Incorporation of Geo-metallurgical and Geochemical Properties in Oil Sands Mine Planning and Waste Management

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ABSTRACT

The primary purpose of oil sands mine planning and waste management is to provide ore from the mine pit to the processing plant and contain the tailings in an efficient manner that will maximize the net present value, and minimize dyke construction cost. However, the presence of mineral solids such as clays, ultra-fines, organic-rich solids and heavy minerals in Alberta's oil sands has been investigated to have an impact on the yield of bitumen recovery and the net present value. These minerals possess certain physical and chemical properties such as particle size, cation exchange, layer charge density, and surface properties, which negatively affect the recovery of the bitumen product during extraction and processing. This paper reports on the ore characterization of oil sands and define the ore types in terms of bulk geochemistry and mineral characteristics that affect the processing recovery. A template model consisting of both the geo-metallurgical and geochemical properties that impact processing recovery or waste management will be developed. Pseudo penalties or rewards will be assigned to any material that affects the recovery of bitumen to facilitate ore blending. The equations that will be formulated in this research will contribute positively to the sustainability of the mine plan through optimization and reclamation strategies.

1. Introduction

One of the biggest challenges for oil sands extraction operations is to minimize the number of undesirable events caused by the variation of ore feed. Information on the properties of the incoming ore feed should be the basis used to establish mitigation and control strategies so that operators can proactively deal with the dynamics of the feed. To predict the bitumen recovery and processability of oil sands, comprehensive characterization of mined oil sands is essential. Common properties such as bitumen concentration indicates that ore processing is governed by the interactions of other factors such as mineralogy, connate water chemistry and, particle size which tend to influence the overall performance of the ore (Osacký et al., 2017).

This paper summarizes a literature review of oil sands, oil sands ore mining and processing operations. The primary aim of this study is to understand the various oil sands ore properties and establish a correlation between these properties with respect to bitumen recovery and ore processability. This review also summarizes how these oil sands properties could be incorporated into long-term oil sands mine planning and production scheduling.

2. Oil Sands

2.1. Brief history of oil sands deposition

Although the origin of oil sands remains disputed, most petroleum geologists believe that this resource was formed in the same way as other fossil fuels (conventional oil, natural gas, and coal). Ancient organic matter died and was covered by layers of sediment that exerted sufficient pressure and temperatures to transform the matter into petroleum. It is speculated that the oil sands that exist today formed as a result of ancient oceans that existed millions of years ago covering the areas where the oil sands exist today. As the microscopic marine life within the oceans died, they decomposed with the help of bacteria removing the oxygen and nitrogen, leaving mainly hydrogen and carbon. Heat and pressure then resulted in the layering of rock, silt, and sand over time and cooked the dead organic material for millions of years at temperatures between 50 and 150°C. This formation of oil is similar to that of conventional oil deposits, however, in the case of oil sands, the oil is absorbed into the existing sand. Although scientists are fairly convinced that this is how the oil sands began, exactly the same way as how conventional oil forms, with the one minor difference that sand is involved. The reason that oil sands contain bitumen and not conventional crude oil is a topic that is more controversial, but there are two main theories. The first of these theories is that the oil sands began as a vast reserve of crude oil, and over long periods of time the lighter crude oil escaped or was destroyed microbiologically, leaving behind bitumen. The second theory is that bitumen was formed immediately in a process similar to the formation of oil shale. In this theory, bitumen was released from shales with a large amount of organic matter (kerogen-rich shales) instead of crude oil being released. In both theoretical bitumen formation methods, the bitumen collects around the particles of sand. Instead of migrating through permeable rock as traditional oil would, this bitumen-soaked sand is rather forced to the surface from the pressure of mountain formation (Hepler et al., 1989).

2.2. Geology of oil sands

Canada's oil sands are concentrated mostly in Alberta, extending slightly into Saskatchewan's border. Oil sands deposits are localized in 3 regions, classified as follow; the Athabasca Basin, the Peace River Basin, and the Cold Lake Basin. The Athabasca basin is by far the largest, spanning an area of about 40,000 km² (Conly et al., 2011). All mineable oil sands are located north of Fort McMurray, Alberta within the Athabasca basin, where the deposit can be found very close to the surface (Mossop, 1980).

The mineral deposit for this study is located in the Lower Cretaceous McMurray formation which consists of a dominant continental sequence of uncemented sands and shales overlying an un-conforming surface of Devonian limestone. The McMurray formation is approximately 38 m thick and it is overlain by about 128 m of strata (Hepler et al., 1989). The Athabasca basin consists of the following stratigraphic formation; Muskeg, Pleistocene Unit, Clearwater Formation, McMurray Formation and Devonian carbonates (Masliyah et al., 2011). The topmost layer of the strata is known as Muskeg and is the wet topmost layer of overburden material that contains the seeds and roots of native plants and is used for the topmost layer of the reclaimed land. Before mining, this layer is removed and stockpiled and later used for reclamation works (Masliyah et al., 2011). The Pleistocene unit overlies the Clearwater formation and both are considered as waste rocks lying above the bitumen-bearing McMurray formation. Overburden materials from these layers are normally used for road and dyke construction in the mine depending on the soil properties and its mineral content. The oil-bearing rock type is the McMurray formation which is further classified into three rock types; the Upper McMurray (UKM), the Middle McMurray (MKM) and the Lower McMurray (LKM) (Masliyah et al., 2011). The McMurray formation is made up of coarse sand, fine sand, water, and bitumen. The main element of interest is bitumen which exists in various grades across the formation. The formation rests with profound unconformity on the Devonian carbonates and is unconformably overlain by the Clearwater formation. The LKM is made up of gravel, coarse sand, silt and clay with siderite as cement. The UKM and MKM comprise of micaceous, fine-to- medium-grained sand, silt, and clay, with rare siderite as cement and intra-clasts and pyrite nodules up to 10 cm in diameter (Hein and Cotterill, 2006). Lastly, the Devonian Carbonates (DVN) which is a rock layer that sits below the oil sands (McMurray formation) and is made up of numerous limestone outcrops. A sketch of the vertical profile of an oil sands formation is shown in Fig. 1.

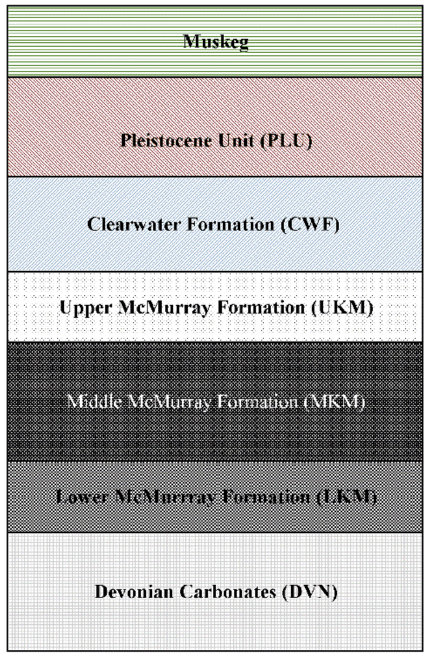

Fig. 1. Sketch of the vertical profile of an oil sands formation.

2.3. Oil sands compositions and properties

Oil sands are a loose sand deposit which contains a very viscous form of petroleum known as bitumen. These unconsolidated sandstone deposits comprise primarily of sand, clay, and water saturated with bitumen. Oil sands are sometimes referred to as tar sands or bituminous sand. Oil sands are composed of 55-80 wt% solid contents (sand, silt, and clays), 0-16 wt% bitumen and 0-7 wt% water. The composition of oil sands is defined based on particle size. For any material passing through a 44 µm (325 US mesh) sieve, it is referred to as fines which include silt, very fine quartz and clay minerals. In addition to this composition, it has been found that heavy minerals are contained in the oil sands as part of the solid contents (Bichard, 1987). These heavy minerals are unique features of the solid contents in oil sands.

The properties of the constituents of oil sands play a vital role in the processability of oil sands ores. Physical and chemical properties such as the nature of the bitumen, the coarse solid size distribution and fine solids and clay content and the salt concentration and type in the formation water all contribute to the efficiency of bitumen floatation and recovery (Masliyah et al., 2011). Furthermore, the surface properties such as surface tension, interfacial tension, and electric potentials of the sand grains and bitumen have an effect on the separation of bitumen from the sand grain with its ultimate floatation. These properties are affected by temperature as well as water chemistry used in the bitumen extraction process (Long et al., 2008). Thus, it is important to understand the compositions and the properties associated with oil sands and bitumen recovery. Each of this composition and properties affecting bitumen recovery will be discussed further in subsequent sections.

2.3.1. Bitumen

Bitumen as an unconventional fossil fuel is an extra heavy oil with high viscosity, density, and heavy metal concentrations, and a low hydrogen to carbon ratio, which makes the oil extraction process more costly, compared to that for conventional oil recovery (Masliyah et al., 2011). Bitumen from oil sands contains high molecular weight and low volatility components, with typical compositions of 83 wt% carbon, 10.6 wt% hydrogen, 4.8 wt% sulphur and, 0.4wt% nitrogen (Basu et al., 1996). The density of bitumen is higher than that of heavy oil and is very close to water. This is an important factor in the bitumen flotation process since this requires a density difference in order for oil to move to the top of the separation vessels. Therefore, air is also required as an additive to effectively reduce the density of the oil and cause the oil droplets to rise during frothing. Bitumen viscosity in-situ varies from several hundred to several tens of thousands Pascal-seconds (Carrigy, 1967). The viscosity of Athabasca bitumen is about 1,000,000 millipascal-seconds (mPa.s) at reservoir temperature, making the bitumen practically immobile; however, this characteristic gives enough material strength to the oil sands to be mineable (Mossop, 1980).

2.3.2. Organic rich solids and ultra-fine clays

Fines are defined as all solid particles smaller than 44 micrometer (μm) in diameter while clays are those fines which are less than 2μm in size, sometimes referred to as ultra-fine. Clays found in oil sands deposits are mostly comprised of kaolinite and illite. Most of the solids in the Athabasca oil sands are composed mainly of quartz sands grains, which are hydrophilic and 99 % water wet. Sand particles with a diameter larger than 44 μm (microns are considered coarse, while those less than 44 μm are considered as fine (Bowman, 1971).

Clays found in oil sands deposits are mostly kaolinite and illite. Also, evidence has shown that a substantial amount of fines are present in the form of thin discontinuous beds (Takamura, 1982). Some other trace minerals, such as mica, rutile, zircon, tourmaline, vanadium, and pyrite, are also found in the sand composition. Fines in the solid component mostly consist of silt and clay. Kaolinite (40-70 wt%) and illite (28-45 wt%) are the dominant clay minerals in Athabasca's oil sands (Chalaturnyk et al., 2002). The other common clay minerals are montmorillonite (1-5 wt%), chlorite (~1 wt%), smectite (~0.3 wt%), and mixed layer clays (~1.7 wt%) such as kaolinite-smectite and illite-smectite. The amount of clays contained in an oil sands deposit is proportional to the number of fines. Therefore, all high fines ores have a high clay content and tend to have a lower bitumen content. These lower grade ores are often described as poor processing since they disrupt the gravity separation process in extraction. Bitumen froth produced from high fines ores tend to be of a lower quality, typically containing less than 50% bitumen and more than 40% water (Masliyah et al., 2011).

Further studies conducted have shown that certain mineral solid fractions are associated with significant amounts Organic-Rich Solids (ORS) (Kotlyar et al., 1988). These organic solids are composed of toluene insoluble organic matter that is physically or chemically adsorbed onto particle surfaces. ORS exist primarily as aggregates of clay, sand, and silt bound together by organic matter that is largely humic in origin. The solids interact strongly with bitumen. During bitumen separation, these solids may report to the bitumen froth, the primary tailings or remain with the middlings, depending on their size and density. As a result of their close association with bitumen, these solids are responsible for significant losses with certain ore types. In the tailings, the solids can contribute to flock structure formation through bonding between particles by free bitumen. In bitumen separation processes, the organic matter associated with various ORS fractions represents an impediment to optimum bitumen separation and upgrading. In this sense, these solids are considered to be active relative to the inactive water wetted quartz particles comprising the bulk of the oil sands ore. Preliminary results indicate that the ORS content of an ore appears to be a better predictor for ore processability than the traditional use of bitumen or fines (~44 μm) contents. Two types of ORS have been recognized. The first type is a coarser fraction, usually less than 44 μm but also occurring as particles greater than 100 μm in diameter. This coarser fraction of ORS typically occurs as aggregates of smaller particles bound together by humic matter and precipitated minerals. During the bitumen separation process, these heavy aggregates transport any associated bitumen into the aqueous tailings, thus reducing overall bitumen recovery. The second type of ORS comprises very thin, ultra-fine clay particles with a major dimension of <0.3 μm in size. These ultra-fine clays, with a surface coating of organic matter, remain with bitumen during the separation process. In bitumen upgrading, these solids may be entrained with volatile overheads and cause problems in downstream operations (Kotlyar et al., 1988).

2.3.3. Heavy minerals in oil sands

The occurrence of heavy minerals in Alberta's oil sands has long been known and has been documented by many researchers (Kaminsky et al., 2008). The most relevant heavy minerals identified were titanium-bearing, zirconium-bearing, and the rare-earth-bearing minerals in a smaller fraction of mineral solids. These minerals are all important from the point of view of economic potential. In general, the heavy mineral concentration in most of the Athabasca McMurray Formation was found to be consistently low averaging about 0.35% titanium dioxide (TiO_2) and 0.032% zirconium dioxide (ZrO_2) in feed grade oil sands. The TiO2 content varied from 0.08 to 1.6% and the ZrO2 content ranged from 0.0012 to 0.13%. Other valuable elements that were identified in the oil sands included rare earth and trace amounts of palladium, platinum, and gold. However, none of these occurred in high enough grades to warrant economic extraction. The distribution of heavy minerals in different range sizes on the surface mineable area of the Athabasca oil sands was studied. It was observed that titanium and zirconium minerals were concentrated in the fine size fractions, and iron minerals in the coarse size fractions. The silicon minerals seem to distribute evenly throughout the size range tested. In terms of size, heavy minerals are typically fine-grained. The 100 mesh (150 mm) size fraction is probably of most interest to potential users of the heavy minerals. It was reported that the 100 mesh fraction made up approximately 55 to 66% of the solid weight of the oil sands. Although bitumen is the primary target of the commercial extraction plants, there is a selective enrichment of the heavy minerals in the bitumen extraction processes as well. The titanium and zirconium minerals seem to move with the bitumen. As the bitumen froths are treated to remove the mineral solids and water, these heavy minerals are concentrated in the froth treatment tailings. Thus, in order to make use of the heavy minerals contained in the oil sands tailings, the heavy minerals need to be separated and upgraded (Kaminsky et al., 2008).

2.3.4. Connate water in oil sands

The water present in oil sands contains dissolved ions such as sodium, calcium, magnesium, chloride, potassium, sulfate and bicarbonate. Bitumen is not in direct contact with the mineral phase because a thin film of water surrounds individual sands grains. The thickness of the water film is predicted to be about 10 nm (Hall et al., 1982). This water film is assumed to be stabilized by electrostatic forces coming from electrical double layers at the oil/water and water/sand grain interfaces (Hall et al., 1982). A thin layer of water separates bitumen from sand particles, and, as the water content of an ore increases, the bitumen content decreases (Takamura, 1982). For higher concentrations of ions in the water, the bitumen content will be lower; this means that rich oil sands have a low salt content and poor oil sands have a high salt content. The pH of most of the oil sands is between 8 and 9, with some acidic ores at higher depths (Masliyah et al., 2011). Also, the bitumen and water contents vary and depend on the ore variation and the clay mineralogy (Kasperski, 2001). Takamura, (1982) presented a description of the generic microscopic structure of Athabasca's oil sands. A microscopic structure of Alberta Oil Sands could be seen in Fig. 2.

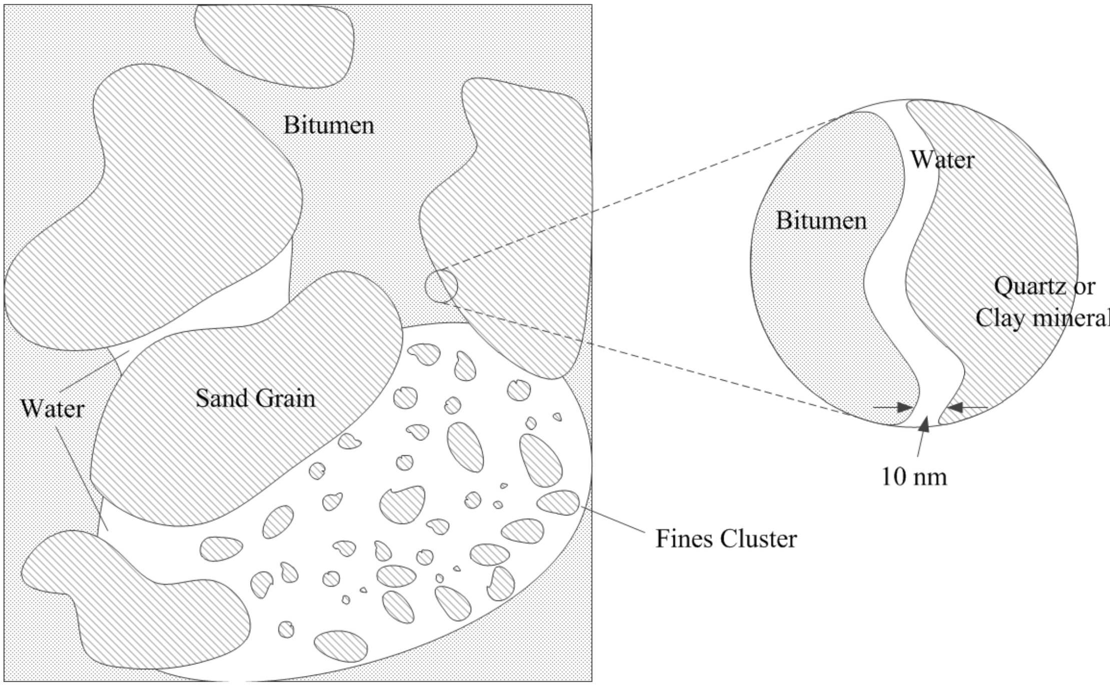

Fig. 2. Microscopic structure of Alberta oil sands modified after Takamura (1982).

3. Oil Sands Classification

There are several ore classification schemes for oil sands based on descriptors such as bitumen content, fines content and ore processability as indicated in Table 1 (Kaminsky, 2008). The most common method of classifying oil sands ore is based on its grade. A high-grade ore is considered to contain more than 10% bitumen, a mid-grade ore contains 8 - 10% bitumen, and a low-grade ore contains less than 8% bitumen. Likewise, a high-fines ore contains more than 18% fines while low-fines ore contains less than 6% fines. Processability indicates the quantity of bitumen that is being recovered in the froth. When more than 80% of bitumen and 90% of total bitumen recovery are obtained from the froth, it is referred to as a good processing ore (Kasperski, 2001). Froth quality and settling behavior are also sometimes considered as factors in processability, but most processability curves report recovery only. A high-quality froth will contain about 66% bitumen, 25% water, and 9% solids or a 7:1 bitumen to solids ratio (Kasongo et al., 2010).

Table 1: Oil sands ore classification.

Methods Classification	Content (wt%)	Ore Classification
Bitumen	>10 Between 8-10 <8	High Medium Low
Fine Content	>18 <6	High Fines Ore Low Fines Ore
Processability	Bitumen >10 Fines < 6 Bitumen < 8 Fines > 18	Good Processing Ore Good Processing Ore Poor Processing Ore Poor Processing Ore

4. The Effect of Oil Sand Properties in Bitumen Recovery

According to the Alberta Energy Regulator (AER) (Alberta Energy Regulator, 2016), there are four criteria used collectively to establish the volume of bitumen that an operator is required to recover each year from its mining and processing operations. The criteria are:

- **Cut off grade**: This is defined as the minimum bitumen content of the oil sands that would be classified as ore. The standard cutoff grade is 7 weight percent bitumen.
- **Minimum mining thickness:** This is the minimum thickness of ore that can be separated from waste or waste that can be separated from ore. It has been set at 3 meters
- **Total Volume to Bitumen in Place ratio (TV: BIP):** This the minimum value for TV/BIP that would be used to determine the pit crest limits. It is set at 12.
- **Processing Plant recovery:** This is a variable factor based on the average bitumen content of the as-mined ore. If the average bitumen content of the as-mined ore is 11 weight percent bitumen or greater, the recovery factor is 90 weight percent. If the average bitumen content of the as-mined ore is less than 11 weight percent bitumen, recovery is determined as shown in Eq. (1), where x is the average weight percent bitumen content of the as-mined ore:

$$Recovery = -202.7 + 54.1(x) - 2.5(x^2) \tag{1}$$

The recovery of bitumen from oil sands ore during extraction depends on certain different process variables. The variables can be classified into three main groups namely; ore properties, water chemistry, and operating conditions. Extensive research works have been conducted in order to recognize and clarify the involved factors that could impact bitumen recovery during bitumen extraction process from oil sands ores (Sanford, 1983; Dai and Chung, 1995; Basu et al., 1996; Masliyah et al., 2004; Long et al., 2008; Wallwork et al., 2008) as shown in Table 2. For this research, the focus is based only on the ore properties since it involves the mine-to- mill concept. Thus, ore properties such as bitumen grade, fines contents, types of fines, and mineralogy of sands and fines will be considered in this review.

Table 2: Factors affecting bitumen recovery and oil sands ore processability.

Ore Properties	Water Chemistry	Operating Conditions
Bitumen grade	pH	Temperature
Fines content	Presence, valence and concentrations of ions	Mechanical mixing and residence time
Types of fines	Presence and concentrations of surfactants	Slurry density
Mineralogy of sands and fines	Presence and concentrations of carbonates	Aeration
Weathering of ores	Presence and concentrations of dispersants and polymers	Bubble size

4.1. Effect of organic-rich solids in bitumen recovery

Bitumen is usually separated from the inorganic matrix by a surface layer of interstitial water which allows bitumen to be liberated from its bulk mineral component. But the humic content associated with organic-rich solids tend to adsorb and bind the bitumen to both internal and external aggregate surfaces thus reducing the recovery of bitumen. The size and density of ORS are vital properties that need to be considered in bitumen recovery. Small particles of ORS report with the froth along with the liberated bitumen. If the particles are not discarded to the tailings during the froth cleaning process, it will remain with the bitumen froth and adversely affect the quality of the bitumen. Coarser and higher density aggregates will not float with the bitumen fraction rather they will remain with the middling or settle with the primary tailings along with the associated bitumen thus reducing the recovery (Kotlyar et al., 1988).

4.2. Effect of ultra-fine clays in bitumen recovery

In the oil sands industry, it has been recognized that the coarse sands do not cause any problem throughout the extraction process. However, the fines (<44 μm) content plays an important role during the oil extraction process. Bitumen recovery decreases with increasing fines content in warm water extraction (Chalaturnyk et al., 2002). It is illustrated that small particle size is a contributing factor affecting bitumen recovery but comparison tests with ultra-fine silica particles (<0.3 μm) showed that mineralogy is a more important parameter (Wik et al., 2008). Nano and micro-sized minerals, mainly clay minerals, are most detrimental (Hooshiar et al., 2012). These minerals may interact with the solvent, bitumen and connate water due to their small particle size, high specific surface area, swelling capacity, cation exchange capacity, layer charge and, specific physicochemical properties. The presence of fine solids in oil sands have been found to adversely interfere with interactions among bitumen droplets. Fine solids also minimize bitumen coalescence thus, producing small-sized bitumen droplets which are more difficult to contact with air bubbles. Coated bitumen droplets form steric barriers between bitumen and air bubbles which makes it difficult for the bitumen to attach and engulf the bubbles. This results to an increase in slurry viscosity, and possibly gelation, which slows the flotation of formed bitumen-bubble aggregates. The bitumen froth quality and its floatation kinetics becomes reduced due to the fine solids appearing in the froth with recovered bitumen and slurry water (Liu et al., 2008).

The mineralogy of clay minerals in the Alberta oil sands has been studied and a summary can be found in Mikula et al. (2008). Based on such studies, the mineralogy of clay minerals in the Alberta oil sands deposit varies across the deposit. Kaolinite, illite, smectite, and chlorite are found to be the major clay minerals in the Alberta oil sands deposits with the first two being the most abundant. In one of the studies conducted by Zhou et al. (1999), to investigate the effects of fine solids with different surface properties on oil extraction, it shows that the addition of fine solids has a negative impact on bitumen extraction. The bitumen recovery decreased with the solids addition, compared with no solids addition. Also, the smaller solids (e.g. < 5 mm silica) reduced bitumen recovery more than the coarser solids (e.g. < 40 mm silica). This could be attributed to the physical barriers built between bitumen and bubbles by suspended fine solids, increasing the difficulty for direct bitumen-bubble contact. Since finer solids are more easily suspended in the slurry, they would be more likely to block direct bitumen-bubble contact than coarser solids, thereby retarding the flotation more severely. In another study conducted by Liu et al. (2008) to investigate the role of fine clays in bitumen extraction from oil sands, it was observed that in the absence of calcium, montmorillonite clays were weakly attached on the bitumen surface. However, with the addition of 1 millimolar (mM) of calcium-montmorillonite clay was attached strongly to the bitumen surface. The reason for the strong attachment was due to a low electrostatic double-layer force and an increased adhesive force between bitumen and montmorillonite clays which acted as a barrier for bitumen - air attachment and bitumen - bitumen coagulation, thus, led to poor bitumen recovery.

Although many efforts have been made to demonstrate the impact of bulk properties of oil sands ore on bitumen recovery, it is equally important to understand the clay characteristics and mineralogy of organic-rich solids and ultrafine clays in the oil sands. Both extraction recovery and product quality are significantly affected by interactions between organic materials and clay minerals. These interactions produce clay-organic matter complexes which make the bitumen extraction process more complicated. Therefore, it is crucial to understand the influence of water, bitumen, and solids, on the extraction process (Hooshiar et al., 2012).

5. Oil Sands Mining and Waste Management

5.1. Oil sands mining and mine planning

The first stage in any typical oil sand mining operation is to remove approximately 30 m of overburden material prior to the oil sand ore can be mined. The overburden is stripped using a truck and shovel fleet. The overburden stripped material is stored for later reclamation of the mined out area. The ore body thickness generally varies from 20 to 90 meters. The underlying oil sand is mined using large mining shovels, transported in mining trucks, and sized in double roll crushers. The oil sand is then mixed with water in a processing tower to create an oil sand slurry, and this slurry is pipelined to a central extraction plant. After mining and processing the oil sands ore, more than 80% of the tailings are deposited in tailing dams (Masliyah et al., 2011). A significant amount of tailings material has caused several environmental issues. A typical mine plan strategy describes 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 was developed by Lerchs and Grossmann as LG algorithm (Lerchs and Grossmann, 1965).It determines which blocks are within the optimal pit. With the optimal pit limit, the decision to make is the order that the blocks should be extracted so as to generate the maximum NPV.

The implementation of an exact solution to solving mine planning problem is thorough mathematical programming. Mine planning models are divided into short term and long term models. Strategic decisions such as the 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 considered in short-term mine planning (Badiozamani and Askari-Nasab, 2014).

5.2. Waste management

Oil sand tailings are produced as a by-product of the bitumen extraction process and are deposited in large tailings ponds. Tailings are characterized by having poor consolidation and water release properties. The tailings slurry is a mixture of sand particles, dispersed fines, water and residual bitumen. It contains approximately 55 wt% solids, of which 82 wt% is sand, 17 wt% are fines smaller than 44 µm and 1 wt% is residual bitumen. When tailings are pumped into the tailing ponds, the coarse solids settle out very rapidly to form dykes and beaches. Most of the fines and residual bitumen are carried in the run-off slurry that flows over the already formed beach. The run-off slurry stream arrives at the water's edge in the tailings pond with a suspended solids concentration of about 3-8 wt%. These fine tailings solids settle quickly over several days to create a zone with 20 wt% solids content and a "free water zone" that contains little solids. This water is recycled as extraction water. Below the free water zone, solids settling continue within the fine tailings; however, the suspension starts to develop non-Newtonian properties which make further settling an even slower process (Sheeran, 1993). Over 2 to 3 years, fines tailings settle to 30 wt% solids with a stable slurry structure denominated mature fine tailings (MFT). This suspension has very high viscosity and yield stress (MacKinnon, 1989; Kasperski, 1992). Further, de-watering occurs very slowly and it takes several centuries for the MFT to reach the consistency of soft solids. Even after 40 years, the MFT does not have enough strength to support the overburden or soil horizon replacement required for reclamation (Sheeran, 1993; Eckert et al., 1996). A schematic cross-section of an oil sands tailings pond is shown in Fig. 3.

The two main challenges in managing oil sands tailings are environmental challenges and space limitations defined in the lease agreements. The environmental challenges include the toxicity of the tailings pore water and land reclamation. In dealing with this, dewatering techniques have been developed to decrease the volume of water in the tailings and to recycle the water to the processing plant. The regulatory requirement from Energy Resources Conservation Board (ECRB) referred to as Directive 085, requires oil sands companies to reduce the volume of fluid tailings and convert them to trafficable landscapes (Kalantari et al., 2013). Based on these facts, tailings management represents a real environmental impact, primarily related to water usage and recycling. The production of one barrel of bitumen requires approximately 12 barrels of water, where about 70 % of this water is recycled and the remaining 30 % comes from the river, leaving a net requirement of almost 4 barrels of water per barrel of bitumen. This remaining water is tied up in the pore spaces of the sand, silt, and clay in the tailings, and is effectively lost to the process (Mikula et al., 2008).

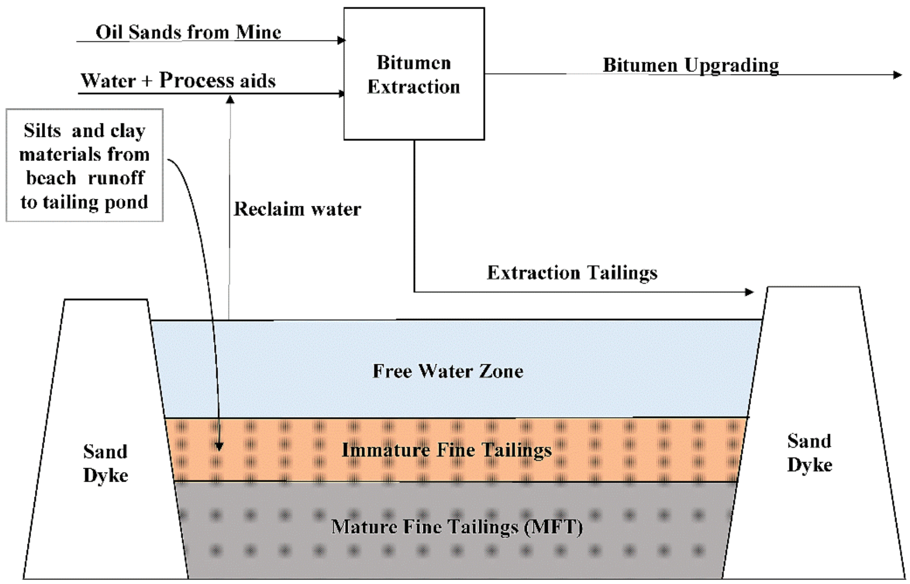

Fig. 3. Cross section of an oil sands tailing basin modified after Beier and Sego (2008).

5.3. Integrating mine planning and waste management in oil sands.

The objective of a typical mine plan is the maximization of Net Present Value (NPV) over the mine-life which is subjected to a number of constraints. Most of the constraints in mine planning models are technical constraints. Examples of constraints are the capacities of mining and processing in each period, the limitations on the grade range as required by processing plants and the precedence constraints to control the vertical order of extraction of the mining-blocks (Badiozamani and Askari-Nasab, 2014). Considering the environmental issues related to the oil sands surface mining, two concepts can be integrated into the long-term mine planning optimization framework, thus tailings management and solid waste management. The solution to such an integrated model provides sustainable production planning in the oil sands mining operation.

The regulatory requirement by the Alberta Energy Regulator (AER) Directive 082 requires oil sands mining companies to integrate their waste management strategy into their long-term production plans. It also requires mining companies not to leave behind any material containing more than 7% bitumen. In order to reduce the environmental footprints, dyke construction should take place simultaneously as the mine advances and each push back become available for dyke construction. The material required for the dyke construction mainly comes from the mining operation. The dyke material includes Overburden (OB), Inter-burden (IB) and Tailings Coarse Sand material (TCS) (Ben-Awuah and Askari-Nasab, 2013). The above mentioned regulatory requirement and environmental issues makes the waste management strategy a necessary part of oil sands long-term production planning. 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 studied the effect of oil sands mine planning on tailings management, in terms of Composite Tailings (CT) production, is published by Kalantari et al., (2013). The authors investigated the linkage between long-term mine planning and CT production in the presence of uncertainty. A tailings model including the tailings mass-balance relations is developed to map the tonnage of the ore feed to the final CT tonnage. However, the capacity of the tailings facility and the deposition of produced CT are not considered explicitly in the long-term mine planning model. A review of the literature reveals that there are not many research works addressing the linkage between tailings management and mine planning. On the other hand, the ERCB forces Alberta oil sands operators, through Directive 085, to publish their tailings management plans (McFadyen, 2009). For solid waste management, the material required for construction of dykes comes mainly from mining and processing operations, as overburden, inter-burden, and coarse tailings sand (Ben-Awuah, 2013).

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, 2009; Ben-Awuah and Askari-Nasab, 2011). However, there are a number of complexities in modeling and solving an integrated optimization framework.

A Mixed Integer Linear Programming (MILP) model for long-term mine planning is known to be an NP-hard problem (Gleixner, 2009). 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 and Askari-Nasab, 2011). A team of geologists, geotechnical and mine planning engineers, tailings planners, and operations engineers work on dyke construction plan, 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 by partitioning the empty pit by constructing a number of internal dykes (Ben-Awuah, 2013).

Ben-Awuah and Askari-Nasab, (2013) proposed an integrated optimization framework for long-term open pit mine planning in oil sands surface mining. The authors considered 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 proposed a mixed integer goal programming model and considers two destinations for the extracted material: the overburden and inter-burden 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 used for dyke construction. Fig. 4 illustrates the strategic production planning for an oil sands deposit containing K mining cuts and M push backs. Mining-cuts are made up of blocks within the same level that is grouped together based on their attributes; location, rock type and grade using an agglomerative hierarchical clustering algorithm by Tabesh and Askari-Nasab (2011). The proposed model is a comprehensive mine planning model that covers the solid waste disposal and dyke construction planning.

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, 2009). A review of reclamation plans published by the oil sands operators proves that the material used for capping the closure phase, such as the overburden and tailings coarse sand, comes from the mining and processing operations. This shows another potential development in typical mine planning models by the inclusion of a material required 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. 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. An integrated model for long-term mine planning, with respect to reclamation material handling and tailings capacity constraints has been proposed and 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.

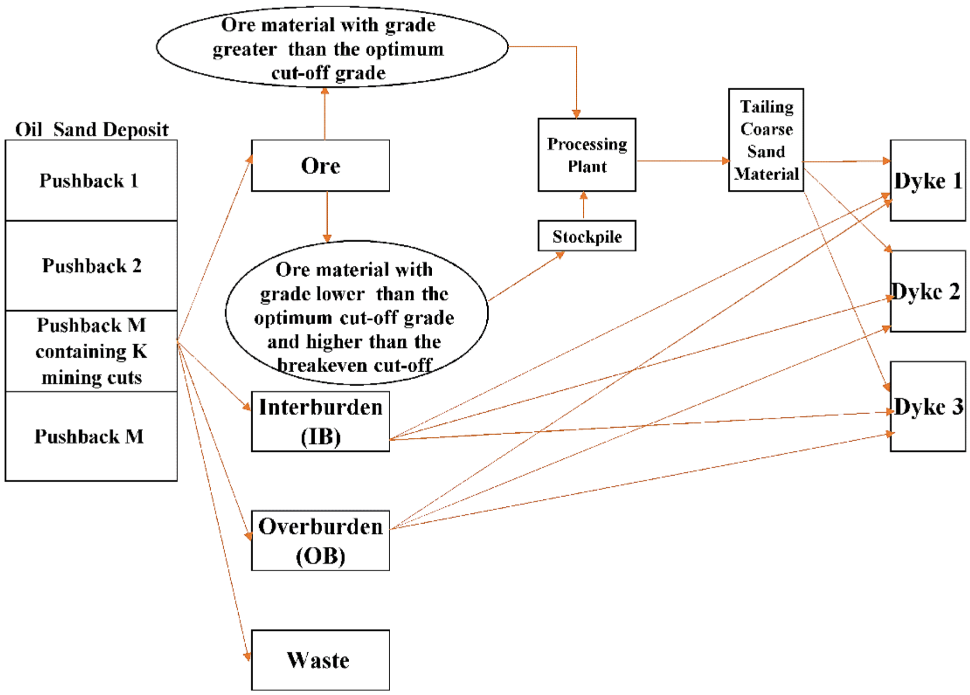

Fig. 4. Oil sands production planning and waste management modified after Ben-Awuah and Askari-Nasab (2013).

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 took further steps in integrated mine planning by including the tailings management, in terms of composite tailings production and deposition, in the mine planning optimization framework (Badiozamani and Askari-Nasab, 2014).

6. Open Pit Optimization and Production Scheduling

The operation and management of a large open pit mine is an enormous and complex task, particularly for mines having a life of many years. Optimization techniques can be successfully applied to resolve a number of important problems that arise in the planning and management of a mine. These applications include: ore-body modeling and ore reserve estimation; the design of optimum pits; the determination of optimal production schedules; the determination of optimal operating layouts; the determination of optimal blends; the determination of equipment maintenance and replacement policies (Caccetta and Giannini, 1986).

A fundamental problem in mine planning is determining the optimum ultimate pit limit of a mine. The optimum ultimate pit limit of a mine is defined to be that contour which is the result of extracting the volume of material which provides the total maximum profit whilst satisfying the operational requirement of safe wall slopes. The ultimate pit limit gives the shape of the mine at the end of its life. Usually, this contour is smoothed to produce the final pit outline. Optimum pit design plays a major role in all stages of the life of an open pit: at the feasibility study stage when there is a need to produce a whole-of-life pit design; at the operating phase when pits need to be developed to respond to changes in metal prices, costs, ore reserves, and wall slopes; and towards the end of a mine's life where the final pit design may allow the economic termination of a project. At all stages there is a need for constant monitoring of the optimum pit, to facilitate the best long-term, medium-term and short-term mine planning and subsequent exploitation of the reserve. The optimum pit and mine planning are dynamic concepts requiring constant review. Thus the pit optimization technique should be regarded as a powerful and necessary management tool. Further, the pit optimization method must be highly efficient to allow for an effective sensitivity analysis. In practice, one needs to construct a whole spectrum of pits, each corresponding to a specific set of parameters. The ultimate pit limit problem has been efficiently solved using the Lerchs-Grossmann and graph-theoretic algorithm also known as Picard's network flow method. These methods are based on the block model of an orebody (Lerchs and Grossmann, 1965; Picard, 1976).

Production scheduling in surface mining is defined as the sequence in which blocks of the ore orebody are extracted and moved in order to maximize the net present value subject to mining, economic and processing constraints (Caccetta and Giannini, 1986).Typically, the constraints related to the mining extraction sequence are: mining, milling and refining capacities; grades of mill feed and concentrates; stockpile-related restrictions; a range of logistics issues and various operational requirements such as minimum pit bottom width and maximum vertical depth. The definition of block models gives a starting point for the production scheduling optimization task. Block models divide the orebody into small blocks which are dependent on pit slopes, orebody dip, grade distribution and the type of equipment being used (Caccetta and Giannini, 1986). Each block is assigned certain attributes using either kriging or inverse distance interpolation techniques. These attributes include density, grade, and tonnages. Using the cut-off grade optimization techniques, the blocks are then divided into ore and waste. The size of the blocks created can be in the order of millions thus requiring movement over a long period of time. This movement of blocks demands adequate scheduling considering the physical and operational constraints (Khan and Niemann-Delius, 2014).

The techniques used by Operation Research (OR) in mine production planning are collectively grouped into two main approaches which include (i) deterministic approach and (ii) uncertainty-based /stochastic approach. In the deterministic approach, it assumes all inputs to have fixed known real values from which a sequence of possible solutions are generated. The number of sequence point is defined by the technique that is being used and the technique terminates each sequence of points once a solution has been reached or when the number of iterations has been exhausted. Linear programing, integer programing and mixed integer linear programming use this type of technique. (Hickman, 2014). One of the major drawbacks on the deterministic approach is that the optimal scenario is affected by uncertainties related to input parameters. These uncertainties are categorized as in-situ grade uncertainty, economic uncertainties such as capital and operating costs and technical mining specification uncertainty such as extraction capacities and slope considerations (Dimitrakopoulos and Ramazan, 2008; Hickman, 2014). Meanwhile, in stochastic approach, it uses some form of randomness when searching for feasible solutions (Hickman, 2014). The input to stochastic approach takes into account the variabilities of each input parameter. Their outputs do not give one optimum solution but a range of solutions with some form of distribution to give the user a feel of variability for the solution. The use of stochastic techniques works best when using evolutionary algorithms (Hickman, 2014).

Due to the complexity and size of the problem all these approaches suffer from one or more of the following limitations: (i) they cannot cater for most of the constraints that arise; (ii) they yield only suboptimal solutions and in most cases without a quality measure; (iii) they can only handle small sized problems. The most commonly applicable method is parameterization which was initially introduced by Lerchs and Grossman (1965). In these technique, a set of nested pits is generated, starting with the final pit contour, by varying the economic parameters. For each parameter value, the Lerchs-Grossman algorithm is applied to generate the optimum pit. The most widely used software packages that use this method include: Whittle's Four-D and Four-X and Earthworks NPV Scheduler (Ver. 3.2.5). The latter product has a restricted tree search procedure that is used to re-sequence the pushbacks in an effort to improve the NPV (Meagher et al., 2014).

Stochastic mine planning is a relatively recent development aimed at addressing uncertainty in ore supply from an orebody, commodity prices and metal demand, as well as expanding to other issues of uncertainty in mine planning. The application of stochastic optimization in mine scheduling problems have proven to substantially increase the net present value to about 30% compared to other deterministic approaches used (Ramazan and Dimitrakopoulos, 2018).

6.1. Operation research methods used in mine scheduling problems

Production scheduling requires efficient optimization techniques in order to realize the benefits. Several optimization techniques have been applied. These operation research methods include linear programming (Johnson, 1968), mixed integer programming (Gershon, 1983), branch and cut (Caccetta and Hill, 2003), dynamic programming (Onur and Dowd, 1993), fundamental tree algorithm (Ramazan, 2007), lagrangian parameterization (Dagdelen, 1986), simulated annealing and genetic algorithms (Denby and Schofield, 1995) and neural networks (Denby et al., 1991). The main goal of an open pit mine production scheduling problem in oil sands mining is to specify the sequence in which blocks should be removed from the mine in order to maximize the total discounted profit from the mine subject to a variety of constraints. These constraints include; the mill throughput, the volume of material extracted per period, the blending constraints, and stockpile related constraints, and logistics constraints. In order to achieve this goal, mathematical formulations which satisfy these constraints are developed (Gershon, 1983; Caccetta and Giannini, 1986).

6.2. Linear programming

The Linear Programming (LP) model was proposed by Johnson as an optimization technique in mine scheduling problem (Johnson, 1968). The LP model considered the time value of money, different processing types and also the dynamic cutoff grade strategy. In order to solve the LP model, the large multi-period production planning model is decomposed first into a master problem and a set of sub-problems by using Dantzig - Wolf decomposition principles. Each sub-problem is then solved as a single-period problem that has the same characteristics as the ultimate pit limit problem. This can be done using a maximum network flow algorithm. After solving all sub-problems, solving the master problem is relatively simple. Although Johnson's method generated optimum results for each period individually, however it does not solve totally the mine scheduling problem in a long term., The variables were linearly continuous, which was responsible for fractional block extraction. Also, the LP model provided situations in which some portion of a block was extracted while all the overlying blocks have not been mined. This drawback causes some percentage of overlying blocks to be suspended in air. Another disadvantage of this model was that it had too many constraints (nine slope constraints per block), which itself limits the number of blocks that can be handled by the model (Johnson, 1988).

6.3. Mixed integer programming

The problem of partial mining block associated Johnson's LP model was latter addressed by Gershon (1983) who discussed a Mixed Integer Programming (MIP) model that would allow partial blocks to be mined if all precedent blocks have been completely removed. The key to this formulation was adding additional decision variables to Johnson's LP model. The advantages of the MIP model compared to the linear programming model was that, it provided a more practical extraction sequence in mine scheduling. Partial block mining was allowed on the condition that all blocks preceding the partially mined block have been mined. The net result of this model was that only one constraint per block was required. The main disadvantage of this model was its inability to handle large problems using commercial software because it contains too many binary variables. In addition, because of increasing the size of the model, the dynamic cut-off grade concept could not be considered (Gershon, 1983).

6.4. Integer programming

6.4.1. Lagrangian relaxation approach

This is another research method used in solving mine scheduling problem. A binary linear programming formulation usually involves a large number of zero – one variables, which is beyond the capacity of current commercial packages. Several approaches have been proposed by researchers to solve such models. Dagdelen and Johnson (1986) used a lagrangian relaxation approach to solve the open-pit production planning problem. The objective function is to maximize the NPV, subject to block precedence and production capacity constraints (Dagdelen, 1986). The authors relax the mining capacity constraints and added penalty in the objective function accordingly. The sub-gradient algorithm is used to update the Lagrangian multipliers for small-scale problems. The Lagrangian multipliers are adjusted using the sub-gradient method until the optimum schedule is obtained. At each step, a problem similar to an ultimate pit limit problem should be solved. In cases where there are no multipliers that can result in a feasible solution for the constraints, this method may not converge to an optimum solution. This problem is named the gap problem. Caccetta et al., (1998) tested this method on a real ore body with 20979 blocks and six time periods. The schedule obtained was within 5% of the theoretical optimum. Another drawback of this algorithm is that it does not consider the dynamic cutoff grade concept during scheduling (Caccetta et al., 1998). Akaike and Dagdelen extended the work by Dagdelen and Johnson (1986), using an iterative procedure to update the values of Lagrangian multipliers. Akaike and Dagdelen then transformed the integer programming model by the use of the Lagrangian relaxation method, so that the transformed problem has the same characteristics as the final pit design problem. This problem can then be interactively solved changing the Lagrangian multipliers by using the sub-gradient method to converge it to the optimum solution of the primal problem. The authors also improved the efficiency of the sub-gradient method to reach the optimal solution much faster. The most important advantages of this algorithm are the use of the dynamic cutoff grade concept with the stockpile option with zero – one variables during the scheduling process. This will improve the NPV of a mining project. The disadvantage of this method is the possibility of a gap problem occurring, which means that it may not lead to an optimum solution (Akaike and Dagdelen, 1999).

6.4.2. Clustering Approach

The next approach to solve an Integer Programming (IP) model of production planning in an open pit mine is the clustering approach, which was applied by Ramazan et al. (2005). Clustering means classifying the large amount of data into relatively few classes of similar objects. This is the reason for complexity reduction in the considered application, which allows for improved decisions based on the information gained. Ramazan et al. (2005) combined ore and waste blocks together to decrease the number of binary variables in the IP model. They introduced the fundamental tree as any combination of blocks within the push backs, such that the blocks can be profitability mined and obey the slope constraints so that no sub-set of chosen blocks can be found that meets the above two requirements. This re-blocking (clustering) process is done using an LP mathematical formulation so that the information available for individual blocks is not lost (Ramazan et al., 2005).The authors created three fundamental trees that can be used for the LP model where tree I can be mined first; trees II and III are then feasible to mine in the suggested order. After defining the fundamental trees, their precedence relations should be determined using the cone template. Each fundamental tree is treated as a mining block containing a certain ore tonnage, metal content and quality parameters. Then a binary variable is assigned to each fundamental tree for each production period except the last one. In order for the IP model that uses fundamental trees to be handled by commercial software such as CPLEX*, the material within the final pit limit is divided into smaller volume by determining 3 to 5 push backs. Finally, fundamental trees should be scheduled by an IP formulation that contains all the mining and milling operational constraints and tree sequence requirements. The advantages of using clustering approach is that it reduces the binary variables and eliminates the gap problem. It also generates more NPV than other scheduler software. Its disadvantages are that it needs to generate pushbacks before scheduling. More than one iteration is needed to generate fundamental trees. Finally, its application is complicated, the optimality of the solution depends on the optimality of the generated pushbacks (Ramazan et al., 2005).

6.5. Mixed integer linear programming

Many combinatorial optimization problems that are formulated as Mixed Integer Linear Programming (MILP) problems can be solved by branch-and-cut methods. These are exact algorithms consisting of a combination of a cutting plane and branch-and-bound algorithms. These methods work by solving a sequence of linear programming relaxations of the IP problem. Cutting plane methods improve the relaxation of the problem to more closely approximate the IP problem. Branch-and-bound algorithms proceed by a sophisticated divide and conquer approach to solve problems. It is usually not possible to solve a general IP problem efficiently using just a cutting plane approach; it is necessary to also use branching, which results in a branch-and-cut approach (Mitchell, 2002).

Caccetta and Hill (2003) outlined their branch-and-cut procedure for solving IP models of Long-Term Production Plan (LTPP) problems. Because of the commercialization of their software, they did not provide full details of their algorithm. Explicit incorporation of all constraints (like maximum vertical depth, minimum pit bottom width and stockpile option) in the optimization procedure is a key advantage of their algorithm. Also, it can produce good solutions for medium mine production planning problems. However, obtaining optimal solutions for large problems is difficult. On a large model containing about 209600 blocks and ten scheduling periods, they could obtain a solution within 2.5% of the optimum within four hours. Another disadvantage of this method is that they did not optimize the cutoff grade during the optimization process. It should be noted that for large and/or hard problems, branch-and-cut methods can be used in conjunction with heuristics or meta-heuristics to obtain a good (possibly optimal) solution, and also to indicate how far from optimal this solution may be obtained. MILP formulations, do not consider the smoothness of the scheduled patterns, which relates to equipment movement in a period and to equipment access. Also, geological uncertainty is ignored in the MILP optimization model. Thus, the schedules that are manually generated, are often outside the specified operating range and certainly far from optimal. The usual approach is to first determine the final pit outline and then through a series of refinements mining schedules are generated. The final pit outline is determined by smoothing the contour produced by solving the ultimate pit limit problem. The ultimate pit limit is the maximum value pit resulting from the mining of ore and waste blocks under the assumption that all mining could be done in one period (Caccetta and Hill, 2003).

6.6. Stochastic integer programming

The complexity of mine scheduling problem is increased by uncertainties due to the sparse variability of geological data. The uncertainty of the ore grade may cause discrepancies between planning expectations and actual production. Various authors presented methodologies to account for grade uncertainty and demonstrate its impact. Godoy and Dimitrakopoulos (2004) presented a new risk-inclusive long-term production plan (LTPP) approach based on simulated annealing. A multistage heuristic framework was presented to generate a schedule that minimizes the risk of deviations from production targets. The authors reported a significant improvement in NPV in the presence of uncertainty; however, heuristic methods do not guarantee the optimality of the results. Also, these techniques can be difficult to implement, and many parameters may need to be chosen in order to get reasonable results. Osanloo et al. (2008) proposed a risk-based algorithm for surface mine planning. A predefined distribution function is used for some variables such as commodity price, mining cost, processing cost, investment required, grade and tonnage. Different schedules are generated for a number of realizations of the grades. The proposed method leads to multiple schedules reflecting the grade uncertainty. Koushavand et al. (2014) used simulated orebodies to show the impact of grade uncertainty on production scheduling. They used simulated orebody models one at a time in traditional optimization methods; however, this sequential process does not optimize accounting for uncertainty. Ramazan and Dimitrakopoulos (2018) suggested a mixed integer linear programming (MILP) model maximize NPV for each realization. Then, the probability of extraction of a block at each period is calculated. These probabilities are used in the second stage of optimization to arrive at one schedule however the uncertainty is not used directly in the optimization process. Ramazan and Dimitrakopoulos (2018) also presented a Linear Integer Programming (LIP) model to generate optimal production schedules. Multiple realizations of the block model were considered. This model has a penalty function; the cost of deviations from the target production and is calculated based on the geological risk discount rate (GRD), which is the discounted unit cost of deviation from target production. The authors use linear programming to maximize a new function that is NPV fewer penalty costs. It is not clear how to define the GRD parameter (Ramazan and Dimitrakopoulos, 2018).

Stochastic integer programming (SIP) provides a framework for optimizing mine production scheduling considering uncertainty. A specific SIP formulation is briefly shown to generate optimal production schedules, using equally probable simulated orebody models as input, without averaging the related grades (Dimitrakopoulos and Ramazan, 2008). The optimal production schedule is then the schedule that can produce the maximum achievable discounted total value from the project, given the available orebody uncertainty described through a set of stochastically simulated orebody models. The proposed SIP model allows the management of geological risk in terms of not meeting planned targets during actual operation. This is unlike the traditional scheduling methods that use a single orebody model, where risk is randomly distributed between production periods while there is no control over the magnitude of the risks on the schedule. The objective function of the SIP model is constructed as the 'maximization of a profit function'. The profit function is defined as the total expected NPV minus the cost of deviations from planned production targets. The general form of the objective function is expressed in Eq. 2.

$$Max\sum_{t=1}^{P}\left[\sum_{i=1}^{N}v_i^t b_i^t-\sum_{s=1}^{M}\left(c_u^{to}d_{su}^{to}+c_1^{to}d_{sl}^{to}+c_u^{tg}d_{su}^{tg}+c_l^{tg}d_{sl}^{tg}+c_u^{tq}d_{su}^{tq}+c_l^{tq}d_{sl}^{tq}\right)\right] \tag{2}$$

Where *P* is the total production periods, *N* is a number of blocks, and b_i^t is the decision variable for when to mine block *i* (if mined in period *t*, b_i^t is 1 and otherwise b_i^t is 0). The *c* variables are the unit costs of deviation (represented by the *d* variables) from production targets for grades and ore tonnes. The subscripts *u* and *l* correspond to the deviations and costs from excess production (upper bound) and shortage in production (lower bound), respectively, while *s* is the simulated orebody model number, and *g* and *o* are grade and ore production targets.

The objective function shown in Eq. 2 is used for maximizing the total discounted economic value and also managing the risk of not meeting production targets using conditionally simulated orebody models. Traditionally, one orebody model, a smooth image of the deposit, is used for maximizing NPV. However, when the expected deviations from the planned amount of ore tonnage having a planned grade and quality in a schedule are high in actual mining operations, the traditional model is unlikely to achieve the resultant NPV of the planned schedule. So, the NPV to be generated from actual mining can be far from optimal even if the schedule is optimized using a traditional true optimizer, MIP model. Therefore, the SIP model is developed to consider the minimum of the deviations together with maximization of NPV to generate achievable NPV (Ramazan and Dimitrakopoulos, 2018).

When constructing the objective function, a constant value is initially assigned for each of the cost parameters representing the cost at time 0 (base cost). Then, the risk discounting parameter (*f*) is introduced to determine the cost at different time periods by discounting the base cost using *f*. The risk-discounting concept is then incorporated into the SIP model (Dimitrakopoulos and Ramazan, 2003). If *f* is set to 0, the deviations in production targets can be expected to result in more or less the same level between different production periods because the cost of a unit deviation will be the same in all periods. However, the distribution of deviations will also depend on how the variability in grade and ore tonnage is distributed over the deposit and on how the relative magnitude of the costs for the deviations used in the SIP model compare with the economic values of the blocks. The Geological Risk Discount rate (GRD) allows the management of risk to be distributed between periods. If a very high GRD is used, the lowest risk areas in terms of meeting production targets will be mined earlier, and the most risky parts will be left for later periods. If a very small GRD or a GRD of zero is used, the risk will be distributed at a more balanced rate among production periods, depending on the distribution of uncertainty within the mineralized deposit. The c variables in the objective function are used to define a risk profile for the production, and the NPV produced is the optimum for the defined risk profile. It is considered that if the expected deviations from the planned amount of ore tonnage having planned grade and quality in a schedule are high in actual mining operations, it is unlikely to achieve the resultant NPV of the planned schedule. Therefore, the stochastic integer programming model contains the minimization of the deviations together with the NPV maximization to generate practical and feasible schedules and achievable cash flows.

In the model constraints, the deviation parameters are calculated within the SIP model by using the related constraints that consider each of the simulated orebody model. Stochastic constraints that use simulated multiple orebody realizations are considered because they are feasible for any value of decision variables. Stochastic constraints related to grade blending are used to satisfy not only the grade requirement at the mill but also the requirements for quality parameters (Dimitrakopoulos and Ramazan, 2003).

7. Geostatistics Approaches in Reserve Estimation

Estimating recoverable reserves is one of the important processes in the mining industry during production for grade control as well as mine planning. The main aim of grade control in mines is to differentiate between material that is above cut-off grade and material that is below cut-off grade through recoverable reserve estimation. Since drilling does not cover the whole area to be mined, recoverable reserve estimation aims at predicting the quality (grade) and quantity (tonnage) over an area where drilling was not done, from a limited number of data. From the estimates, a decision can be made whether to mine the material as ore (above cut-off) or waste (below cut-off). According to Sinclair and Blackwell (2002), the term local/recoverable reserve estimation is not defined rigidly but is used in the general context of point estimation or the estimation of small blocks or units on the scale of a Selective Mining Unit (SMU). The most important goal is to provide estimates that are accurate and reliable. In mining, geostatistical techniques are preferred for recoverable reserve estimation compared to other techniques. Since not all areas where mining is done are drilled and sampled, geostatistical techniques were developed to aid in estimating the grade and tonnage of an area based on nearby sample values. Geostatistics has been described as the application of the theory of regionalized variables to the estimation of mineral deposits (Matheron, 1971). The idea of using geostatistics for local reserve estimation in the mining industry was introduced around 1951 by Krige, (1951).

The use of geostatistics in the mining industry can be dated to as far as the 1970's. Apart from reserve estimation, geostatistical techniques are also used for mine planning as well as testing the importance of using different types of machinery on the output of the mine (Journel and Huijbregts, 1978; Clark, 1979). Currently, the technique is commonly used in other disciplines like hydrogeology, meteorology and contour mapping (Royle et al., 1981). In mining, geostatistics' emphasizes the geological context of the data and the spatial relationship between data. Compared to other methods of resource estimation, geostatistics is a better method for estimating grade and tonnage of the ore reserves. Unlike classic techniques which examine the sample data's statistical distribution, geostatistics incorporates both the statistical distribution of sample data and the spatial correlation between the sample data, hence addressing more earth science problems. Geostatistical techniques use the variogram, which relies on the spatial distribution and internal structure of data and not only on the actual values. If the variogram is good (robust) it provides estimates that are a good representation of the spatial distribution of the input data (Samal et al., 2008). The technique is based on the theory of regionalized variables, which states that the interpolation from points in space should not be based on a smooth continuous object (Matheron, 1971). Unlike classical statistics that considers grade to be randomly distributed, geostatistical techniques consider the changes of mineralization in relation to the trend direction of the ore body. It also considers the area of influence and continuity or lack of continuity of mineralization within the ore body. Other techniques like inverse distance weighting and polygonal estimation do not provide a measure of the accuracy of estimates, geostatistical techniques provide not only the estimates but also the measure of the accuracy of the estimates. Apart from the estimated mean grade, it also gives the estimated variance or spread of the grade. The estimated variance is used in risk analysis of the reserve estimate, especially in conditional simulation (Samal et al., 2008).

7.1. Conditional simulation

In the context of mining, the simulation means imitation of conditions (Sinclair and Blackwell, 2002). It is conditional if the resulting realizations honor the actual/original data at their locations. The method is mainly used for continuous variables like grade, height and age and its basic principle is to obtain an appropriate simulation of a point and its value must be drawn from its conditional distribution given the values at some nearest points. In the mining industry, it is used in the study of grade continuity, recoverable reserve estimation, optimizing sampling plans for advanced exploration, evaluation of resource estimation and also in mine planning (Sinclair and Blackwell, 2002), mill optimization (Journel and Isaaks, 1984) and financial risk analysis (Ravenscroft, 1992). In mining, it can also be used to assess the variability of the spatial distribution of the mineralization, risk sensitivity analysis in the mine planning process and effect of block size on ore variability. During mine production, conditional simulation can be used for reconciliation by comparing predicted grades in the resource model with the actual grades sampled at the process plant. In the geostatistical simulation, a system of model realizations is generated which present a range of possibilities (Vann et al., 2002). Conditional simulation generates maps of the grades of mineralization at a point honoring the sample grades' histogram, the variogram or spatial continuity of the sample grades as well as the grades at sample locations (Deutsch and Journel, 1992). The calculated histogram and variogram of simulated values and sample grades should be similar. Usually, it is the small-scale ore variation that causes ore misclassification in mining, it is important that these small-scale variations are reproduced like in conditional simulation since they affect the ore-waste selection process. In mineral resource estimation, Conditional Simulation was introduced to correct the smoothing effect that other techniques like Ordinary Kriging (OK) have on estimates (Matheron, 1971). As an estimation technique, it creates a pattern of values with the same statistical and spatial characteristics similar to true grades. In so doing, smoothing of data is minimized. Unlike other estimation techniques, the uncertainty attached to each estimate can be known when conditional simulation has been used. When assessing uncertainty attached to the prediction of a variable, or when realistic scenarios are required for post-processing algorithms, for instance, simulation of production, the spatial model can be used for simulation purpose rather than estimation (Rambert, 2005). Unlike kriging, simulation generates a series of realistic outcomes, having equal probabilities with each outcome honoring the input data, the spatial model and also the distribution model. Simulation has to reproduce statistical and geostatistical characteristics of variability (histogram and variogram) of the data (Vizi, 2008). Consequently, geostatistical simulation generates a set of values forming one of infinite possible 21 realizations which have simulated values having the same model of variogram as the experimental one and simulated values following the same distribution as the experimental ones. It is not uncommon for estimates to have some error or uncertainty since predictions can be inaccurate. Some of the errors can be due to widely spaced data used, geological variability, some approximations made in the estimation process and also the limitations of the models used. Apart from resource estimation, conditional simulation is considered to be the best option in predicting uncertainty for estimates since the uncertainty can be predicted at different scales by simply averaging up the simulated values (Rossi and Deutsch, 2013). In addition, using a set of simulated realizations obtained by conditional simulation, a model of uncertainty at each location can be provided. The model can be examined by predicting the uncertainty at locations where there is data from drill holes or previous production data. Rossi and Deutsch (2013) further stated that the probability intervals can then be created by counting the number of times that the true values fall within those intervals, thus determining if the predicted percentage is verified. The uncertainty model depends on the Random Function model used and can be used to characterize risk. In grade control risk analysis is used in making economic decisions, through evaluating the consequence of grade uncertainty and the best choice is considered based on the maximum profit or minimum loss choice. Furthermore, the uncertainty model as described by the realizations provides all the information required to optimize decision-making under uncertainty (Rossi and Deutsch, 2013). Techniques like ordinary kriging do not allow the confidence interval to be calculated using its variance. However, simulations can be used to build confidence intervals empirically, since many different simulations of a variable are calculated, there is information at each point, and there is access to a complete empirical distribution; therefore being able to evaluate the probability for a given variable to take a value belonging to a given interval (Vann et al., 2002). The main objective is to reproduce the variance of the input data, both in univariate sense and spatiality through the histogram and the variogram or another covariance model respectively. Consequently, conditional simulation provides an appropriate platform to study any problem relating to variability, in such a way that other techniques like kriging cannot (Vann et al., 2002). Sinclair and Blackwell (2002) summarized the procedure as generating a number of realizations of the same location in space. These individual simulations at each point give a probability distribution for the grade at a specific point. These distributions are then used in many ways in which estimation of the probability that the grade is above a certain cut-off grade at a particular point is one of the uses. One of them is where the distributions in a specified block are combined and averaged to estimate the grade of that particular block or the probability that the block grade is above a certain cut-off grade. Some of the simulation techniques that are used in the mining industry are turning bands, sequential Gaussian and sequential indicator simulation. In this review, sequential Gaussian simulation will be considered.

7.1.1. Sequential Gaussian simulation

There are many simulation algorithms but Sequential Gaussian Simulation (SGS) is one of the simplest and widely used. Kriging gives an estimate of both mean and standard deviation of a variable at a point, hence the variable at each point can be represented as a random variable following a normal distribution. SGS uses a random deviate from the normal distribution selected according to a uniform random number representing the probability level rather than the mean as an estimate (Bohling, 2005).

SGS is an algorithm which simulates nodes after each other sequentially, subsequently using simulated values as a conditioning data. It is necessary to use standard Gaussian values in SGS method, therefore the data are transformed into Gaussian space. SGS creates realizations of normal random variables and performs a Gaussian transformation of the data. A simulated value at a visited point is randomly drawn from the conditional cumulative distribution function, defined by the kriging mean and variance, based on neighborhood values. At a new randomly visited point, the simulated value is conditional to the original data and previously simulated values. Finally, the simulated normal values are transformed back into the simulated values for the original variables. The process is repeated until all points are simulated for each realization throughout the grid (Deutsch and Journel, 1992). An illustrated basic steps in SGS algorithm is shown in Fig. 5 (Deutsch and Journel, 1992):

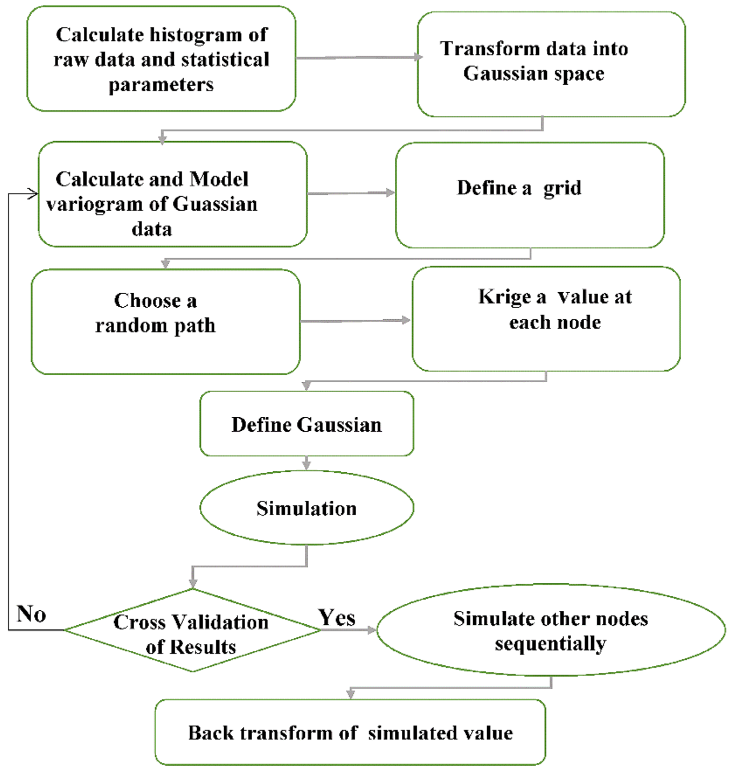

Fig. 5. The basic steps in the SGS algorithm modified after Deutsch and Journel (1992)

7.2. Kriging and ordinary kriging

Kriging is one of the earliest and commonly used techniques in mine operations for grade control purposes especially in estimating grade and tonnage of an area. It has been defined as a generic term that is applied to a range of methods of estimation that depend on minimizing the error of estimation, commonly by a least square procedure (Sinclair and Blackwell, 2002). Just like all geostatistical techniques, the basis of the technique is on the assumption that the variable to be estimated is a regionalized variable i.e. samples are related in space. The technique is applied upon meeting underlying assumptions of second-order stationarity which implies that at a minimum the mean and variance of the sample data remain invariant in space (Journel and Huijbregts, 1978). This means that the mean for the data must be constant at any location. To ensure that the weight functions are based on the variation of the observed variable as a function of its distance, kriging makes use of the variogram (Clark, 1979) . The advantage of using kriging as an estimation technique is that the kriged estimate is accompanied by a corresponding kriging standard deviation. Furthermore, the maps and/or calculations of the standard errors can be produced without actually taking the samples. The technique relies on the spatial relationship of the data. Both kriging and inverse distance weighting rely on distance in assigning weights, however, in kriging, the weights are based on both distances between points and also on the spatial relationship of the points. With kriging estimation, the variogram model, search parameters, and sample number form the basis for assigning kriging weights (Clark, 1979). Kriging uses the variogram, which does not depend on the actual value of data, but rather on its spatial distribution and internal spatial structure. In minimizing the estimation error, it finds a combination that is best for sample weights used in kriging process. The kriging variance obtained from the kriging technique can be used in the classification of resources. Based on how information has been used to estimate each block, the kriging variance can be used to rank the blocks of the resource model. This is done by using relative thresholds since the values do not have any physical or geological meaning. Alternatively, a visual comparison of the kriging variance can be used for defining resource categories (Rossi and Deutsch, 2013). Universal kriging, simple kriging, indicator kriging, co-kriging and ordinary kriging are some of the types of kriging techniques (Isaaks and Srivastava, 1989). These techniques have been categorized into two, linear kriging of which ordinary kriging is one example and non-linear kriging which includes indicator kriging and disjunctive kriging. However, the choice of technique to use is mainly dependent on the type of the deposit, homogeneity of the data and what one is trying to achieve i.e. is it only the mean of the data or the whole distribution of data values, is it global estimates or local estimate and is it point estimate or block estimate (Isaaks and Srivastava, 1989).

Ordinary kriging is one of the estimation techniques commonly used in mining for grade control for mineral resource estimation. The technique is considered to be linear interpolator since it is based on the linear weighted average and assumes that the mean of the data is constant but also not known (Clark, 1979).

The distance from the estimation point and spatial correlation of the samples greatly influence the sample weight values. In ordinary kriging, the spatial correlation structure of the data influences the weighting of neighboring data points rather than by the power of their inverted distance like the inverse distance weighting method. Upon close evaluation, the kriging approach is similar to the inverse distance weighting method. However, the major difference is that ordinary kriging weights are assigned based on the variogram model thereby taking the spatial relationship into consideration.

Using the variogram in computing weights helps to minimize the expected error in the least square way. It is for this reason that ordinary kriging is sometimes said to produce the best linear unbiased estimate and some authors have associated ordinary kriging with the acronym B.L.U.E.; Best Linear Unbiased Estimator (Isaaks and Srivastava, 1989; Sinclair and Blackwell, 2002). It is considered to be linear since the weighted linear of data being estimated make up the estimate. The unbiased nature of the results is due to the absence of residual and estimation errors. Ordinary kriging is considered to be best since the variance of errors is mostly minimized through a linear combination of surrounding sample that are used to make predictions by assigning weights to the surrounding samples. Some estimation techniques like inverse distance weighting are also considered to be unbiased as well as linear like the ordinary kriging technique, however, ordinary kriging aims at reducing the error variance hence distinguishes it from these techniques. However, kriged estimates tend to be smoother than the input data.

7.3. Comparison between conditional simulation and ordinary kriging

Conditional simulation and ordinary kriging are techniques commonly used in the mining industry for resource estimation. Just like other geostatistical techniques, both techniques use variogram in determining the spatial relationship of data. Estimation errors through the kriging variance and block variance are provided along with the kriged estimates. The kriging variance forms the basis for Conditional Simulation. Although both techniques are used to provide estimates, their main goals are different. Ordinary kriging aims at providing unique estimates which minimize the local estimation variance while Conditional Simulation's purpose is to provide a set of maps of showing the grade, which honors the known reality and is likely to represent unknown reality at any location (Schofield and Rolley, 1997). Its ability to represent the spatial continuity of high grades and local variability of grades makes Conditional Simulation a better technique over ordinary kriging. Whilst the techniques are commonly used for resource estimation, Conditional Simulation also provides a direct way of quantifying the uncertainty in knowing the true grade of mining unit attached to an estimate in the form of a histogram, unlike ordinary kriging. Since conditional simulation generates several simulations of the grade of the deposit, there is direct access to a histogram of the possible grade for any particular point in the deposit. Furthermore, each value generated is independent of other values generated in other simulations and is more likely to be the true grade value at that particular location. This makes conditional simulation a better technique than ordinary kriging in describing the local uncertainty of the grade mineralization through direct access to the grade distribution through averaging of simulated values. Although kriging variance may be used to provide a description of the uncertainty, it requires an assumption about the shape of the histogram of possible grades which practically is not realistic. Another limitation of kriging variance is that it assumes that the estimation variance is independent of the magnitude of the grade being estimated, contrary to most mineral deposits which have a variability of grades directly related to the magnitude of the grade (Schofield and Rolley, 1997). This becomes a limitation on using kriging variance to describe uncertainty in knowing the true grade of mining unit. It does not allow assessment of risk associated with the resource. Simulations attempt to sample at the unknown location using constraints like statistical moments of data, thereby the requirements of stationarity are stricter than that of kriging. Although ordinary kriging is considered to be the Best Linear Unbiased Estimator, the smoothing effect it has on estimates is one of the technique's main disadvantages. Local variability is not preserved as a result of smoothing and does not reproduce the histograms of the original data well like conditional simulation (Asghari et al., 2009).

On the other hand, conditional Simulation honors the original data and has a less smoothening effect on estimates and preserves local variability. However, with increasing sampling density like that of blast hole data, maps from both ordinary kriging and conditional simulation gradually become similar to the true map of reality because they both honor the sample values at the sample locations (Deutsch and Journel, 1992; Asghari et al., 2009).

8. Summary and Remarks

It is clearly seen from the relevant literature that ore properties such as bitumen grade, amount of fine content, type of fine content, mineralogy of both sand and fines and ore weathering have a significant impact on bitumen recovery and ore processability. If these variables are not controlled, they can decrease the quality of the bitumen and thus reduce the economic value of the mine plan. It could additionally pose an environmental issue in the tailings if this variable is not controlled.

The mine and tailings long-term plans define the complex strategy of the displacement of ore, waste, overburden, and tailings over the mine life. The objective of the long-term mine plans is to minimize the environmental footprint and maximize the cash flow. Limitation of space because of lease conditions, the scale of operations and construction of external and in-pit dyke impoundments add to the complexity of planning in oil sands mining. Oil sands long-term mine plans are driven by the quantity and quality of tailings produced downstream. Production scheduling is an important aspect of mine planning and design. Maximizing the NPV and considering the sequence of material that has to be mined over time, under the defined constraints, can be used to schedule for long-term production. However, oil sands mine planning and waste management are faced with limitations such as risks and uncertainties associated with the tailing process and only relying on deterministic models.

Mine planning and waste management problems in oil sands can be achieved by using a combination of mixed integer, linear and goal programming formulations. The aim of using goal programming is to enable the optimization solution to try to achieve a set of goals where some goals can be balanced off against one another depending on their significance. Hard constraints can also be converted to soft constraints which otherwise could lead to infeasible solutions (Ben-Awuah and Askari-Nasab, 2013). Stochastic integer programming models offer a framework to address uncertainty in key inputs of mine production schedules, in areas such as grade and rock type uncertainties. Mathematical formulations based on stochastic integer programming has shown to generate the optimal production schedule (Dimitrakopoulos and Ramazan, 2008). Hence, its application in the mine plan will allow the management of uncertainties associated with ore grades and waste disposal.

9. Research Methodology

The main goal of this research is to develop, implement, verify and validate an integrated mine planning optimization framework using stochastic integer programming that will address the related domains of bitumen grade uncertainty and oil sands waste management. The application of a stochastic integer programming model in this research will allow the increase of the bitumen recovery which will also maximize the net present value. The implementation of solid waste management into the mine plan will also contribute to an increase in the net present value of the operation over the mine life. Fig. 6 illustrates a summary of the methodology that will be used for this research.

In order to achieve the research goal, the related literature is reviewed, including the applications of the operations research methods in mine planning, oil sands waste management, and factors affecting bitumen recovery. Afterwards, a geological data containing bitumen ore properties such as bitumen, fines, water, organic rich solids and ultrafine clays will be modeled and imported into GEMS software to develop a suitable block model that will be used for this research. The next part of the research will involve finding the final pit limits for a real-case oil sands block model, using the 3-dimensional LG algorithm (Lerchs and Grossmann, 1965) and this will be conducted in Whittle software. A number of scenarios will be 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 will then be used for experimental studies through the proposed stochastic integer programming model.

The required matrices for the deterministic MILP model are prepared in MATLAB, and the TOMLAB/CPLEX 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 to the LP-relaxation optimal solution. Once the deterministic approach is completed, a stochastic approach will be considered where uncertainties such as bitumen grade and rock type will be considered.

Block modelling will be done using conditional simulation in order to meet the objectives of this research. The stochastic approach will be conducted on the developed block model by performing estimation using kriging. Cross validation for the kriging results will be conducted for accuracy of the results. Finally, multiple realizations will be generated using Sequential Gaussian Simulation (SGS). The simulation results obtained will then be used to compare with the kriging results.

A simulation optimization framework/tool would be presented at the end of the research to account for uncertainties in mining operations for robust long term production planning and proactive decision making. This framework/tool will use a discrete event simulation model of mine operations, which interacts with a goal programming based mine operational optimization tool to develop an uncertainty based long term schedule. Using scenario analysis, this framework will allow the planner to make proactive decisions to achieve the mine's operational and long-term objectives.

10. Expected Scientific and Industrial Contribution of the Proposed Research

Oil sands processability and waste management are major environmental concerns in Alberta’s oil sands industry. The presence of clay, fines, ultrafine and organic-rich solids reduces the quality of bitumen during extraction. Also, environmental challenges caused by the oil sands tailings production led to setting regulations for oil sands tailings operations. According to the Directive 074, the oil sands production operators are required to satisfy the conditions and regulations set by this directive (McFadyen, 2009).

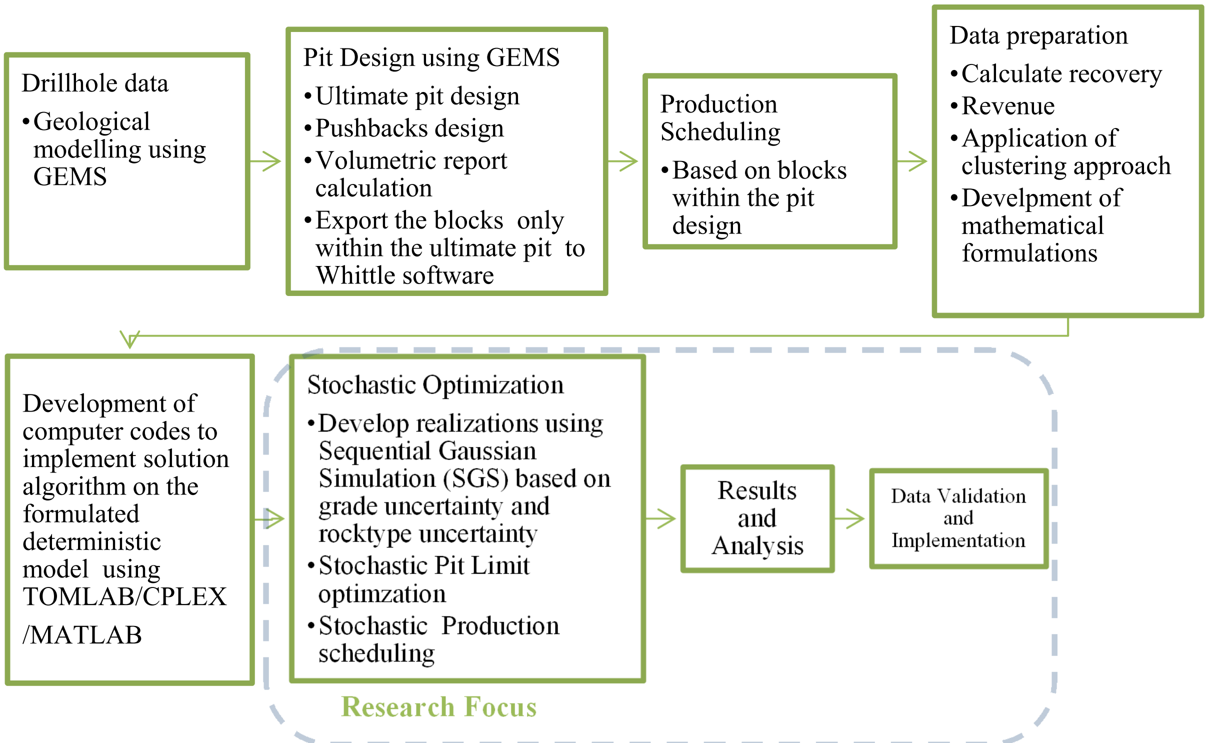

Fig. 6: Summary of research methodology.

The aim of these regulations is to ensure that the fluid tailings produced at the end of the oil sands production process, will become a reclaimable and trafficable landscape in order to overcome the environmental challenges caused by oil sands industry. In addition, the tailings production should meet the limitations on the deposition area specified by the directive (McFadyen, 2009).

Hence, the main contribution of this research is to develop an integrated framework for improving the bitumen recovery and to optimize the mine production schedule with respect to tailings and waste management. Mathematical formulations and simulation models based on uncertainties will be developed to contribute to the oil sands industry in mine planning and waste management by assisting in the improvement of bitumen recovery during extraction as well as the quality of the tailings and waste generated at the end of the oil sands production process. The main limitation of current oil sands mine plans is in over-estimating and under-estimating the quantity of the final tailings produced. Furthermore, the lack of an accurate relation between the oil sands long-term mine plans and the final product can lead to serious problems such as limitations in deposition area. An important industrial contribution of this research is a methodology/tool that will enables mine planners to modify and re-evaluate the oil sands mine plans based on the deposition area constraint, and the amount of tailings which is expected to be produced based on the mine plans. Also, a methodology/tool will be developed based on Sequential Gaussian Simulation (SGS), that will enable mine and tailings planners to assess and quantify uncertainties associated with the quantity and quality of bitumen recovered and tailings produced. The outcome of this research is expected to contribute towards the improvement of bitumen recovery and development of oil sands tailings management strategies, which will result in overcoming some of the environmental challenges associated with the oil sands production process.

11. Conclusion

Conditional simulation such as sequential Gaussian simulation is shown to be an appropriate framework to generate equally probable resource models used for risk analysis in mine planning

(Lantuéjoul, 2010). The combination of multiple simulated models provides the necessary tool to assess uncertainty associated with predictions of the attributes studied. Obtaining the local distribution of values by generating multiple simulations makes it possible to predict the magnitude of the fluctuations of an attribute for a given mining scenario. Through a mine-to-mill framework, fluctuations in geological and engineering parameters and their consequence in mine planning and scheduling can be anticipated thus enabling decisions that help to improve the net present value of the operation over the mine life.

12. References

[1] Akaike, A. and Dagdelen, K. (1999). A strategic production scheduling method for an open pit mine. *proceedings of the 28th Application of Computers and Operation Research in the Mineral Industry*, 729-738.

[2] AlbertaEnergyRegulator (2016). Directive 082. *Operating Criteria: Resource Recovery Requirements for Oil Sands Mine and Processing Plant Operations*,

[3] Asghari, O., Soltni, F., and Bakhshandeh Amnieh, H. (2009). *The Comparison Between Sequential Gaussian Simulation (SGS) of Choghart Ore Deposit and Geostatistical Estimation Through Ordinary Kriging.* Vol. 3,

[4] Badiozamani, M. M. and Askari-Nasab, H. (2014). Integration of reclamation and tailings management in oil sands surface mine planning. *Environmental modelling & software*, *51* 45-58.

[5] Basu, S., Nandakumar, K., and Masliyah, J. H. (1996). A Study of Oil Displacement on Model Surfaces. *Journal of Colloid and Interface Science*, *182* (1), 82-94.

[6] Beier, N. and Sego, D. (2008). The oil sands tailings research facility. *Geotechnical news*, *26* (2), 72-7.

[7] Ben-Awuah, E. (2013). *Oil sands mine planning and waste management using goal programming.* Vol. 74,

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

[9] Ben-Awuah, E. and Askari-Nasab, H. (2013). Incorporating waste management into oil sands long term production planning. *Mining Technology*, *122* (1), 33-45.

[10] Bichard, J. A. (1987). Oil sands composition and behaviour research. The research papers of John A. Bichard 1957-1965. Alberta Oil Sands Technology and Research Authority, Edmonton, AB, paper Document Number,

[11] Bohling, G. (2005). Introduction to geostatistics and variogram analysis. C and PE 940, 17 October 2005.

[12] Bowman, C. W. (1971). The Athabasca Oil Sands Development—50 Years in Preparation. in *Origin and Refining of Petroleum*, Vol. 103, *Advances in Chemistry*, AMERICAN CHEMICAL SOCIETY, pp. 81-93.

[13] Caccetta, L. and Giannini, L. (1986). *Optimization techniques for the open pit limit problem*. in Proceedings of Proc. Australas. Inst. Min. Metall, pp. 57-63.

[14] Caccetta, L. and Hill, S. P. (2003). An Application of Branch and Cut to Open Pit Mine Scheduling. *Journal of Global Optimization*, *27* (2), 349-365.

[15] Caccetta, L., Kelsey, P., and Giannini, L. (1998). *Open pit mine production scheduling*. in Proceedings of APCOM 98: Computer Applications in the Mineral Industries International Symposium, pp. 65-72.

[16] Carrigy, M. A. (1967). Some sedimentary features of the athabasca oil sands. *Sedimentary Geology*, *1* 327-352.

[17] Chalaturnyk, R. J., Don Scott, J., and Özüm, B. (2002). Management of oil sands tailings. *Petroleum Science and Technology*, *20* (9-10), 1025-1046.

[18] Clark, I. (1979). *Practical geostatistics.* Vol. 3, Applied Science Publishers London,

[19] Conly, F. M., W Crosley, R., and Headley, J. (2011). *Characterizing sediment sources and natural hydrocarbon inputs in the lower Athabasca River, Canada.* Vol. 1, Pages 187-199.

[20] Dagdelen, K. (1986). Optimum open pit mine production scheduling by Lagrangian parameterization. *Proc. of the 19th APCOM*, 127-142.

[21] Dai, Q. and Chung, K. H. (1995). Bitumen—sand interaction in oil sand processing. *Fuel*, *74* (12), 1858-1864.

[22] Denby, B. and Schofield, D. (1995). *The use of genetic algorithms in underground mine scheduling*. in Proceedings of Proceedings of the 25th international symposium application of computers mineral industries, pp. 389-394.

[23] Denby, B., Schofield, D., and Bradford, S. (1991). Neural network applications in mining engineering. *Department of Mineral Resources Engineering Magazine, University of Nottingham*, 13-23.

[24] Deutsch, C. V. and Journel, A. G. (1992). *GSLIB: Geostatistical Software Library and User's Guide. Hauptbd.* Oxford university press,

[25] Dimitrakopoulos, R. and Ramazan, S. (2003). *Managing risk and waste mining in long-term production scheduling of open pit mine*. in Proceedings of 2003 SME Annual Meeting & Exhibit, Feb, pp. 24-26.

[26] Dimitrakopoulos, R. and Ramazan, S. (2008). Stochastic integer programming for optimising long term production schedules of open pit mines: methods, application and value of stochastic solutions. *Mining Technology*, *117* (4), 155-160.

[27] Eckert, W. F., Masliyah, J. H., Gray, M. R., and Fedorak, P. M. (1996). Prediction of sedimentation and consolidation of fine tails. *AIChE Journal*, *42* (4), 960-972.

[28] Gershon, M. E. (1983). Mine scheduling optimization with mixed integer programming. *Min. Eng.(Littleton, Colo.);(United States)*, *35* (4),

[29] Gleixner, A. M. (2009). Solving large-scale open pit mining production scheduling problems by integer programming.

[30] Godoy, M. and Dimitrakopoulos, R. (2004). Managing risk and waste mining in long-term production scheduling of open-pit mines. *SME transactions*, *316* (3),

[31] Hall, A. C., Collins, S. H., and Melrose, J. C. (1982). *Stability of Aqueous Wetting Films in Athabasca Tar Sands.* Vol. 23,

[32] Hein, F. J. and Cotterill, D. K. (2006). The Athabasca Oil Sands — A Regional Geological Perspective, Fort McMurray Area, Alberta, Canada. *Natural Resources Research*, *15* (2), 85-102.

[33] Hepler, L. G., Hsi, C., Alberta Oil Sands, T., and Research, A. (1989). *AOSTRA technical handbook on oil sands, bitumens and heavy oils.* Alberta Oil Sands Technology and Research Authority, [Edmonton, Alta.]

[34] Hickman, D. A. (2014). Particle swarm optimization for energy minimization of molecular systems.Thesis, Colorado School of Mines. Arthur Lakes Library,

[35] Hooshiar, A., Uhlik, P., Ivey, D. G., Liu, Q., and Etsell, T. H. (2012). *Clay minerals in nonaqueous extraction of bitumen from Alberta oil sands: Part 2. Characterization of clay minerals.* Vol. 96, Pages 183-194.

[36] Isaaks, E. H. and Srivastava, R. M. (1989). An introduction to applied geostatistics. Oxford university press, paper Document Number,

[37] Johnson, T. (1988). Application of the Max Flow algorithm to ultimate pit design. *Engineering design: better results through operations research methods*, 518-531.

[38] Johnson, T. B. (1968). Optimum open pit mine production scheduling. CALIFORNIA UNIV BERKELEY OPERATIONS RESEARCH CENTER, paper Document Number,

[39] Journel, A. and Isaaks, E. (1984). Conditional indicator simulation: application to a Saskatchewan uranium deposit. *Journal of the International Association for Mathematical Geology*, *16* (7), 685-718.

[40] Journel, A. G. and Huijbregts, C. J. (1978). *Mining geostatistics.* Academic press,

[41] Kalantari, S., Ben-Awuah, E., and Askari-Nasab, H. (2013). Towards an integrated oil sands mine plan and composite tailings plan. *International Journal of Mining, Reclamation and Environment*, *27* (2), 103-126.

[42] Kaminsky, H. (2008). *Characterization of an Oil Sand Ore and Process Streams.*

[43] Kaminsky, H., H. Etsell, T., G. Ivey, D., and Omotoso, O. (2008). *Characterization of Heavy Minerals in Alberta Oil Sands.* Vol. 21, Pages 264-271.

[44] Kasongo, T., Zhou, Z., Xu, Z., and Masliyah, J. (2010). Effect of clays and calcium ions on bitumen extraction from athabasca oil sands using flotation. *The Canadian Journal of Chemical Engineering*, *78* (4), 674-681.

[45] Kasperski, K. (1992). A review of properties and treatment of oil sands tailings. *AOSTRA Journal of Research*, *8* 11-11.

[46] Kasperski, K. L. (2001). Extraction and water chemistry, Canadian Oil Sands Network for Research and Development (CONRAD) Oil Sands Extraction Fundamentals and Process Water Workshop, 7-8 May 2004. paper Document Number,

[47] Khan, A. and Niemann-Delius, C. (2014). *Research Article Production Scheduling of Open Pit Mines Using Particle Swarm Optimization Algorithm.* Vol. 2014,

[48] Kotlyar, L. S., Ripmeester, J. A., Sparks, B. D., and Montgomery, D. S. (1988). Characterization of organic-rich solids fractions isolated from Athabasca oil sand using a cold water agitation test. *Fuel*, *67* (2), 221-226.

[49] Koushavand, B., Askari-Nasab, H., and Deutsch, C. V. (2014). A linear programming model for long-term mine planning in the presence of grade uncertainty and a stockpile. *International Journal of Mining Science and Technology*, *24* (4), 451-459.

[50] Krige, D. (1951). A Statistical Approach to Some Basic Mine Valuation Problems on the Witwatersrand. *Journal of the Chemical, Metallurgical and Mining Society of South Africa*, *52* (6), 119-139.

[51] Lantuéjoul, C. (2010). *Conditional simulations.*

[52] Lerchs, H. and Grossmann, I. (1965). Optimum Design of Open Pit Mines, Canadian Institute of Mining Bulletin, 58.

[53] Liu, J., Xu, Z., and Masliyah, J. (2008). Interaction between Bitumen and Fines in Oil Sands Extraction System: Implication to Bitumen Recovery. *The Canadian Journal of Chemical Engineering*, *82* (4), 655-666.

[54] Long, J., Drelich, J., Xu, Z., and Masliyah Jacob, H. (2008). Effect of Operating Temperature on Water-Based Oil Sands Processing. *The Canadian Journal of Chemical Engineering*, *85* (5), 726-738.

[55] MacKinnon, M. (1989). Development of the tailings pond at Syncrude’s oil sands plant: 1978–1987. *AOSTRA J. Res*, *5* (2), 109-133.

[56] Masliyah, J., Zhou, Z. A., Xu, Z., Czarnecki, J., and Hamza, H. (2004). *Understanding Water-Based Bitumen Extraction From Athabasca Oil Sands.* Vol. 82, Pages 628-654.

[57] Masliyah, J. H., Czarnecki, J., and Xu, Z. (2011). *Handbook on theory and practice of bitumen recovery from Athabasca oil sands - Volume 1: Theoretical basis.* Pages 115-116.

[58] Matheron, G. (1971). The theory of regionalised variables and its applications. *Les Cahiers du Centre de Morphologie Mathématique*, *5* 212.

[59] McFadyen, D. (2009). Directive 074: Tailings Performance Criteria and Requirements for Oil Sands Mining Schemes. *Energy Resources Conservation Board, Calgary, AB, Canada*,

[60] Meagher, C., Dimitrakopoulos, R., and Avis, D. (2014). Optimized open pit mine design, pushbacks and the gap problem—a review. *Journal of Mining Science*, *50* (3), 508-526.

[61] Mikula, R., Munoz, V., Kasperski, K., Omotoso, O., and Sheeran, D. (1998). *Commercial implementation of a dry landscape oil sands tailings reclamation option: consolidated tailings*. in Proceedings of Proceedings 7th UNITAR Conference, pp. 907-921.

[62] Mikula, R. J., Omotoso, O., and Kasperski, K. L. (2008). The chemistry of oil sands treatment: Production to treatment. Edmonton, AB: University of Alberta Geotechnical Center and Oil Sands Tailing Research Facility, pp. 10 pages.

[63] Mitchell, J. E. (2002). Branch-and-cut algorithms for combinatorial optimization problems. *Handbook of applied optimization*, 65-77.

[64] Mossop, G. D. (1980). Geology of the Athabasca Oil Sands. *Science*, *207* (4427), 145.

[65] Onur, A. and Dowd, P. (1993). *Open-pit optimization - Part 2: Production scheduling and inclusion of roadways.* Vol. 102, Pages 105-113.

[66] Osacký, M., Geramian, M., Uhlík, P., Čaplovičová, M., Danková, Z., Pálková, H., Vítková, M., Kováčová, M., Ivey, D. G., Liu, Q., and Etsell, T. H. (2017). Mineralogy and Surface Chemistry of Alberta Oil Sands: Relevance to Nonaqueous Solvent Bitumen Extraction. *Energy & Fuels*, *31* (9), 8910-8924.

[67] Osanloo, M., Gholamnejad, J., and Karimi, B. (2008). *Long-term open pit mine production planning: A review of models and algorithms.* Vol. Reclamation and Environment, Pages 3-35.

[68] Picard, J.-C. (1976). Maximal closure of a graph and applications to combinatorial problems. *Management science*, *22* (11), 1268-1272.

[69] Ramazan, S. (2007). The new fundamental tree algorithm for production scheduling of open pit mines. *European Journal of Operational Research*, *177* (2), 1153-1166.

[70] Ramazan, S., Dagdelen, K., and Johnson, T. (2005). Fundamental tree algorithm in optimising production scheduling for open pit mine design. *Mining Technology*, *114* (1), 45-54.

[71] Ramazan, S. and Dimitrakopoulos, R. (2018). Stochastic optimisation of long-term production scheduling for open pit mines with a new integer programming formulation. in *Advances in Applied Strategic Mine Planning*, Springer, pp. 139-153.

[72] Rambert, F. (2005). *Introduction to Mining Geostatistics*. in Proceedings of 67th EAGE Conference and Exhibition-Workshops,

[73] Ravenscroft, P. J. (1992). Recoverable reserve estimation by conditional simulation. *Geological Society, London, Special Publications*, *63* (1), 289-298.

[74] Rossi, M. E. and Deutsch, C. V. (2013). *Mineral resource estimation.* Springer Science & Business Media,

[75] Royle, A., Clausen, F., and Frederiksen, P. (1981). Practical universal kriging and automatic contouring. *Geoprocessing*, *1* 377-394.

[76] Samal, A. R., Mohanty, M. K., and Fifarek, R. H. (2008). Backward elimination procedure for a predictive model of gold concentration. *Journal of Geochemical Exploration*, *97* (2-3), 69-82.

[77] Sanford, E. C. (1983). Processibility of athabasca oil sand: Interrelationship between oil sand fine solids, process aids, mechanical energy and oil sand age after mining. *The Canadian Journal of Chemical Engineering*, *61* (4), 554-567.

[78] Schofield, N. and Rolley, P. (1997). *Optimisation of ore selection in mining: Method and Case Studies*. in Proceedings of Proceedings Third International Mining Geology Conference,

[79] Sheeran, D. (1993). *An improved understanding of fine tailings structure and behaviour*. in Proceedings of Proceedings fine tails symposium, oil sands–our petroleum future conference. Edmonton: AOSTRA Publications, pp. 19.

[80] Sinclair, A. J. and Blackwell, G. H. (2002). *Applied Mineral Inventory Estimation.* Cambridge University Press, Cambridge,

[81] Soane, D., Ware, W., Mahoney, R., and Kincaid, K. (2010). *Oil sands tailings treatment via surface modifications of solids with polymers*. in Proceedings of Proceedings of the 2nd International Oil Sands Tailings Conference, pp. 5-8.

[82] Tabesh, M. and Askari-Nasab, H. (2011). Two-stage clustering algorithm for block aggregation in open pit mines. *Mining Technology*, *120* (3), 158-169.

[83] Takamura, K. (1982). Microscopic structure of athabasca oil sand. *The Canadian Journal of Chemical Engineering*, *60* (4), 538-545.

[84] Vann, J., Bertoli, O., and Jackson, S. (2002). *An overview of geostatistical simulation for quantifying risk*. in Proceedings of Proceedings of Geostatistical Association of Australasia Symposium" Quantifying Risk and Error, pp. 1.

[85] Vizi, L. (2008). A case study in uniform conditioning of local recoverable reserves estimation for Jelšava magnesite deposit-level 220.

[86] Wallwork, V., Xu, Z., and Masliyah, J. (2008). Bitumen Recovery with Oily Air Bubbles. *The Canadian Journal of Chemical Engineering*, *81* (5), 993-997.

[87] Wik, S., Sparks, B. D., Ng, S., Tu, Y., Li, Z., Chung, K. H., and Kotlyar, L. S. (2008). Effect of process water chemistry and particulate mineralogy on model oilsands separation using a warm slurry extraction process simulation. *Fuel*, *87* (7), 1394-1412.

[88] Zhou, Z. A., Xu, Z., Masliyah, J. H., and Czarnecki, J. (1999). Coagulation of bitumen with fine silica in model systems. *Colloids and Surfaces A: Physicochemical and Engineering Aspects*, *148* (3), 199-211.