	5.2%	4.1%	3.1%	2.6%	6.3%	-	-
Max grade	6.6%	5.9%	0.0%	9.8%	8.1%	4.5%	6.5%	6.4%	6.3%	-	-
Mean	2.7%	2.3%	0.0%	4.7%	6.5%	4.3%	3.9%	4.4%	6.3%	3.4%	2.3%
Median	0.0%	0.0%	0.0%	4.8%	6.4%	4.1%	3.7%	4.5%	6.3%	-	-
Stdev.	3.0%	2.9%	0.0%	3.3%	0.8%	0.2%	0.9%	1.4%	0.0%	1.6%	1.1%
Rock Unity	66%	66%	100%	55%	84%	97%	58%	100%	62%	79.3%	16.0%

In the developed MILP model, mining-cuts are used to determine the destination of the extracted material, while mining-panels are the production scheduling units. As a result, the decision about the timing and portion of material to be extracted is made at the panel level. When a panel of material or a portion of it is extracted, the destination is determined according to the mining-cut it belongs to. Therefore, different destinations can be considered for material portions extracted together as one panel.

Experiments A3, A4, and A5 are performed to verify the effect of different mining-cut sizes, and experiment A6 is designed to show the effect of the mining-panel size. The same input parameters for A1 and A2 are used for A3 to A6, as presented in Table 6.

Table 10 summarizes the results of A3 to A5. The average number of mining-blocks in each mining-cut for A3, A4, and A5 is 20, 30, and 40, respectively. The maximum number of mining-blocks contained in each mining-cut is 25, 50, and 75 for A3 to A5, respectively.

Table 10: Comparing the parameters and results of experiments A3, A4, and A5.

Expr.	Mining Direction	Num periods	Interest rate	Num blocks	Num cuts	Num panels	Mining Cap. (Mt)	Processing Cap. (Mt)
A3	W-E	10	10%	16,878	942	25	200	35
A4	W-E	10	10%	16,878	570	25	200	35
A5	W-E	10	10%	16,878	428	25	200	35
Expr.	Total (Mt)	Mineralized (Mt)	Processed Ore (Mt)	Recovered Bit. (Mt)	Gap	Run time (s)	NPV (M$)	NPV Improvement
A3	1,237	374	312.5	36.59	0.0%	15	3,892	0.6%
A4	1,237	374	312.5	36.54	0.0%	16	3,882	0.3%
A5	1,237	374	312.6	36.49	0.0%	4	3,870	-

This means that the mining-cut resolution decreases from A3 to A5. This has resulted in a very slight decrease in the NPV, from $3,892M in A3 to $3,870M in A5. In general, the MILP is expected to generate higher NPV when the resolution is higher. This is because with a higher resolution, the model is capable of separating the material better, since the mining-cuts are more homogeneous and the dilution factor will be less, especially when the high grade and low grade material are well separated (like gold veins). However, in the case of oil sands, the main McMurray formation is homogeneous itself, meaning that the bitumen grade does not change considerably over the formation. That is why increasing the mining-cut resolution only has slightly improved the NPV. Figure 22 and Figure 23 illustrate a sample bench showing a high resolution case (A3: 20 mining-blocks per mining-cut) and low resolution case (A5: 40 mining-blocks per mining-cut), respectively.

The objective of experiment A6 is to show the effect of mining-panel resolution on the NPV, compared to experiment A3. In A6, the pit is subdivided into nine pushbacks, resulting in 70 mining-panels. For A3, every three of these nine pushbacks are combined to make three larger pushbacks, resulting in 25 large mining-panels (Table 7). Two mining-panel resolutions are illustrated in Figure 24 and Figure 25.

Table 11 summarizes the results of experiments A3 and A6. With an increase in the mining-panel resolution from 25 to 70 mining-panels, the NPV improves 2%, from $3,892M to $3,959M. Although it is expected to have better NPV for higher resolution, the improvement is small because of the nature of the oil sands deposit at this site.

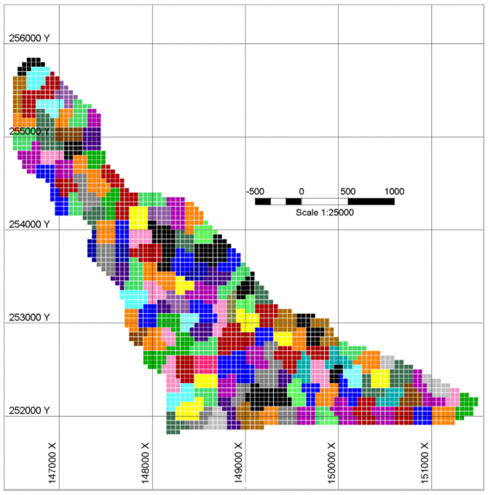

Figure 22: Average 20 mining-blocks per mining-cut (A3).

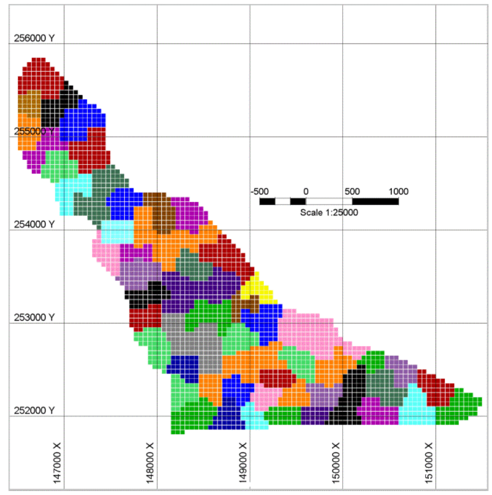

Figure 23: Average 40 mining-blocks per mining-cut (A5).

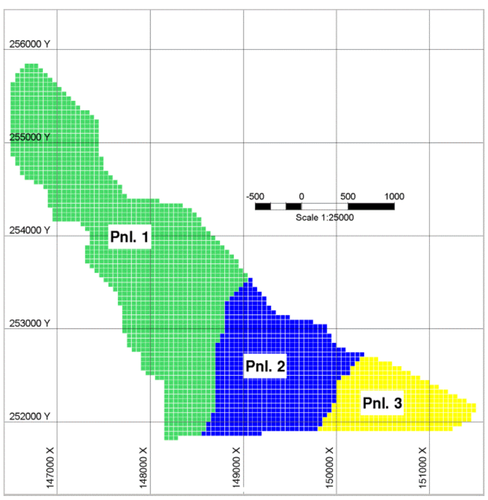

Figure 24: Three pushbacks, total of 25 mining-panels (A3).

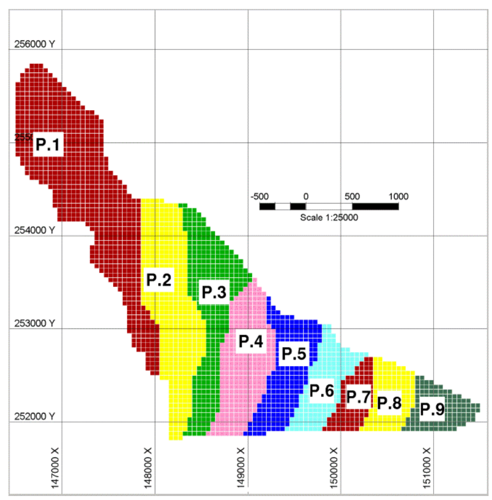

Figure 25: Nine pushbacks, total of 70 mining-panels (A6).

Table 11. Comparing the parameters and results of experiments A3 and A6.

Expr.	Mining direction	Num periods	Interest rate	Num blocks	Num cuts	Num panels	Mining cap. (Mt)	Processing cap. (Mt)
A3	W-E	10	10%	16,878	942	25	200	35
A6	W-E	10	10%	16,878	972	70	200	35
Expr.	**Total (Mt)**	**Mineralized (Mt)**	**Processed ore (Mt)**	**Recovered bit. (Mt)**	**Gap**	**Run time (s)**	**NPV (M$)**	**NPV improvement**
A3	1,237	374	312.5	36.59	0.0%	15	3,892	-
A6	1,237	374	313.7	37.03	0.0%	63	3,959	2%

4.3.3. Case study 1: Conclusion

The NPV values for experiments A3 to A6 are compared in Figure 26. This figure shows that for this case study, the NPV is sensitive to the mining direction (sharp increase from A1 to A2 in Figure 26) and the mining-panel resolution (increase from A3 to A6). However, the mining-cut resolution does not change the NPV significantly, as there is not any considerable difference among the NPVs of A3, A4, and A5.

Based on the NPV values reported in Table 8, W-E is selected as the mining direction for further experiments in the next case studies. Production in the W-E direction has improved the NPV by 5% compared to that of the S-N. This is consistent with the conclusion from the scenario analysis in Whittle (Table 5), where the W-E direction generated an 8% higher NPV compared to the S-N direction when both pits were considered for the Milawa-balanced production schedule.

The solution is not overly sensitive to the mining-cut size: increasing the mining-cut resolution from 40 to 20 mining-blocks per mining-cut has improved the NPV only 0.6% from \$3,870M to \$3,892M. That is because the bitumen is scattered over the pit with a relatively low grade. Larger mining-cuts will not significantly change the grade distribution of the aggregated material within mining-cuts. In this case study, the largest weight in clustering has been assigned to the mining-blocks' spatial locations rather than rock type or grade. The experiments' results show that the mining-panel resolution is more important than the mining-cut resolution in this case. That is because the mining decision is made in the mining-panel level. With smaller mining-panels, the optimizer has more flexibility to extract material over given time periods due to the more flexible precedence between the smaller mining-panels. However, the cost of more resolution is a longer solution time, because more decision variables and a larger number of precedence relations will be involved in the model. This has happened for A6 (\$3,959M NPV) with 70 mining-panels and 63 seconds CPU time, compared to A3 (\$3,892M of NPV) with 25 mining-panels and 15 seconds CPU time.

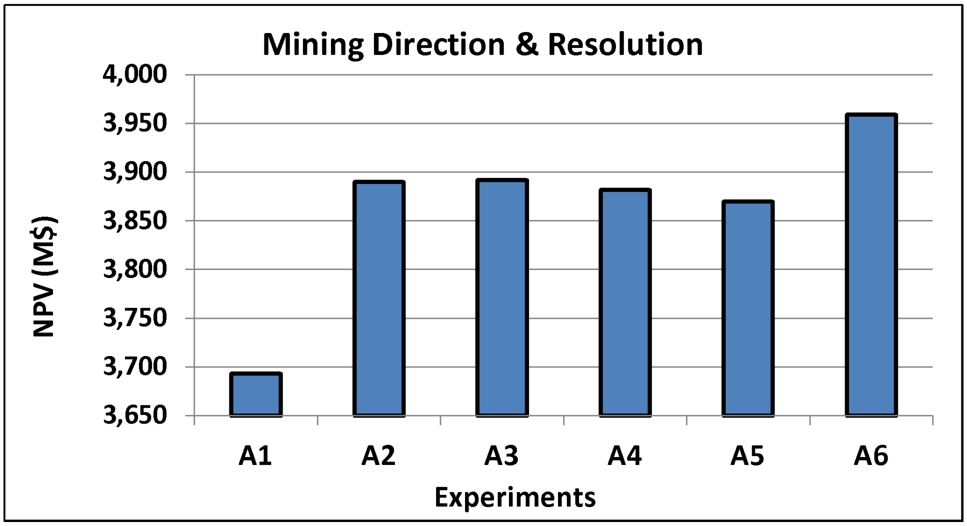

Figure 26: Comparing the generated NPVs for experiments A1 to A6.

4.4. Case Study 2: Dyke Construction and CT Deposition

The main contribution of this research is development of an integrated framework for mine and tailings planning optimization. The feature added to the production schedule is waste management, in terms of dyke construction and CT deposition. In brief, the rationale for including waste management in mine planning is to accommodate the produced tailings generated at the end points of the bitumen extraction process, in tailings facilities constructed using overburden and interburden material extracted in mining operations. Mine production, ore processing, tailings deposition, and dyke construction are interconnected through the flow of waste material. Moreover, the generated NPV from such an integrated optimized model is higher than the summation of NPVs gained from optimized sub-problems. Case study 2 is designed to investigate how tailings management (in terms of CT production) and the solid waste management (in terms of dyke construction) can be integrated in the production schedule and how the overall NPV is sensitive to such integration.

4.4.1. Design of Dykes and CT Cells

In the proposed model, it is assumed that the produced CT will be deposited mainly in a number of in-pit CT cells shaped by internal dykes and pit walls. The external tailings facility also acts as a buffer to accommodate the excess of the mature fine tailings (MFT) when the CT production has not yet started or when the internal dykes are not available. This happens in the early periods when the mining operations have not advanced enough to clear the dyke footprints. Also, the external tailings facility (ETF) works as a buffer by providing space for tailings storage, when for any reason the in-pit facilities are not available for tailings deposition. ETFs are an essential part of any oil sands mining operation. However, the design of external dykes for ETF is out of the scope of this research. It is assumed that an ETF with a sufficient amount of legacy exists and acts as a buffer for CT deposition. There are three main methods of dyke construction: upstream, downstream, and centerline (Figure 27). The internal dykes are constructed gradually as the mining operations continue and clear the foot print area, and the required material for dyke construction becomes available. The method considered for in-pit dykes in this case study is centerline construction, based on what is illustrated in Figure 28 (Lahaie and Chan, 1988).

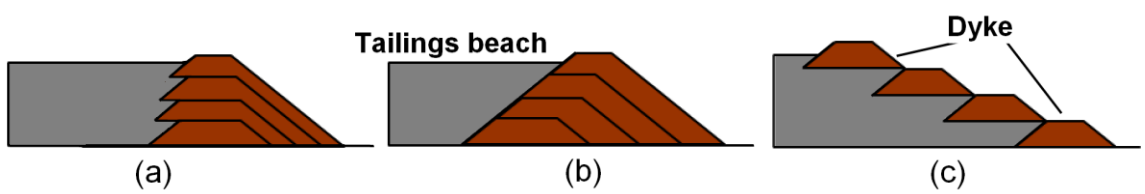

Figure 27: Centerline construction (a), downstream construction (b), and upstream construction (c), after (Vick, 1983).

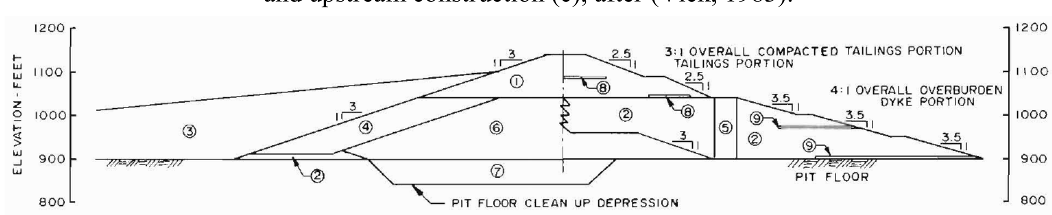

Figure 28: Internal dyke design, after (Lahaie and Chan, 1988).

The dimensions presented in Figure 28 are the basis for dyke design in the case studies of this thesis. The height of the dykes can reach up to 120m, equal to the height of eight mining benches. In real dyke construction, the thickness of dyke lifts is not more than half a meter. However to simplify the modeling, the resolution of dyke lifts is assumed to be 15m, equal to the bench height. Each dyke is 880 meters wide at the toe, and with an overall angle of 18°, can rise up to the height of 120m. The dyke wall is 30 meters wide at the crest. A cross section of the designed dyke is illustrated in Figure 29.

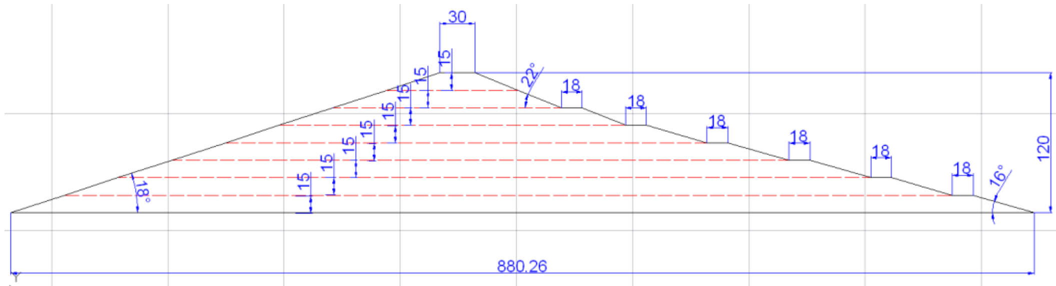

Figure 29: Internal dyke design: cross section showing eight construction levels.

The new feature to be examined in this case study is the option to include or exclude in-pit dyke construction and CT deposition to verify their effect on the model's performance. Before raising the internal dyke walls, the first step is to choose the dykes' footprints. To generate a feasible dyke construction schedule, the dyke footprints must have already been cleared. It means that the extraction of material in the pit must have advanced enough so that the area required for dyke construction is available. To guarantee a feasible schedule, dyke footprints are selected from among pushback footprints. This selection is made based on the volume of material in pushbacks and the potential volume of CT to be produced from processing the extracted material. Since the pushbacks are extracted following a precedence order, no material will be left behind before constructing a dyke, and the dyke footprint has been cleared already.

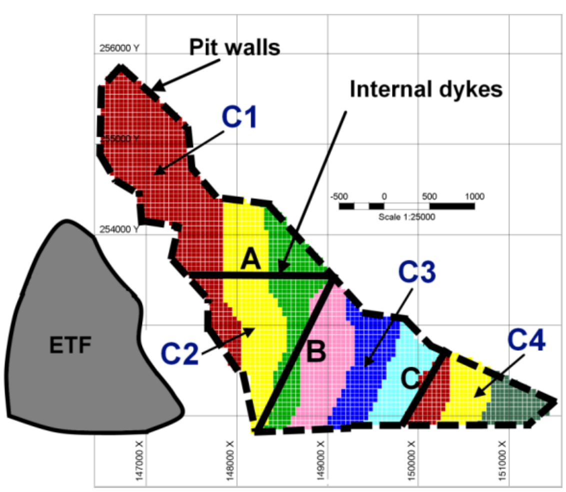

Figure 30: Schematic view of dykes' footprints, CT cells, and the ETF (Case study 2).

Table 12: Mapping of pushbacks to CT cells (case study 2).

Pushback #	Pushback volume (Mm³)	Dividing dyke	Dyke volume (Mm³)	CT cell	CT cell volume (Mm³)
-	-	-	-	ETF	148
1,2,3	387	A	84	C1	152
				C2	103
4,5,6	173	B	98	C3	97
7,8,9	73	C	53	C4	47

Figure 30 illustrates a plan view of the dyke footprints and the schematic ETF used in Case study 2. Table 12 shows how the pushbacks are assigned to CT cells. The total volume of each CT cell is the volume of corresponding pushbacks, minus the occupied volume of the dykes that are constructed for each CT cell.

Table 13: Experiments' specifications and parameters: Case study 2.

Expr.	# of periods	Mining direction	# of panels	# of cuts	Dyke construction	In-pit CT deposition	Experiment purpose
A6	10	WE	70	972	Included	Included	Integrated MILP
B1	10	WE	70	972	N. included	N. included	Dyke constr. effect
B2	10	WE	70	972	Included	N. included	CT deposition effect

The dataset used for the second case study is the block model data of pit one, similar to the first case study (Table 6). Based on the conclusions made in Case study 1, the W-E is chosen as mining direction, with nine panels containing mining-cuts, each with 20 mining-blocks. The three experiments in this case are presented in Table 13.

4.4.2. Discussion: Dyke Construction and CT Deposition

Three experiments of A6 (from Case study 1), B1, and B2 are implemented and compared in this case study. In A6, the MILP model includes the constraints for dyke construction and in-pit CT deposition. In this case, the ETF works only as a buffer, and since it has a limited capacity, the in-pit CT cells must be prepared for CT storage. In order to meet such a requirement, the overburden and interburden (OI) and tailings coarse sand (TCS) material must be produced and used for the construction of in-pit dykes. Solving the MILP for A6 generates an NPV of \$3,959M over 10 years. It has resulted in the extraction of 1,237 Mt of material, including 314 Mt of mineralized material, 264 Mt of OI, and 659 Mt of waste. Processing the mineralized material generates 37 Mt of bitumen and 92 Mt of

TCS. A total of 227 Mm^3 of CT is produced, from which 148 Mm^3 (65%) is deposited in the ETF and the rest (79 Mt) is deposited in the in-pit CT cell C1. The total material usable for dyke construction is 356 Mt (OI and TCS), from which 159 Mt is used to construct Dyke A and the rest are sent to the waste dump. The production schedule for A6 is presented in Figure 31.

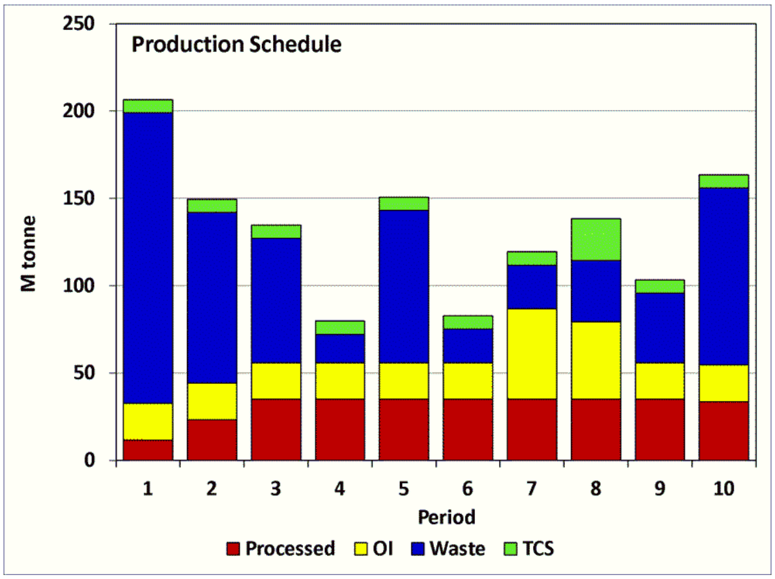

Figure 31: Production schedule (A6).

Figure 32 illustrates how the nine pushbacks are extracted. Pushback mining follows the W-E direction, and the generated schedule ensures that before mining starts in one pushback, the previous pushback has already been extracted. In this way, the footprint of Dyke A as the first in-pit dyke is cleared after pushback three has been completely extracted (in the sixth period).

The only in-pit dyke being constructed is Dyke A and its construction begins after pushback three has been completely extracted in period six. Dyke A has been constructed over periods six, seven, eight, and a small portion in period nine (Figure 33). During periods one to seven when the in-pit cell is not yet ready for tailings deposition, the produced CT is sent to the ETF, as illustrated in Figure 34. After CT cell 1 is completed, in period 8, the CT is deposited in this CT cell over periods 8 to 10. Figure 35 illustrates the periods in which the eight lifts of Dyke A are constructed, as well as the start and end periods of CT deposition in the ETF and in CT cell 1. Experiment A6 generates a $3,959M NPV.

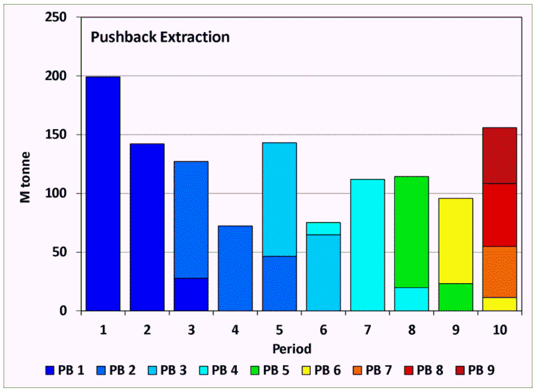

Figure 32: Pushback extraction schedule (A6).

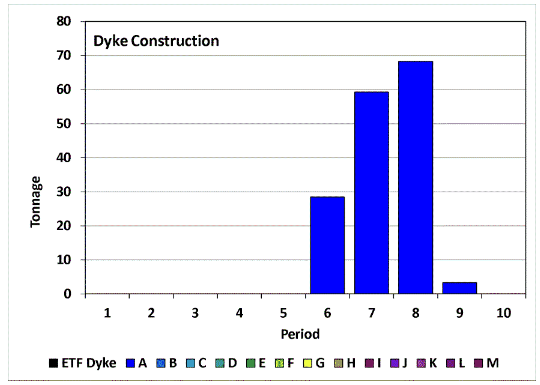

Figure 33: Dyke construction schedule (A6).

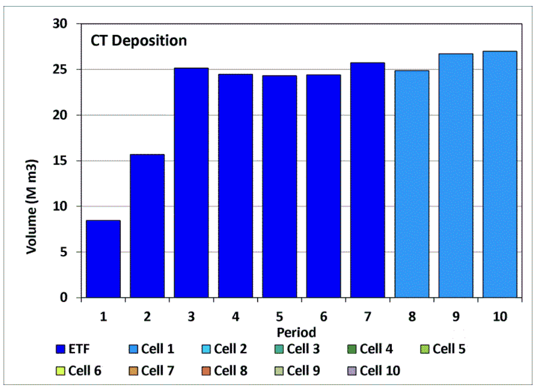

Figure 34: CT deposition schedule (A6).

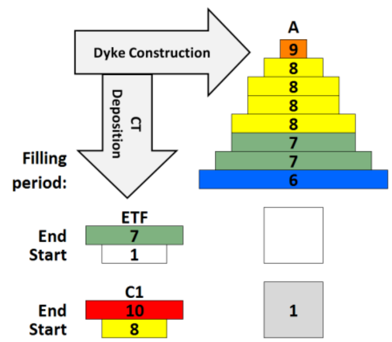

Figure 35: Construction of Dyke A and CT deposition in the ETF and CT cell 1(A6).

For experiment B1, the MILP constraints that control the in-pit CT deposition are relaxed by assigning a very large capacity for the ETF and making it the predecessor for all in-pit CT cells. Further, the dyke construction is excluded from the model by assigning zero values for the minimum amount of OI and TCS material required for dyke construction. That means all of the low grade material will be extracted as waste and nothing will be considered for dyke construction. The production schedule optimized for B1 is presented in Figure 36. The resulting CT deposition schedule is illustrated in Figure 37, showing that the CT has been sent only to the ETF for deposition. The NPV generated over 10 periods for B1 is \$4,189M, which is 6% higher than the NPV of A6, where the in-pit dyke construction and CT deposition are included.

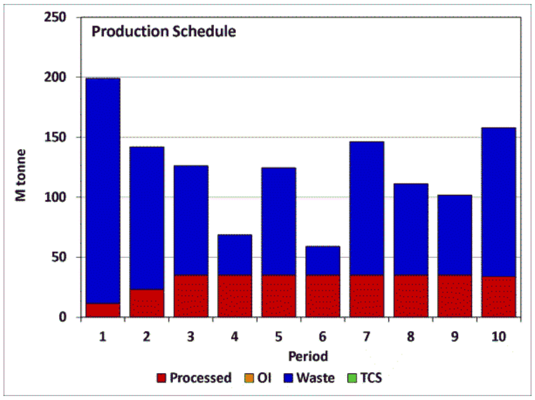

Figure 36: Production schedule (B1).

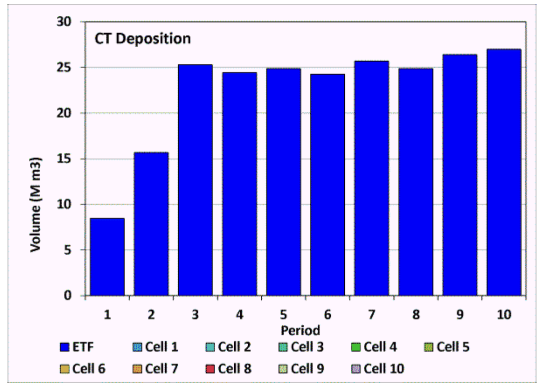

Figure 37: CT deposition schedule (B1).

In the next experiment, B2, the MILP constraints that control in-pit CT deposition are relaxed by assigning a very large capacity for the ETF and making it the predecessor for all in-pit CT cells. In this case, again, the in-pit dykes are not constructed. However to show how dyke material extraction influences the NPV, some of the material is extracted as OI and TCS, but is sent to the waste dump. In this way, the extra cost associated with mining the dyke material is quantified in the NPV, while the cost of in-pit CT deposition is ignored. The production schedule in this case is very close to experiment A1, where ore, OI, TCS, and waste material are present in the final schedule (Figure 31). Since the ETF has a very large capacity, there is no need for in-pit CT deposition and, hence, no dyke is constructed. The resulting CT deposition schedule is the same as case B1 (Figure 37). The dyke construction is excluded from the model by assigning zero values for the minimum amount of OI and TCS material required. That means all of the low grade material will be extracted as waste and nothing will be considered for dyke construction. The production schedule optimized for B1 is presented in Figure 36. The resulting CT deposition schedule is illustrated in Figure 37, and shows that the CT has been sent only to the ETF for deposition. The NPV generated over 10 periods for B2 is $3,994M, which is 1% higher than the NPV of A6, where the in-pit dyke construction and CT deposition are included. The results for experiments A6, B1, and B2 are summarized in Table 14.

Table 14: Comparing the parameters and results of experiments A6, B1 and B2.

Expr.	Total (Mt)	Mineralized (Mt)	Processed ore (Mt)	Recovered bit. (Mt)	Extracted OI (Mt)	Produced TCS (Mt)	Run time(s)	NPV (M$)	NPV imprv.
A6	1,237	374	313.7	37.03	264	92	63	3,959	-
B2	1,237	374	313.7	37.03	210	75	66	3,994	1%
B1	1,237	374	313.9	37.07	0	0	20	4,189	6%

4.4.3. Case study 2: Conclusion

The results for the three experiments — A6, B1 and B2 — are compared in Figure 38, in terms of the generated NPV. In A6, OI and TCS are extracted as the required material for dyke construction and are used for in-pit dykes to prepare CT cell 1. The ETF and CT cell 1 both accept CT. The corresponding NPV is \$3,959M. The CPU time is 63 seconds, and 564 integer variables and 8,578 constraints are involved in the final MILP.

In B2, the in-pit dyke construction is relaxed. Although some of the material is extracted as OI or TCS, it has not been used for constructing dykes. The produced CT has been sent to the ETF. B2 has generated an NPV of \$3,994M that is only a 1% increase compared to A6. B2 includes 548 integer variables, 8,534 constraints, and was solved in 66 seconds.

In B1, the constraints for in-pit dyke construction and CT deposition are relaxed. There is not any material extracted as OI or TCS, no dyke is constructed, and the entire produced CT has been sent to the ETF. B1is the relaxed version of the MILP problem, comparable to the Whittle schedule where there is no extra cost associated with dyke construction or CT deposition. There is a 6% improvement in the generated NPV, compared to A6. The number of integer variables and constraints are 548 and 8,524, respectively. The CPU time is 20 seconds.

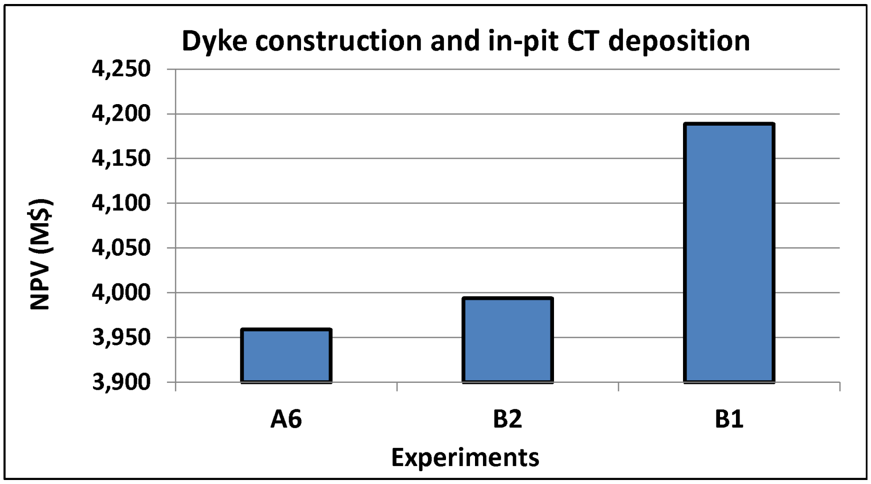

Figure 38: Comparing the generated NPVs for experiments A6, B1, and B2.

Including two features of in-pit dyke construction and CT deposition adds to the constraints of the model. The inclusion causes the NPV to decrease, as the feasible solution area for the MILP is less than the problem without such constraints. If there is an unlimited capacity for the ETF, which never happens in real cases, there is no need to extract dyke material for in-pit dyke walls, nor is the CT required to be deposited in-pit. The 6% reduction in the NPV is the cost of a limited area that makes the mine planners considers in-pit dyke construction and CT deposition.

4.5. Case Study 3: Implementation of the Integrated MILP Model

Carrying out the previous experiments in case studies one and two showed that the best mining direction is W-E, the higher mining-panel resolution will generate higher NPV, and the in-pit dyke construction and CT deposition can be well integrated with the long-term mine-planning model. Using these findings, this case study is designed to show how the proposed integrated model works on a real large-scale oil sands dataset. This dataset includes both pits one and two, mining-panels are used as the mining units, and mining-cuts are used for processing. The model is implemented on a Dual quad-core Dell Precision T7500 computer at 2.8 GHz, with 24GB of RAM.

A plan view from the mine site, including pits one and two, is illustrated in Figure 39. It shows the mining-panels resulting from 27 pushbacks designed in the W-E direction. Dyke footprints (A to M), in-pit CT cells (C1 to C10), and a schematic view of the ETF are also illustrated on the plan view.

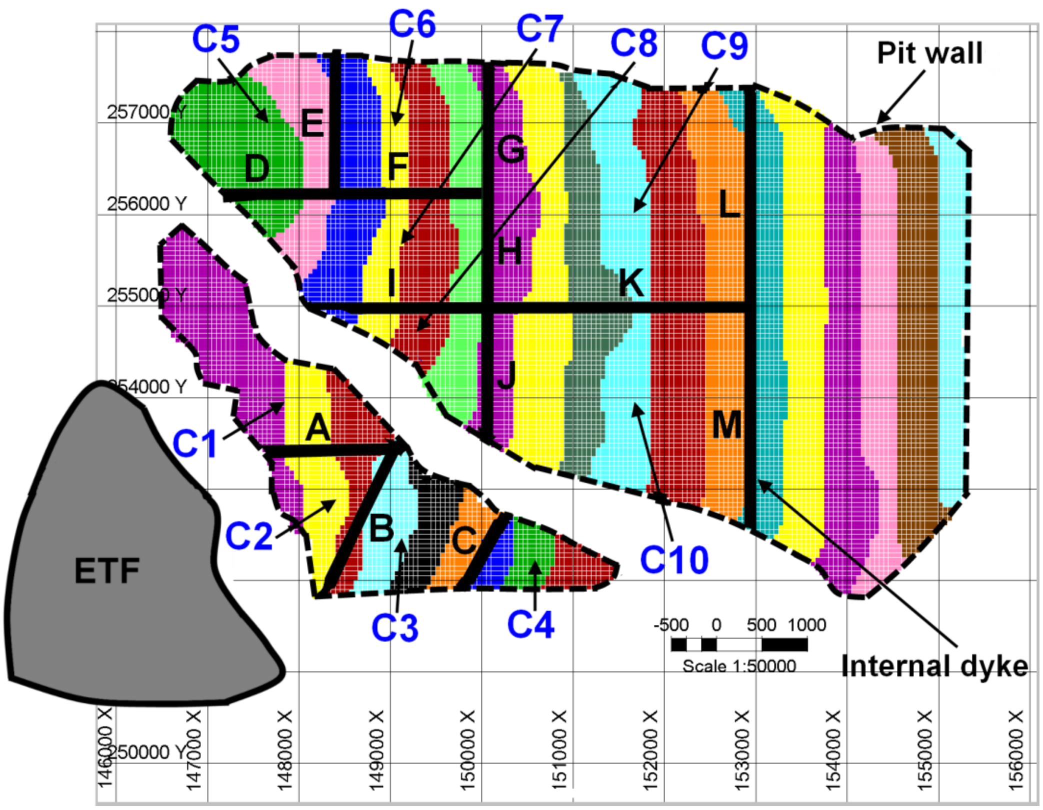

Figure 39: Plan view of the pits with dykes A to M and CT cells C1 to C10.

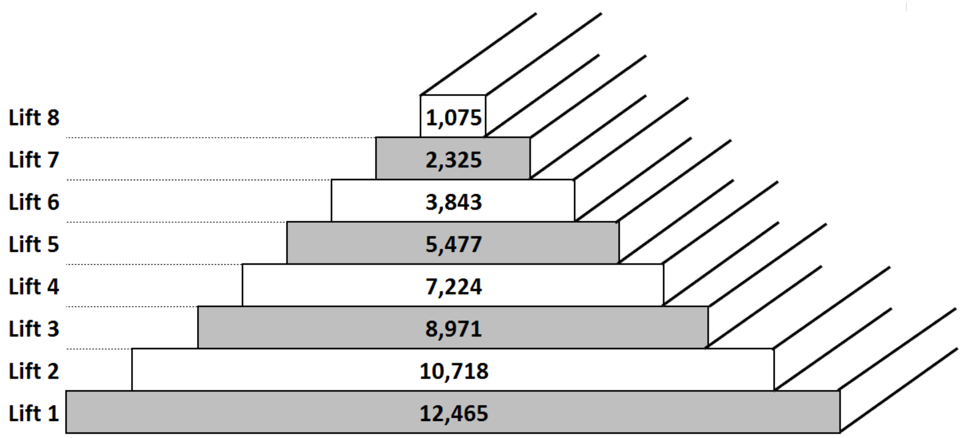

Figure 40: Dyke lifts' cross sectional areas (m^2).

Table 16 shows how the pushbacks provide the space required for CT deposition when the pushbacks are completely extracted. The total volume of each CT cell equals the volume of corresponding pushbacks minus the occupied volume of the dykes that are constructed for each CT cell. Since each dyke divides two CT cells, half of a dyke's volume is deducted from the volume of each cell. The dykes' volumes are calculated by multiplying the cross-section area of the dyke to the dyke length. The dyke lift's cross-sectional surfaces areas are illustrated in Figure 40, which is a schematic figure that shows the surface areas. The real dykes are designed as illustrated in Figure 29.

Table 15: Mapping of pushbacks to CT cells (Case study 3).

Pushbacks	Volume (Mm^3)	Dividing dyke	Volume (Mm^3)	CT cell	Volume (Mm^3)
-	-	-	-	ETF	148
1,2,3	387	A	84	C1	152
				C2	103
4,5,6	173	B	98	C3	97
7,8,9	73	C	53	C4	47
10,11,12 13,14,15	762	D	7	C5	182
		E	9	C6	147
		F	7	C7	105
		I	86	C8	112
16,17,18 19,20,21	1,221	G	71	C9	411
		H	71		
		J	71	C10	447
		K	133		
22,23,24 25,26,27	1,063	L	123	-	-
		M	123		

Table 16: Input parameters for integrated mine planning MILP model.

Input parameters	Value	Input parameters	Value
Recovered barrel of bitumen per Tonne of bitumen	0.65	Selling cost	0.00
Bitumen price ($/barrel)	90	Ore cut-off grade	7%
Ore price ($/tonne of bitumen)	450	Upper bound (fines grade in ore)	18%
Mining cost ($/Tonne)	4.60	Upper bound (fines grade in OI)	30%
Processing cost ($/Tonne)	5.03	OI density (Tonne/m3)	2.03
Extra OI dyke mining cost ($/Tonne)	0.92	TCS density (Tonne/m3)	1.72
Extra TCS dyke mining cost ($/Tonne)	1.38	Interest rate	10%
CT deposition cost ($/m3)	0.50	Recovery	90%

The values are in squared meters and are calculated based on the dimensions provided in Figure 29. For simplicity, all the dykes are assumed to be orthogonal along the N-S and W-E directions except dykes B and C in pit one. The specifications of the dataset and parameters used for this case study are presented in Table 16.

The tonnages of different material types in mining pits one and two are compared in Table 17.

Table 17: Different material tonnages and number of mining-blocks, mining-cuts and mining-panels in mining pits one and two.

Input parameters	Pit 1	Pit 2	Total
Total material (Mt)	1,237	6,217	7,454
Mineralized material (Mt)	374	1,819	2,193
OI material (Mt)	597	3,620	4,217
TCS material (Mt)	278	1,253	1,531
# of Mining-blocks	16,878	81,193	98,071
# of Mining-cuts	972	4,588	5,560
# of Mining-panels	70	144	214

Table 18: Experiments specifications and parameters: Case study 3.

Expr.	# of periods	Mining cap. (Mt)	# of panels	# of cuts	Period aggr. tolerance / multiplier	Experiment purpose
C1	30	350	214	5,560	-	Solving directly
C2	10	900	214	5,560	-	initial solution (cut X)
C3	30	350	214	5,560	2 / 3	Period aggregation (cut X)
C4	10	900	214	2,456	-	initial solution (cut 3X)
C5	30	350	214	2,456	2 / 3	Period aggregation (cut 3X)

4.5.1. Discussion: Solving the MILP Problem Directly

In experiment C1, the proposed MILP model is directly solved to generate an optimized schedule for mine production, dyke construction, and CT deposition over 30 periods. Table 19 shows the mining and processing capacities in each period, equivalent to each year. In order to control the fluctuations of the generated schedule, a minimum and maximum are set for mining and processing capacities in each period. The maximum tonnage of oil sands material that can be sent to the processing plant ramps up from 5 Mt in period one to 40 Mt in period 8, and is fixed to 40 Mt over the next periods up to year 30. The minimum and maximum of mining capacities per period are set in a way to avoid steep jumps from one period to another through two increases in mining capacity in period 8 (from 175 Mt to 228 Mt) and period 20 (from 228 Mt to 322 Mt).

Table 19: Mining and processing capacities per year for experiments C1, C3 and C5.

Period		1	2	3	4	5	6	7	8	9	10
Mining cap. (Mt)	Min	175	175	175	175	175	175	175	228	228	228
	Max	350	350	350	350	350	350	245	245	245	245
Processing cap. (Mt)	Min	2.5	5	7.5	10	12.5	15	17.5	36	36	20
	Max	5	10	15	20	25	30	35	40	40	40
Period		11	12	13	14	15	16	17	18	19	20
Mining cap. (Mt)	Min	228	228	228	228	228	228	228	228	228	322
	Max	245	245	245	245	245	245	245	245	245	350
Processing cap. (Mt)	Min	20	20	20	20	20	20	20	20	20	20
	Max	40	40	40	40	40	40	40	40	40	40
Period		21	22	23	24	25	26	27	28	29	30
Mining cap. (Mt)	Min	322	322	322	322	322	322	322	322	322	0
	Max	350	350	350	350	350	350	350	350	350	350
Processing cap. (Mt)	Min	20	20	0	0	0	0	0	0	0	0
	Max	40	40	40	40	40	40	40	40	40	40

The resulting schedule corresponding to experiment C1 is illustrated in Figure 41. As expected, C1 has resulted in a linear increase in the processing of material from year one to year eight and a uniform processing rate of 40 Mt over periods 9 to 29, except for a 10% drop in period 19. The mining rate follows a three-step incremental pattern in periods 7 and 20. For a reference to the generated schedule, the numerical values of the resulting production schedule are presented in Table 20.

The columns in Table 20 contain the following information: The total material mined is reported in Column two. The column summarizes the high grade oil sands material with an average grade higher than 7% that is sent to the processing plant (Column three), the material extracted as OI for dyke construction (Column five), and the low grade material extracted as waste (Column six). Column four reports the tonnage of TCS material produced in cyclone underflow at the end point of the oil sands hot water extraction process. TCS is part of ore material (column three). However, to integrate dyke material production with mine planning it was essential to define a variable for it separately and control its production to ensure that the required dyke material would be generated in each period. Because TCS plays a key role, it is reported separately in Table 20 and illustrated at the top of each bar in Figure 41. The total tonnage extracted as dyke material is reported in column seven, which is the summation of TCS and OI. The total tonnage of dyke material that has been used in dyke construction is reported in column eight. Comparing Columns seven and eight shows that some of the material extracted as dyke material has not been used in dyke construction. That is because dyke construction follows CT production. In other words, when an excess of CT is produced and cannot be deposited in the ETF, internal dykes will be constructed to provide in-pit space (CT cells) required for CT deposition. Further details are provided regarding the connection between CT deposition and dyke construction, when the corresponding schedules are discussed in the following sections. The waste material plus the unused dyke material are being sent to the waste dumps. The corresponding tonnage is reported in column nine of Table 20. Finally, column ten reports the generated CT volume in each period.

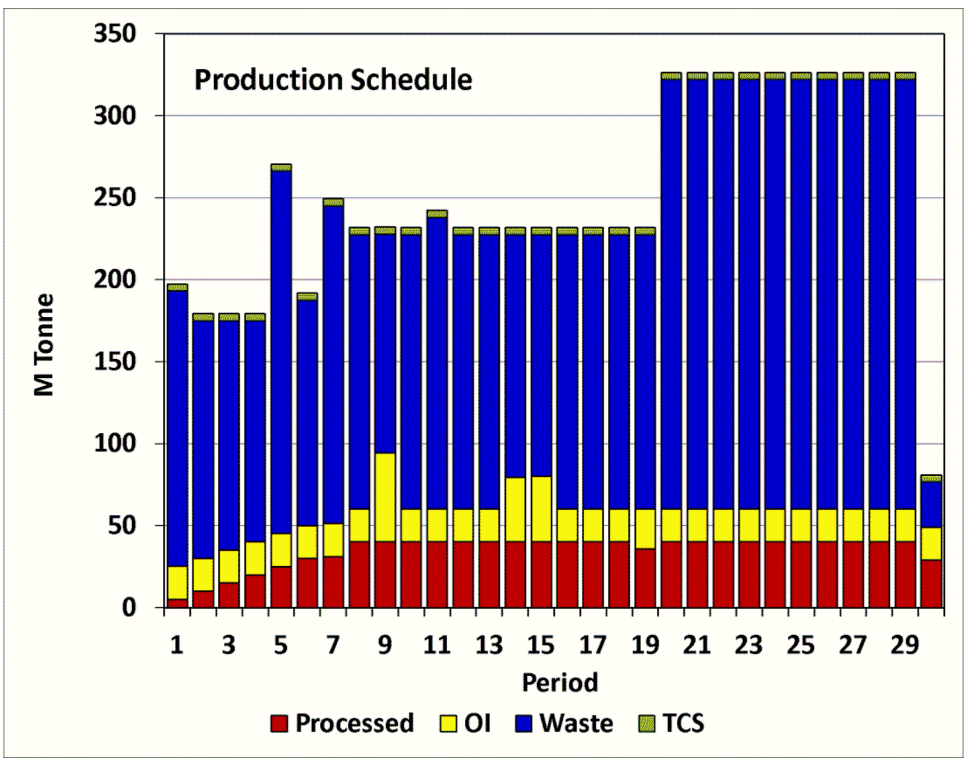

Figure 41: Production schedule for 30 periods, equal to 30 years (C1).

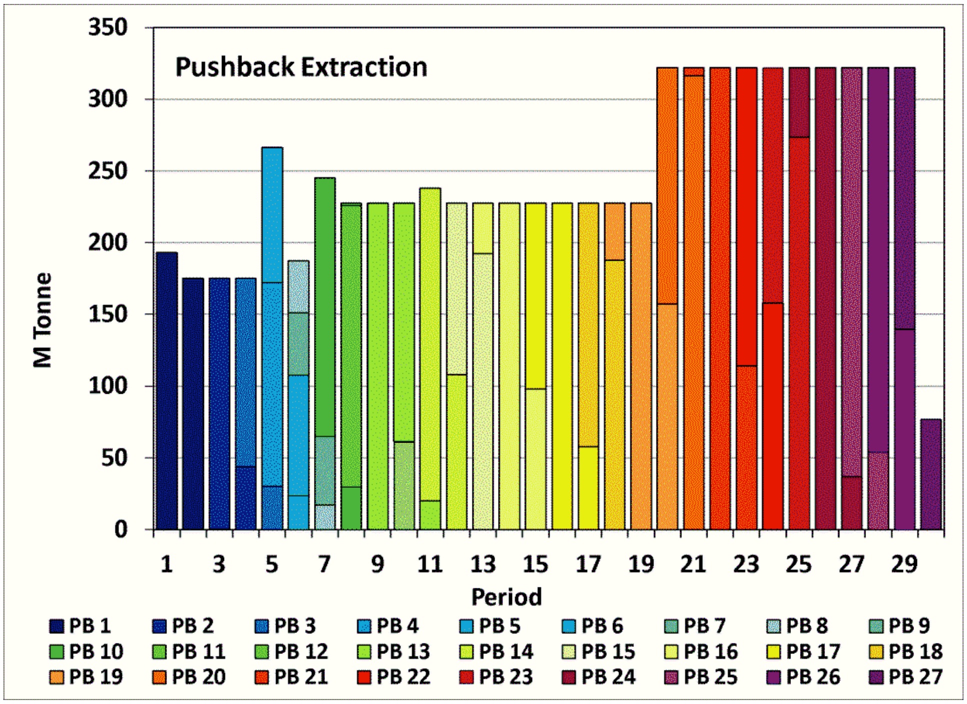

Figure 42: Pushback extraction schedule for 30 periods, equal to 30 years (C1).

Figure 42 illustrates how the pushbacks are extracted over 30 years. Pushbacks one to nine are in pit one and are extracted in order from west to east (one to nine) over periods one to seven. The extraction of pushbacks in the second pit (pushbacks 10 to 27) starts in period seven, after complete extraction of pit one, and continues up to period 30. Figure 43 illustrates the production schedule in a sample bench, showing the period numbers in which the portions are scheduled to be extracted. It shows the extraction progressing in the west-east direction.

The accumulated extraction tonnage over 30 years is illustrated in Figure 44. The accumulated tonnage of mined material has a fairly constant slope, meaning that the operation progresses under a constant rate over 30 periods. This is an ideal mine operations planning and scheduling result when it comes to planning for mining equipment.

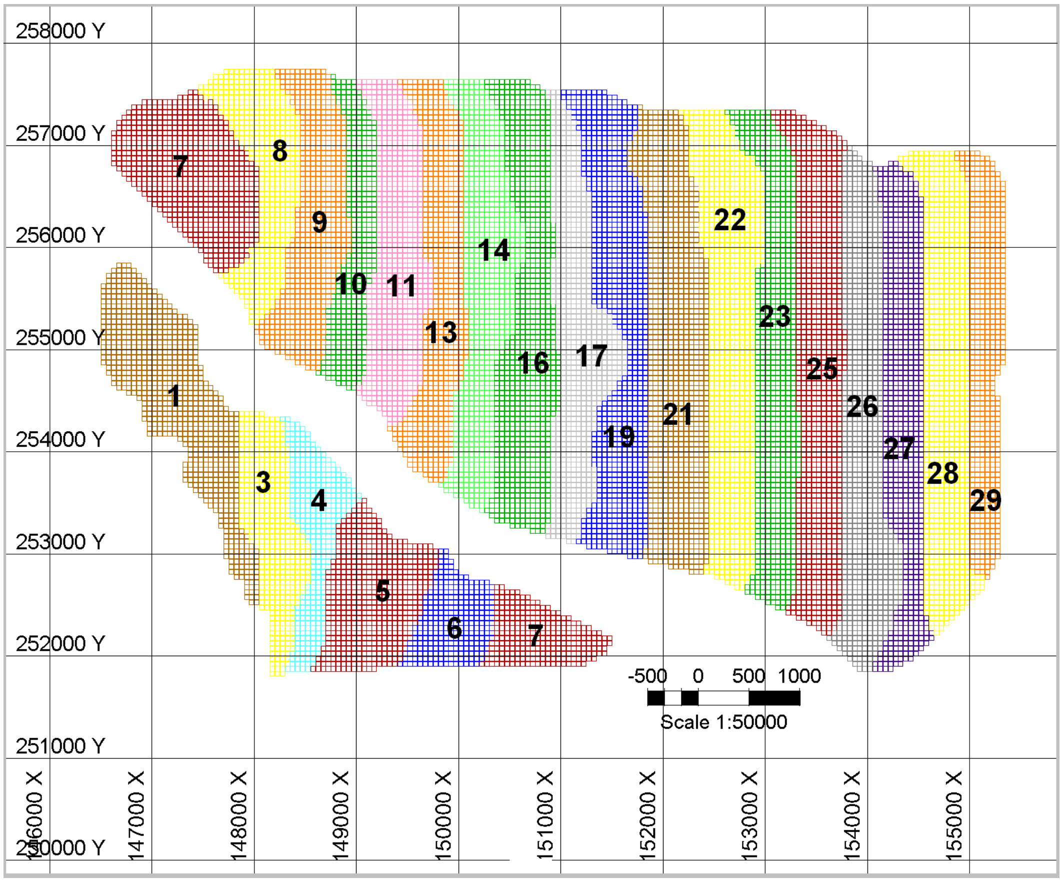

Figure 43: Production schedule in W-E direction (numbers: period of extraction).

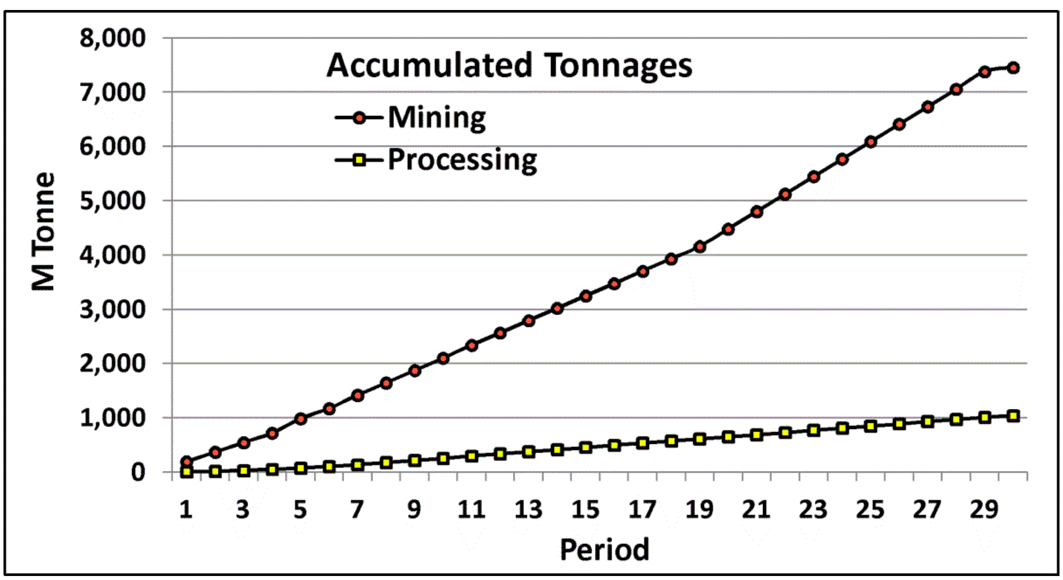

Figure 44: Accumulated tonnages of mined and processed material (C1).

Table 20: Tonnage of mined material and generated CT over 30 years.

Year	Total material Mined (Mt)	Material sent for Processing (Mt)	TCS generated in oil sands processing (Mt)	Material extracted as OI (Mt)	Material extracted as waste (Mt)	Total dyke material generated (Mt)	Dyke material used in dyke construction (Mt)	total material sent to waste dumps (Mt)	Total volume of CT generated (Mm3)
1	193	5	4	20	168	4	24	0	192
2	175	10	4	20	145	7	24	0	169
3	175	15	4	20	140	11	24	0	164
4	175	20	4	20	135	15	24	0	159
5	266	25	4	20	221	18	24	24	221
6	187	30	4	20	137	22	24	24	137
7	245	31	4	20	194	27	24	24	194
8	228	40	4	20	167	25	24	24	167
9	228	40	4	54	133	23	59	59	133
10	228	40	4	20	167	24	24	24	167
11	238	40	4	20	178	25	24	24	178
12	228	40	4	20	167	26	24	24	167
13	228	40	4	20	167	30	24	24	167
14	228	40	4	39	148	30	44	44	148
15	228	40	4	40	147	27	44	44	147
16	228	40	4	20	167	26	24	24	167
17	228	40	4	20	167	27	24	24	167
18	228	40	4	20	167	24	24	24	167
19	228	36	4	24	167	22	29	29	167
20	322	40	4	20	262	24	24	6	280
21	322	40	4	20	262	23	24	24	262
22	322	40	4	20	262	23	24	0	286
23	322	40	4	20	262	25	24	1	285
24	322	40	4	20	262	25	24	1	285
25	322	40	4	20	262	28	24	0	286
26	322	40	4	20	262	24	24	0	286
27	322	40	4	20	262	29	24	0	286
28	322	40	4	20	262	32	24	13	273
29	322	40	4	20	262	37	24	0	286
30	77	29	4	20	28	28	24	1	51
Sum	7,454	1,041	128	681	5,732	708	809	490	6,051

A summary of numerical results of the production schedule is provided in Table 21. The total material tonnage in pits one and two is 7,454 Mt, which has been extracted completely to clear the in-pit space for dyke construction and CT deposition. From the total material tonnage, 2,193 Mt is the mineralized tonnage with a bitumen grade of more than 7%. Based on mining and processing capacities 1,041 Mt from the mineralized tonnage has been processed as ore, resulting in 129 Mt of recovered bitumen, equal to 84 million barrels of bitumen. The total tonnage of extracted OI dyke material and TCS is 681 Mt and 128 Mt, respectively. The integer solution is optimized (0% optimality gap), resulting in an NPV of $2,212M in 106,281 seconds (29.5 hours).

Table 21: Summary of the results: experiment C1.

Total material in pits 1&2 (Mt)	7,454	Extracted OI (Mt)	681
Mineralized material (Mt)	2,193	Produced TCS (Mt)	128
Processed ore (Mt)	1,041	Optimality gap	0%
Recovered bitumen (Mt)	129	Run time (h)	29.5
Recovered bitumen (M barrel)	84	NPV (M$)	2,212

4.5.2. Discussion: Period Aggregation and Mining-Cut Size

Period aggregation refers to solving the production scheduling problem over a large number of periods based on an initial solution for the aggregated periods. This is done by controlling the variables to take value only for specific periods based on the multiplier and tolerance defined for the aggregated solution. For example, long-term mine planning must be optimized over 30 periods with mining and processing capacities of “X” and “Y” for each period (as problem A). It is assumed that an initial solution can be found for the problem over 10 aggregated periods with mining and processing capacities of “3X” and “3Y” for each period, respectively (as problem B). In the solution for B, each of the time periods represent at least three real periods (multiplier of three) for the original problem, depending on the defined tolerance. For example, if a certain mining-block is scheduled to be extracted in period 5, it can be extracted over periods 13, 14, and 15 with a tolerance of two, which results in periods nine to 19 (Figure 47). Therefore, the other variables which determine the extraction of this mining-block in all the other periods are fixed to zero. In this way, the dimension of the “A” problem is reduced significantly and it can be solved over a large number of time periods in a reasonable CPU time. Experiments C2 and C3 are designed to justify the importance of period aggregation in solving the MILP model efficiently and, also, to show how the multiplier and the tolerance are selected for running the disaggregated MILP. The two important factors that are studied in this case study are NPV and solution time.

Experiment C2 is carried out to generate an initial solution to be used in period aggregation. The production schedule and pushback extraction schedule for 10 aggregated periods, equivalent to 30 years, are illustrated in Figure 45 and Figure 46, respectively. Under the resulting schedule, the tonnage of oil sands sent to the processing plant smoothly ramps up from period one to period four, and continues with a uniform processing rate of 150 Mt up to period 10. The tonnage of OI and TCS material produced in each period are enough to construct in-pit dykes, which provide enough space for in-pit CT deposition. The resulting schedule is used as the initial schedule for experiment C3.

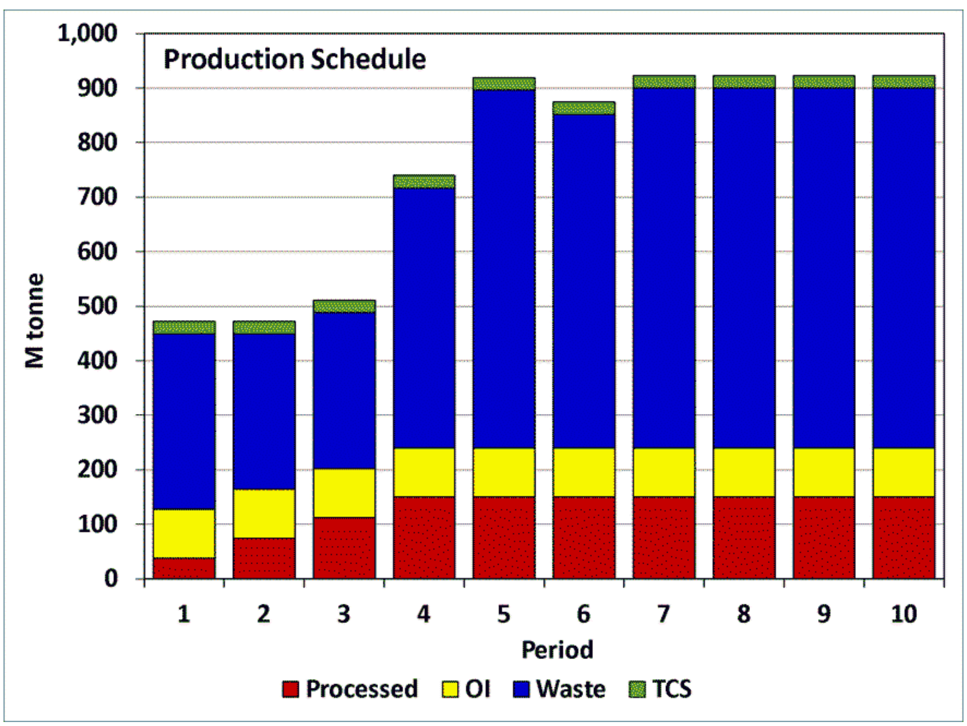

Figure 45: Production schedule for ten aggregated periods.

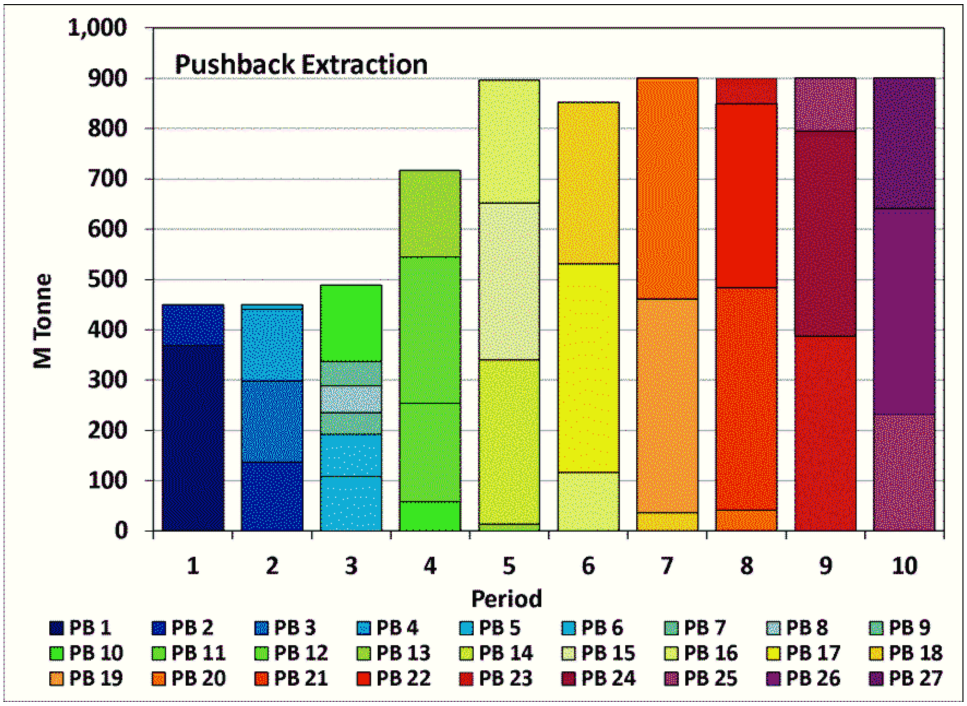

Figure 46: Pushback extraction schedule for ten aggregated periods.

The tolerance used in period aggregation for experiment C3 is two. This means that after multiplying the initial extraction period by three (to map ten aggregated periods to 30 years), two periods before and two periods after the multiplied period numbers are also considered in the schedule and the rest of the periods are fixed to zero. An illustrative example of period aggregation, showing the concept of multiplier and tolerance, is presented in Figure 47.

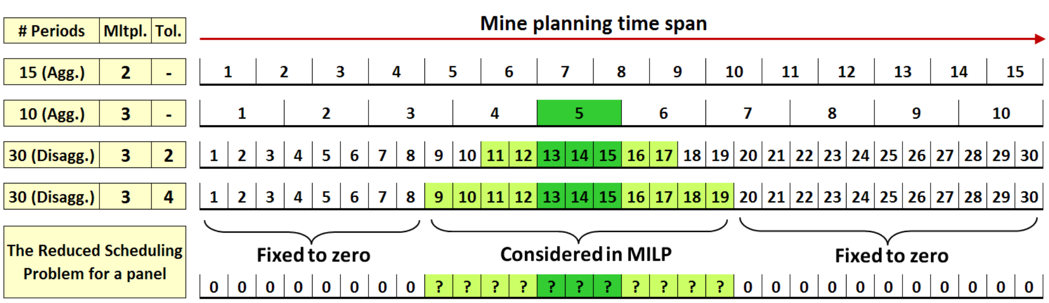

Figure 47: An illustrative example of period aggregation.

The problem is solved over 30 periods in C3, using the initial schedule from C2. C3 has generated an NPV of $2,211,745,415, which is extremely close to the generated NPV in C1 ($2,212,373,689). There are 311,309 decision variables involved in optimizing C3, including 3,624 integer variables. The total number of decision variables and integer variables for C1 are 311,953 and 3,941, respectively. Comparing these numbers shows that the number of integer variables involved in C3 is around 8% less than those involved in C1. However, the CPU time for C3 is only 88 minutes, which is 95% less than the CPU time of C1 (29.5 hours). Two conclusions can be made from comparing these numbers for the studied case: First, the number of integer variables is the most important factor that prolongs the solution time and, second, reducing the number of integer variables consequently reduces the CPU time significantly. In this case, an 8% reduction in the number of integer variables has resulted in a more than 95% decrease in CPU time. The numerical results are compared in Table 22. The resulting production schedule corresponding to C3 is similar to the schedule presented for C1 (Figure 41, Figure 42, and Figure 43).

The last two experiments of this case study are designed to check the effect of increasing the resolution of mining-cuts on NPV and CPU time. Similar to C2, the experiment C4 is carried out to generate an initial solution to be used in period aggregation in experiment C5. In order to compare the results with C3, the maximum number of mining-blocks contained in each mining-cut is increased from 25 (in C1, C2 and C3) to 75 (in C4 and C5). As a result of decreasing the cut-resolution, the NPV dropped 4.3%, from $2,211,745,415 in C3 to $2,119,904,200 in C5. The CPU time is also dropped from 88 minutes in C3 to 25 minutes in C5. The production schedule is similar to experiments C1 and C3. The numerical results of C1, C3 and C5 are compared in Table 22 and Figure 48.

Table 22: Comparing the parameters and results of C1, C3 and C5.

Expr.	# of cuts	# of variables	# of int. variables	Gap	CPU time (min)	change in CPU time	NPV (M$)	NPV Improvement
C1	5,560	311,953	3,941	0%	1,771	-	2,212,373,689	-
C3	5,560	311,309	3,624	0%	88	95%	2,211,745,415	-0.03%
C5	2,456	143,939	3,626	0%	25	99%	2,119,904,200	-4.18%

Figure 48 illustrates the performance of the model, in terms of generated NPV and CPU time for three experiments. Implementing period aggregation has reduced the CPU time significantly by 95% (Figure 48a). However, reducing NPV resulting from implementing period aggregation leads to the negligible value of

0.03% (Figure 48b). This observation justifies implementing period aggregation as a powerful technique that solves the problem efficiently with relatively short CPU time, without losing the solution quality. Aggregation of mining-blocks into larger mining-cuts has resulted in a 4.33% drop of NPV from C3 to C5, in a 4% less CPU time. The problem is not overly sensitive to the size of mining-cuts. That is due to the nature of the bitumen contained in the McMurray formation. The observation in this case study and the tradeoff between NPV loss and CPU-time reduction corresponding to the mining-cut resolution is aligned with the conclusion made in Case study 1: the problem is not sensitive to the size of mining-cuts.

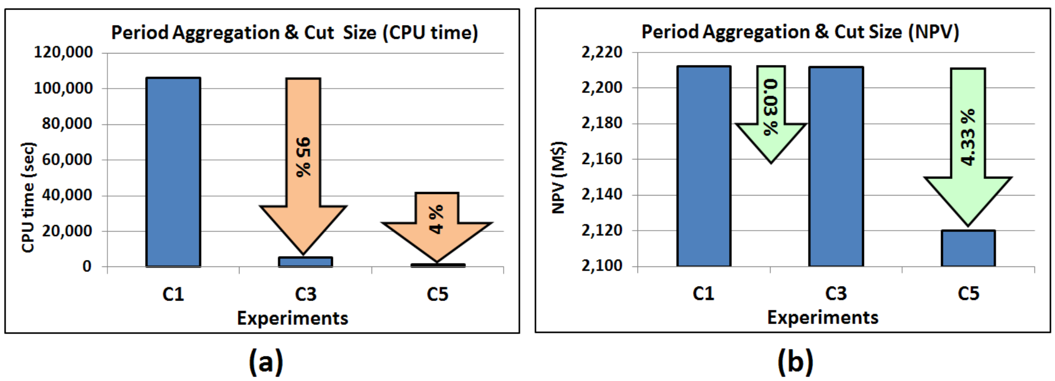

Figure 48: Comparing NPV (a) and CPU time (b) for the experiments in Case study 3.

4.5.3. Discussion: CT Deposition and Dyke Construction Schedules

The generated production schedule includes corresponding schedules for dyke construction and CT deposition. For a clearer picture of this schedule, a combined Gantt chart showing the progress of dykes construction and CT deposition is illustrated in Figure 49.

Dyke construction starts in period five with Dyke A. During the first four periods, no in-pit dyke will be constructed, because the space required to construct Dyke A will only be available after the complete extraction of pushback three in period five (Figure 42). Dyke A will be constructed over periods five to 10. Dyke construction continues with Dyke B (periods ten to 16), Dyke C (periods 16 to 20), Dyke D (periods 20 and 21), Dyke E (periods 21, 23 and 24) and finally part of Dyke F (over periods 28 and 30). The generated schedule follows the dyke precedence in the west-east direction. The volumes of dykes are different, following the length of the specified footprints for dykes (Figure 39). Therefore, they have been constructed in different time periods. As an example, Dyke C is 1,010 m long, less than 55% of Dyke B's length (1,880 m). Because of this difference, it takes less time to construct than Dyke B. The generated dyke construction schedule that shows the material tonnages used for each dyke in each period is illustrated in Figure 50.

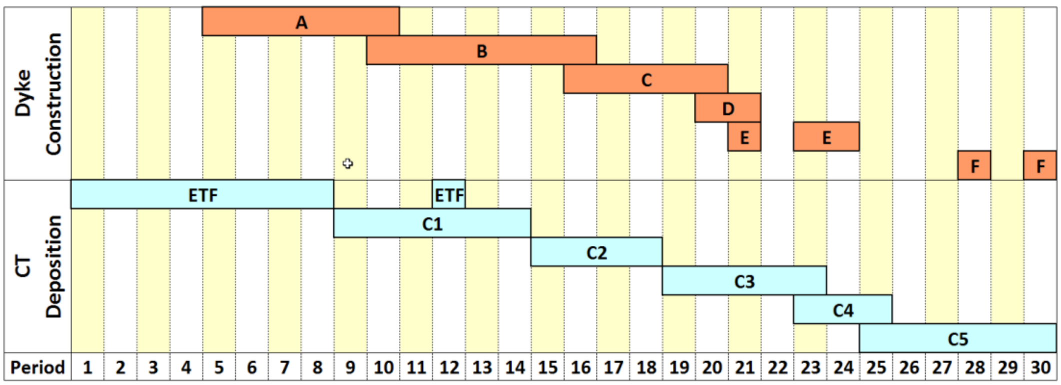

Figure 49: Gantt chart of dyke construction and CT deposition schedules.

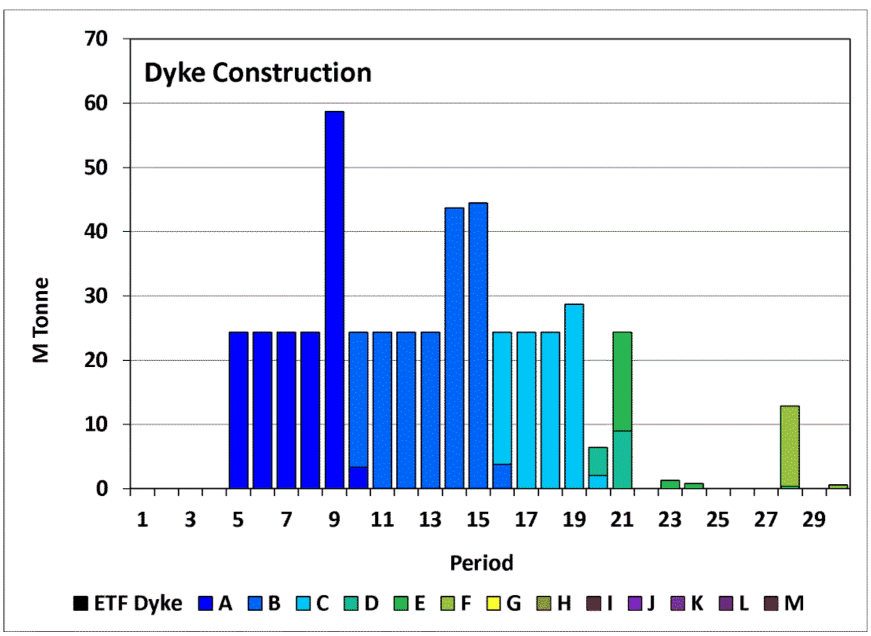

Figure 50: Dyke construction schedule for 30 periods, equal to 30 years (C1).

CT deposition starts in the first period with sending the produced CT to the ETF (Figure 49). Up to period eight, the CT is sent only to the ETF. In period nine and when the main portion of Dyke A is constructed, CT cell 1 starts receiving CT and continues to accommodate it up to period 14, when capacity is reached. CT cells are filled in order, as cell 1 (periods nine to 14), cell 2 (periods 15 to 18), cell 3 (periods 19 to 23), cell 4 (periods 23 to 25) and cell 5 (periods 25 to 30). In addition to the CT cells' precedence order, the other constraint that determines when CT can be deposited in a cell is the completion of dyke walls that shape the CT cell. Figure 49 shows that this constraint has been generally followed. However, there are some overlaps in the construction of cells and deposition of CT in them. That is because of an assumption in modeling the construction of CT cells and CT deposition: of the eight lifts involved in constructing any dyke, when the lower seven lifts are completely constructed, the cell can receive CT and the eighth lift will be constructed at the same time, by depositing sand over the dyke walls. This assumption justifies the overlaps between CT cell construction and CT deposition in Figure 49. The role of an ETF is well illustrated in this case study. The ETF has worked as a buffer to accommodate the produced CT in early periods one to nine, when the in-pit space is not yet ready for dyke construction.

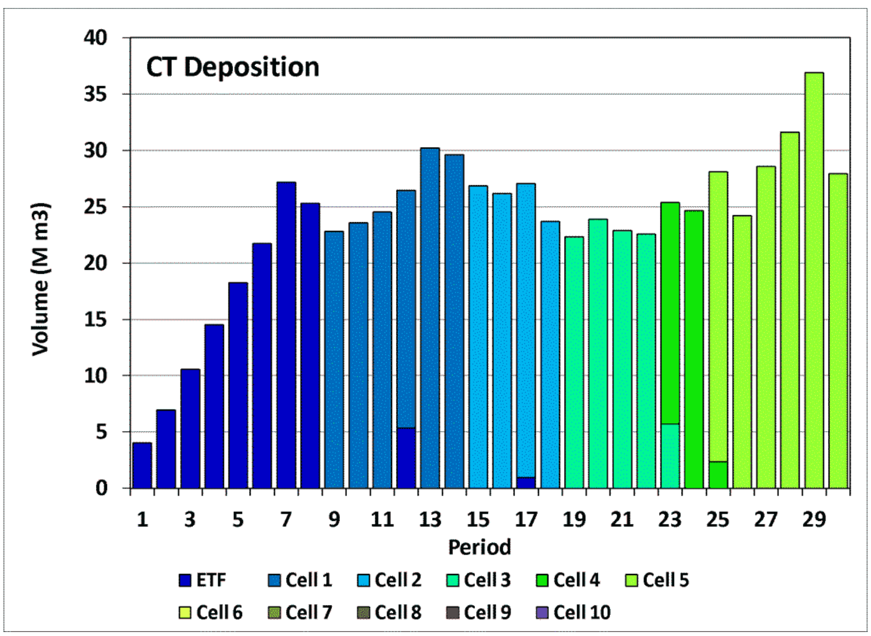

Figure 51: CT deposition schedule for 30 periods, equal to 30 years (C1).

The volumes of CT cells are different, following the volumes of extracted pushbacks and pit dimensions for each cell (Figure 39). This difference has resulted in different capacity of cells and therefore, the cells have been filled with

CT over a different number of time periods. The generated CT deposition schedule, showing the volume of CT deposited in each cell over each period, is illustrated in Figure 51.

The cross-sectional view in Figure 52 illustrates the construction schedule for dyke lifts and the period number in which CT deposition has been started and finished in each CT cell. The highlighted squares with a value of one demonstrate which dykes (in columns) are pre-requisites for each CT cell. For example, CT deposition in CT cell 3 can only be started when Dyke B and the 7th lift of Dyke C are already completed. These dykes are marked as the precedence for CT cell 3. The start deposition period for cell 3 is 19, which is the earliest possible period that CT can be sent to cell 3 after completion of the 7th lift in Dyke C.

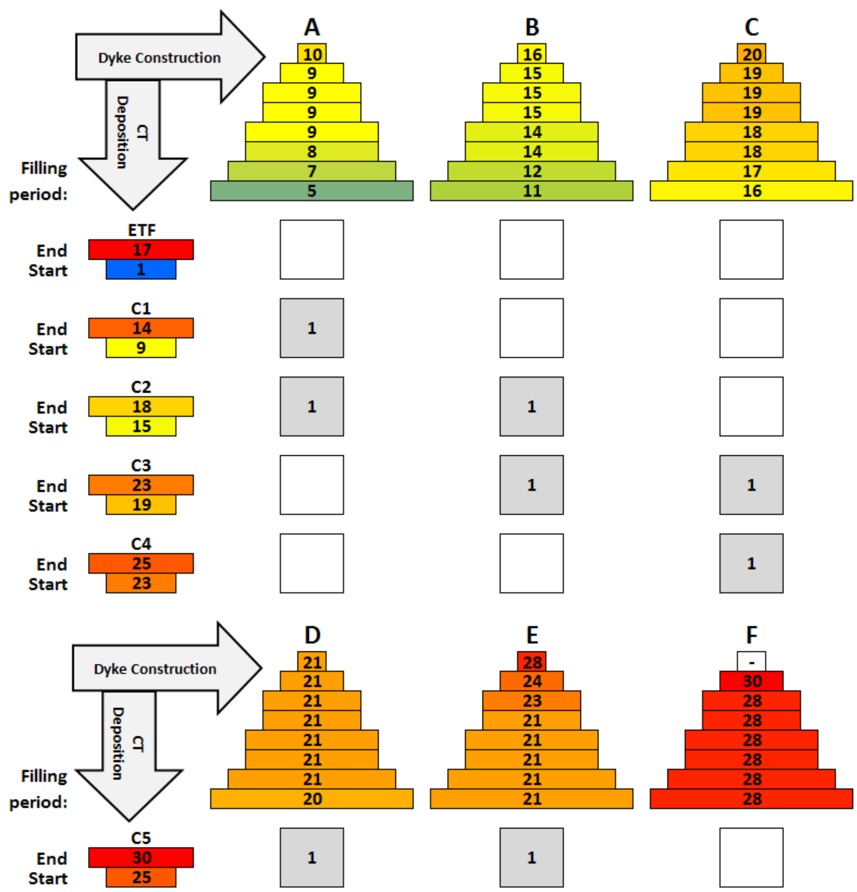

Figure 52: A cross sectional view of dyke lifts' construction & CT deposition (C1).

4.5.4. Discussion: Sensitivity to the Discount Rate

The interest rate, which is used to discount the revenue of the mining over time periods, has been considered as an input parameter to the model. The experiments in Case study 3 are carried out under a 10% discount rate. However, the NPV is sensitive to this parameter. A higher interest rate decreases the NPV comparing to a lower rate, because it discounts the revenue gained in the late periods under a higher rate in the denominator. The multiplier $1/[(1+i)^t]$ is multiplied to the cost and revenue values in the mathematical model to discount them, where "i" is the interest rate and "t" is the period number. Table 23 provides the NPV values for a range of interest rates between five to 12 percent.

Table 23: Sensitivity of the NPV to the interest rate.

Interest rate	NPV (M$)	Improvement (%)
5%	4,968	212%
7%	3,588	125%
9%	2,601	63%
10%	2,212	39%
12%	1,594	-

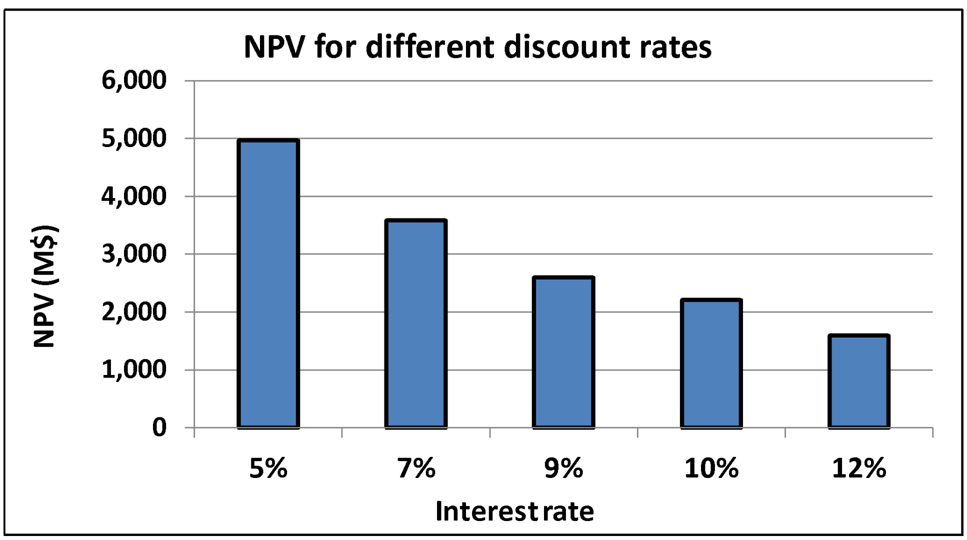

Figure 53: Sensitivity of NPV to the discount rate.

The resulting NPVs are compared in Figure 53. The NPV under a 5% discount rate is equal to $4,968M, and drops gradually to $1,594M for a 12% discount rate. This shows the importance of choosing a realistic rate, especially when the model is run to compare different scenarios in a feasibility study analysis. However, since in this research the focus is on developing a right mathematical tool to be used in decision making, further calibrations of the discount rate are ignored. Instead, an interest rate of 10% is chosen in the experiments, which is proportional to the annual rate of return considered by the industry.

4.5.5. Case study 3: Conclusion

The results of Case study 3 show that dyke construction and CT deposition can be well integrated with the long-term mine planning framework. The resulting schedule is practically minable through a fairly uniform production rate over three time intervals (periods one to six, seven to 19, and 20 to 30) and generates a constant uniform feed to the processing plant. By following a certain mining direction, dyke footprints have been cleared and the pit has become ready for construction. The OI and TCS material required for dyke construction are produced and have been used to raise the dyke walls for in-pit CT cells. The produced CT has been sent to the ETF over the early periods while the in-pit cells are not yet ready. The in-pit cells have accommodated the CT over 21 periods, from periods 9 to 30.

Implementing period aggregation has reduced the CPU time significantly by eliminating a number of integer variables from the model by fixing their values to zero. The real-size production scheduling, dyke construction and CT deposition scheduling problems are solved to optimality (0% gap) in about one hour. The quality of the solution, in terms of NPV, is closely comparable with the NPV generated for the directly-solved MILP without implementing period aggregation. The comparison of this case study results showed that the optimal solution is not overly sensitive to the size of the mining-cuts. In conclusion, the proposed integrated model has successfully optimized the long-term mine production, dyke construction, and CT deposition scheduling problems within an integrated framework in a reasonable solution time.

4.6. Summary and Conclusions

In this chapter, three case studies, covering 13 experiments, are designed and carried out to show how the proposed MILP model performs in integrating waste disposal planning and tailings management with long-term mine planning framework. The experiments are designed to study different contributions of the proposed model, such as handling different mining directions, considering different mining unit resolutions and implementing period aggregation as a means to reduce the problem size and solution time.

The first case study is designed to show how the developed model is able to control the mining direction. Two mining directions that generated higher NPVs in Whittle scenario analysis are compared in Case study 1, in terms of generated NPV. The results show that mining in the W-E direction generates a higher NPV, compared to the S-N direction. Further, the results of Case study 1 suggest that the NPV is more sensitive to mining-panel resolution than to mining-cut resolution. In other words, the model is expected to generate a higher NPV when smaller mining-panels are present, compared to the situation where a smaller number of mining-panels are present. The NPV does not change significantly with changes to the mining-cut resolution. That is because the mining-cuts are formed within the mining-panel boundaries and therefore the mining-panel size is the more important factor. In addition, the material grade does not change significantly from one mining-cut to another, and merging smaller mining-cuts (reducing the mining-cut resolution) will not considerably change the mining-cut's bitumen grade. The W-E direction and larger mining-panel resolution are the subjects of further experiments in the next case studies.

The second case study is designed to show the main contribution of this research, which is the integration of CT deposition and dyke construction within the frameworks of long-term mine production planning. The results show that the dyke construction and CT deposition can be well integrated with the mine plan, the in-pit dykes will be constructed as the mining operations progress and dykes' footprints become clear, and the CT is deposited behind the internal dykes. Such integration adds to the overall costs, as the extra costs corresponding to dyke construction and CT deposition are involved in the integrated model. Therefore, the integrated model is expected to generate a lower NPV compared to the pure mine-planning model. The experiment results in Case study 2 confirm this expectation.

Case study 3 is carried out to test the performance of the proposed MILP model, with all its components, on a large-scale real oil sands data set. The material extracted as OI and TCS is used in dyke construction, the dyke lifts are constructed in order following the W-E mining direction, the CT is deposited in the in-pit CT cells, and the generated schedule provides a smooth and uniform feed to the processing plant. Due to the large number of periods in the long-term mine production scheduling problem, the number of integer variables increases significantly and results in a long solution time. Adding integer variables for dyke construction and CT deposition adds to the complexity of the problem. In this case, it took more than 29 hours to solve the integrated MILP model to optimality. One technique for problem size reduction is to eliminate the redundant variables by fixing their values before initiating the optimization, based on the accumulated mining and processing capacities in each period. In this research, this is referred to as "preprocessing" and has been implemented to reduce the problem size. In addition, the period aggregation has been used to fix a greater number of variables based on the results of an initial aggregated solution. Using the period aggregation, the integrated mine-planning model is solved to optimality in less than 90 minutes. Case study 3 proves that the proposed integrated model works properly for real datasets, is capable of handling material requirements for dyke construction, and can successfully integrate tailings management, in terms of in-pit CT deposition, within the frameworks of mine-production planning.

CHAPTER 5
SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1. Summary of Research

Long-term mine planning determines the order of extracting mining blocks and the destination of the extracted material to maximize the net present value (NPV) of the production over mine-life. A typical mine-planning model includes mine production and ore-processing capacity constraints, spatial precedence order for extracting the material, and blending constraints. However, it is not guaranteed that the NPV maximization subject to the mentioned constraints will result in a practical production schedule. Another important aspect of production planning that needs to be considered is the handling of waste material generated in mine production and ore processing.

In oil sands surface mining, the extracted material is separated based on bitumen grade, and will be sent to a hot water extraction processing plant where bitumen will be separated from sand and clay. Adding hot water results in massive volumes of slurry at the end points of the oil sands processing, known as tailings, which is a mixture of water, sand, fine material, and bitumen residuals. Since the space for holding the tailings slurry is limited to the lease area, the produced tailings volume is an important factor influencing the mine production and oil sands processing. Moreover, according to the recent regulatory requirements of Directive 074 (McFadyen, 2008) legislated by the Energy Resources Conservation Board (ERCB), the oil sands operators are responsible for promoting sustainable oil sands mining through planning for tailings monitoring and site reclamation. Knowing that most of the material used for site reclamation comes from the mining waste material, it is reasonable to include reclamation material requirements in long-term mine planning to make sure that the generated production schedule provides the required reclamation material.

The literature of the mine production planning was reviewed to clarify what has been done so far in modeling the mine production plan. This literature revealed that the basic aspects of mine planning, such as NPV maximization for block extraction sequencing, have been well modeled, using heuristic and meta-heuristic algorithms such as genetic algorithm (Zhang, 2006), and operations research techniques, such as Lagrangian relaxation (Kawahata, 2006) and integer programming (Ben-Awuah, 2013). The costs associated with tailings handling and site reclamation have been considered in mine design (Rodriguez, 2007). However, what is missing from these models is an effective way to merge mine production planning, tailings planning, and solid waste management. A review of the published mine plans and tailings management reports by Alberta oil sands companies showed that companies pre-schedule a mine production plan, use it as an input to waste management and tailings planning, and then adjust the initial production schedule accordingly to ensure that the requirements of Directive 074 will be fulfilled. This also shows the practical need to merge production scheduling and waste management within an integrated mine planning framework.

The proposed mine planning model integrates the long-term production scheduling with tailings management in terms of in-pit CT deposition, and solid waste management in terms of internal dyke construction, over the mine life-time. Figure 54 briefly presents the steps involved in generating the integrated mine and dyke construction schedule. The main input to the proposed framework is the geological block model which specifies the spatial coordinates of the blocks, the grades of different elements present in the pit, and the rock type of each block. This block model is used in pit optimization and pushback design (in Whittle) and also in the mixed integer linear programming (MILP) model. The next input is the hot water extraction flow sheet, used for tailings volumetric calculations in the tailings model. Finally, the hierarchical clustering functions, developed by Tabesh and Askari-Nasab (2013), are used to make the mining cuts within mining panels.

The first step in preparing the data for the MILP is optimizing the pit limits and designing the pushbacks in the specified mining direction. This is done in Whittle through defining different revenue factors and choosing the pushbacks from among the nested pit shells generated by the 3-dimensional LG algorithm. The data of the blocks within the final pit limits are then converted to a data structure compatible for a clustering function in MILP. Panels are defined as the cross-sectional area of each bench within the boundaries of a pushback. Each block in the converted block model data is flagged by a number, showing the panel ID that the block belongs to. The clustering function reads the panel IDs and aggregates the blocks of each panel to make the mining cuts, based on blocks' similarities. The tailings model includes a number of formulations which, in general, obtain the specifications of each block (tonnage and grades) and determine the potential volume of tailings in terms of water, CT, MFT, and sand volume generated at the end points of the tailings process.

Based on the potential tailings volume to be generated and knowing the volume of each pushback, the dykes' footprints are chosen from among the pushbacks' footprints. The volumetric analysis is done to make sure that the designed CT cells have enough capacity to accommodate the CT generated from processing extracted material of previous pushbacks. An ETF is considered to accommodate the generated CT in early periods when the mining operations have not advanced enough to provide space for in-pit CT deposition. The dykes are designed in eight lifts, each to the height of one bench (15m). Before running the MILP model, the volumes of CT cells will be updated by deducting the volume that dykes occupy from CT cells.

Inputs to the MILP are the updated block model data with cuts and panels, the potential tailings volumes for each block, and the volumes of Dyke And CT cells. Based on the specified mining direction, the precedence orders between panels, dyke lifts, and CT cells will be determined. The matrices required for running the MILP are prepared in Matlab. Tomlab/CPLEX (Holmström et al., 2009), a large scale optimization solver that uses a branch-and-cut algorithm for solving the MILP models, is used to solve the integrated model, using a Matlab interface. The model is solved on a Quad-Core Dell Precision T7500 computer at 2.8 GHz with 24GB of RAM. The outputs of the model are three integrated schedules: mine production, dyke construction, and CT deposition over mine-life.

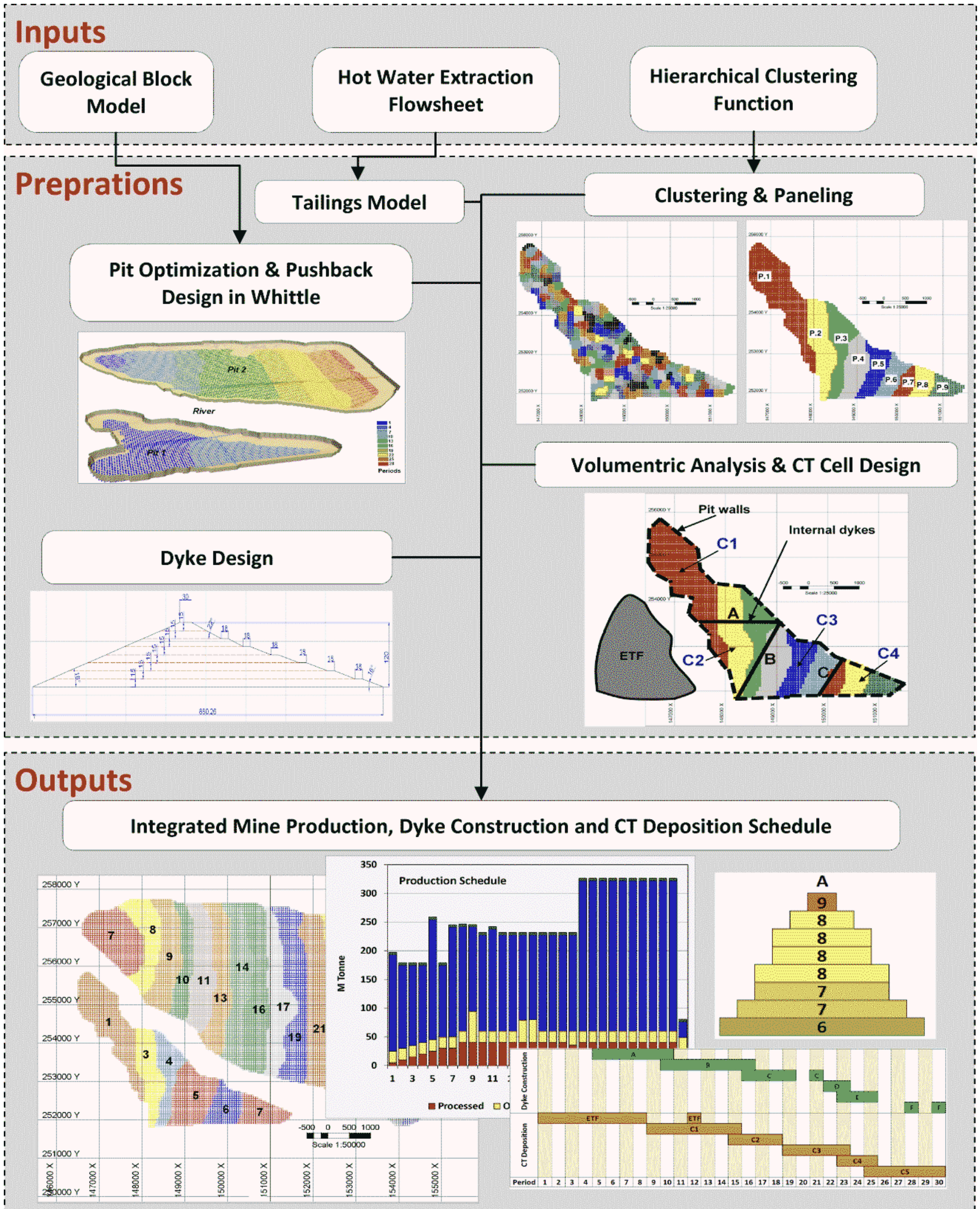

Figure 54: Workflow of the proposed integrated mine planning model.

Three case studies, covering a total of 13 experiments, are designed and implemented to verify the model results. Each case study is designed based on the findings from the previous cases and verifies a version of the MILP model with a newly added feature. Two datasets are used in the experiments. The first dataset includes the block data of a small mining pit with 16,878 mining-blocks and is used for the experiments in Case studies 1, 2 and 3. The second dataset is large-scale oil sands data, including two mining pits with a total of 98,071 mining-blocks. This data is used in Case study 3 to verify the performance of the MILP model on large-scale data over a long period of time. The generated NPV, the CPU time, and the practicality of the generated schedule have been the main measures in comparing the experiments' results. An overview of the case studies with the experiments' purposes is illustrated in Figure 55.

Case study 1 includes six experiments, designed and implemented to determine the best mining direction and investigate how the mining unit resolution influences the NPV. The experiments' results show that mining in W-E direction generates a higher NPV compared to the S-N direction. Resolution of the mining units is a function of cuts and panel sizes. Knowing that the mining cuts are used to separate the ore and waste material, the experiments' results suggest that NPV is not sensitive to the mining-cut resolution. That is because in oil sands mining, the material is homogenous and smaller cuts will not significantly increase the average bitumen grade of the aggregated units. On the other hand, the smaller panels will generate a higher NPV, since they provide more selectivity for the optimizer to schedule the material portions' extraction over mine-life, due to the more flexible precedence constraints.

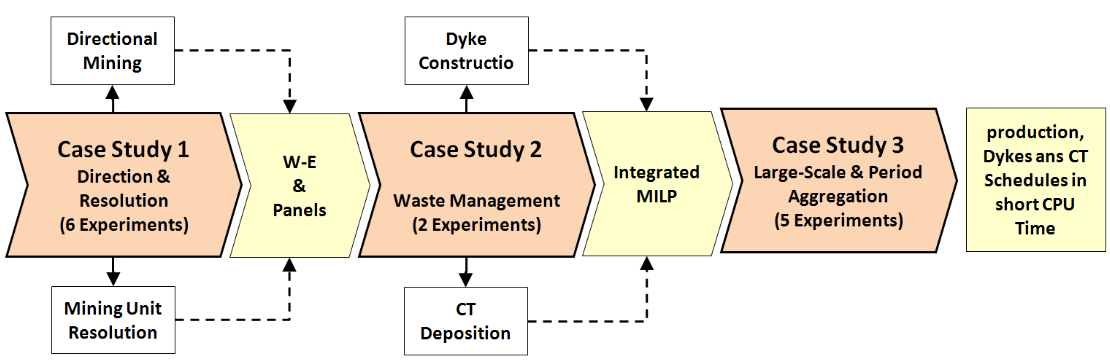

Figure 55: Summary of case studies and design of experiments.

Case study 2 includes two experiments, designed and implemented to study the effect of including new features of dyke construction and CT deposition on the long-term mine-planning model. The conclusions from the first case study, the better mining direction and panel resolution, are implemented in the second case study. The results of the experiments are compared based on the practicality of the generated schedule and the generated NPV. The results show that including internal dyke construction and in-pit CT deposition can be well integrated into the mine-planning framework. The generated mine-production schedule is practically minable, the required in-pit dykes are constructed on time as the mining operations progress, and the CT is deposited in the ETF and in-pit CT cells. Integrating waste management decreases the NPV, as the costs corresponding to dyke construction and in-pit CT deposition are involved in the integrated model. However, the integrated schedule is a practical step towards fulfilling Directive 074 requirements.

Table 24: Summary of numerical results.

Case study	Expr.	# Periods	Direction	# Panels	# Cuts	NPV (M$)	Change in NPV
Case study 1 (Direction & Resolution)	A1	10	SN	31	962	3,693	-
	A2	10	WE	25	942	3,890	+5.3%
	A3	10	WE	25	942	3,892	+5.4%
	A4	10	WE	25	570	3,882	+5.1%
	A5	10	WE	25	428	3,870	+4.8%
	A6	10	WE	70	972	3,959	+7.2%
Case study 2 (Integration)	B1	10	WE	70	972	4,189	-
	B2	10	WE	70	972	3,994	-4.7%
Case study 3 (Large-scale)	C1	30	WE	214	5,560	2,212	-
	C3	30	WE	214	5,560	2,212	0.0%
	C5	30	WE	214	2,456	2,120	-4.2%

In Case study 3, all of the proposed features for the integrated mine production scheduling model are involved and the model is run to verify the performance of the integrated model on a large-scale oil sands dataset. In the first experiments, the integrated MILP model is solved directly to optimality. The model has solved the problem with two mining pits, including 98,071 mining-blocks aggregated into 5,560 mining-cuts and 214 mining-panels in more than 29 hours. Two preliminary experiments are carried out to generate an initial solution for period aggregation. The second experiment uses the initial aggregated solution and solves the problem in less than 90 minutes. There are 214,878 constraints and 1,020,600 variables, including 9,900 integer variables involved in the model. With period aggregation and further preprocessing of variables, the number of constraints entering the branch-and-cut algorithm has been reduced to 81,536, with

311,309 variables including 3,624 integer variables. The problem is solved for the W-E direction. Finally, the last experiment measures the performance of the model, in terms of NPV and CPU time, corresponding to changes in the size of mining-cuts. A summary of numerical results is provided in Table 24, comparing the generated NPVs for different experiments.

5.2. Conclusions

The results show that the research has reached the goals and objectives presented in Chapter 2. An integrated long-term mine production plan has been proposed, developed, and verified through a number of case studies and experiments. It has been implemented on a large-scale oil sands dataset and has generated a minable production schedule in the specified direction that provides in-pit space for dyke construction and CT deposition. The solid waste disposal and tailings deposition have been managed successfully through the dyke construction and CT deposition schedules. Based on the summary of results provided in this section, the following is concluded from this research:

- The literature related to mine planning and waste management has been reviewed. The current literature lacks integration between mine planning and waste management in terms of in-pit deposition of solid waste material and tailings slurry. The implemented framework is a novel topic and helps to fill the current literature gap in strategic open-pit mine planning.
- The theoretical framework for integrating mine planning with waste management has been developed and used in optimizing a long-term strategic production schedule.
- A tailings model has been developed and verified to formulate the volume of tailings slurry and its contents such as water, sand, and fine material that potentially will be produced downstream from the hot water extraction process. The tailings model also calculates the volumes of composite tailings (CT) and mature fine tailings (MFT) that can be generated from further processing tailings slurry.
- Pushback design, paneling, and clustering techniques have been implemented to aggregate the mining blocks and ensure that the mining production follows a

minimum mining width necessary to maneuver trucks and shovels, and follows the practical selective mining units.

- The internal dykes and in-pit CT cells have been designed and implemented successfully in the model and have resulted in a smooth production of dyke material over the mine-life.
- Two techniques are developed and implemented to reduce the problem size through fixing a number of decision variables before running the MILP. The first technique is preprocessing, which eliminates the variables based on the accumulated mining capacities. The other technique is period aggregation which uses an initial aggregated schedule and helps to solve the production scheduling problem efficiently (small CPU time) over many time periods.
- An integrated mine production, dyke construction, and CT deposition scheduling model has been developed and verified through a number of experiments. The generated schedule is practically minable, follows a certain direction, provides a smooth feed for the oil sands processing plant, provides the material required to construct in-pit dykes, and accommodates the produced CT in the ETF and in-pit CT cells.

5.3. Contributions of PhD Research

The main contribution in this research is the development of an integrated framework for optimizing the long-term mine production schedule, including waste management in terms of in-pit tailings deposition and dyke construction. The problem is modeled as a mixed-integer linear programming model, which is capable of the dynamic classification of the extracted material through determining the material destinations based on capacities, blending constraints, and dyke material requirements. In brief, the research contributions can be listed as:

- Development and verification of an integrated model for long-term mine production, in-pit dyke construction, and CT deposition scheduling that maximizes the NPV over the mine-life, and minimizes the dyke construction costs and the costs associated with the deposition of CT in the external tailings facility (ETF) and in-pit CT containments.

- Development and verification of a tailings model to calculate the volume of tailings slurry; slurry contents such as water, sand and fine material; and products of further tailings processing such as CT and MFT that can be potentially produced from the processing of each block. This feature enables the model's oil sands industrial user to fine-tune the production schedule according to any modifications in the tailings model.
- Implementation of directional mining that enables the construction of internal dykes and deposition of CT in the in-pit CT cells, as the mining operations advance and clear the footprints of internal dykes.
- Successful implementation of two problem size-reduction techniques (preprocessing and period aggregation) to make the problem tractable (in terms of CPU time) for large-scale datasets under the current software and hardware. This feature provides efficient implementation of the model, which is essential in sensitivity analysis and choosing among decision alternatives regarding mining direction, size of aggregate units, mining and processing capacities, and details on the design of dykes and CT cells.
- Providing the right tool for oil sands operators in Alberta to fulfill the requirements of sections 4.0, 4.2, and 4.5 of Directive 074 (ERCB) through development of an integrated framework for optimization of mine production and waste disposal schedules in terms of dyke construction and CT deposition.

5.4. Recommendations

The presented MILP model optimizes the long-term mine production scheduling problem, tailings production and deposition schedule, and in-pit dyke construction planning. It provides a novel framework to integrate mine planning and waste disposal management, which clearly adds value to the current body of knowledge under the topic of open-pit mine planning. However, a number of limitations are involved in the proposed model. Addressing them and including corresponding aspects to the integrated model will improve the results and make them more compatible with the requirements of practical strategic mine planning. The following is recommended as further steps in this research area:

- The only source of tailings in the proposed model is the CT produced from further processing of the slurry, which itself is generated in the hot water processing of extracted oil sands from mining pits. In other words, the model does not include any other sources of tailings for deposition in the ETF and in-pit tailings containments. To make the model more practical, the other sources of tailings slurry, produced from processing extracted material of other pits, should be considered for deposition. In addition, the model should handle the flow of tailings slurry between tailings containments, which is a common practice in the current method of composite tailings production.
- The proposed tailings model is based on the CT technology. Although this is one of the successful technologies in tailings dewatering, there are other technologies modified for special situations, such as atmospheric fine drying (AFD) used in ETFs. Also, new technologies such as non-segregated tailings technology (NST) are emerging for in-pit storage of tailings products. The tailings model can be improved by supporting the other technologies of tailings dewatering and storage.
- The proposed model assumes that the geological block model includes deterministic values. In practice, there is an uncertainty involved in estimating material grade and rock types. Also, it is assumed that the ore price, here the selling price for a barrel of bitumen, is a constant value. Knowing that the bitumen selling price fluctuates over time following changes in the global energy market, the model must be re-optimized under new bitumen prices every time. Consideration of a stochastic model that captures the uncertainty in grade and ore price is another step towards generating a more robust production schedule.

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