Near-Face Stockpile Open Pit Mining: a Method to Enhance NPV and Quality of the Plant Throughput[1]

Hongshuo Gong[a], Mohammad Tabesh[b], Ali Moradi Afrapoli[c] and Hooman Askari-Nasab[a]

a. Mining Optimization Laboratory (MOL) University of Alberta, Edmonton, Canada

b. Teck Resources Limited, Vancouver, Canada

c. IntelMine Laboratory, Laval University, Quebec, Canada

ABSTRACT

Nowadays, stockpiles are of great importance in open pit mine production scheduling and are widely used for different reasons while being placed in different locations. Near face stockpile (NFS) mining method is a new mining concept which could decouple the whole mining flow into two weakly related subsystems, which are the mining subsystem and processing subsystem. There are many theoretical advantages in comparison to the traditional open-pit mining method, such as higher tolerance on uncertainties without compromising production, higher equipment utilization, less operating cost, better blending results, etc. The introduction of NFS, however, requires reconsideration of production planning in open pit mines. In this paper, we developed a mixed integer linear programming model to solve long-term production scheduling problem in open pit mines. To quantitatively measure the performance of the NFS mining method, we implemented the model in a real mining case study and compared the results with the traditional open pit mining method with an out-of-pit crusher. The results reveal that we can improve the net present value by 9.3% and the plant head grade by above 58% by implementing the NFS method.

1. Introduction

More than 90% of the minerals are extracted using surface mining methods including open pits (Osanloo & Paricheh, 2020). Open pits are usually multi-million/billion-dollar long-term projects with two main subsystems: mining (mostly discrete processes) and processing (mostly continuous processes). As the transportation of material throughout these two weakly coupled systems vary in nature, their integration is a challenging problem that pushes the whole project away from optimality. Stockpiling (Koushavand et al., 2014) and in-pit crushing and conveying (IPCC) (Paricheh & Osanloo, 2020) have been introduced to improve the interaction of these two subsystems. When IPCC system is implemented in an open pit mine, the ore stockpiling option is removed as materials are being fed to the in-pit crusher directly from shovels. In this paper, we introduce a new concept by integrating IPCC and stockpiles called the *near-face stockpile (NFS) open pit mining method* that facilitates the integration of the two abovementioned subsystems while keeping the advantages of both IPCC and stockpiles, implementing this new mining method results in an improvement in the quality of material delivered to the processing plant and an increase in the net present value (NPV) of the whole project.

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The concept of stockpiling in the open pit mines can be used for any type of material piled for usage later on in the mine life (Darling, 2011). Although not recommended due to the economic and environmental challenges, waste materials are delivered to waste stockpiles (Adrien Rimélé et al., 2018) for the mines that have in-pit tailings disposal areas to be built later in the mine life. Oil sands mines in Canada are explicit examples of such an operation. However, the main role of stockpiles in open pit mines is as a buffer in the blend control process (Rezakhah & Newman, 2020). The location of the ore stockpiles, for the purpose of minimizing the rehandling costs, is usually outside of the pit rim and as close to the main crusher as possible.

With the introduction of IPCC systems, the crusher which is the connecting point between mining and processing operation is moved inside the pit and closer to the operating mining faces. Finding the optimal location of the crusher inside the pit is a challenging task and is either treated as a stand-alone optimization problem (Paricheh et al., 2017) or a subproblem which is a part of the long-term production scheduling task (Paricheh & Osanloo, 2020). The location optimization varies based on the type of the IPCC system. The IPCCs are categorized into three main classes: fixed, semi-mobile, and fully mobile systems (Utley, 2011). In the NFS method, the mobile crusher with the medium to long-term relocation strategy is the desired class as the in-pit crusher and the stockpile could be relocated when needed. This means that the equipment could be placed and reassembled in different benches with the development of the pit while the mine expands year by year. Figure 1 shows the basic layout of the NFS mining method.

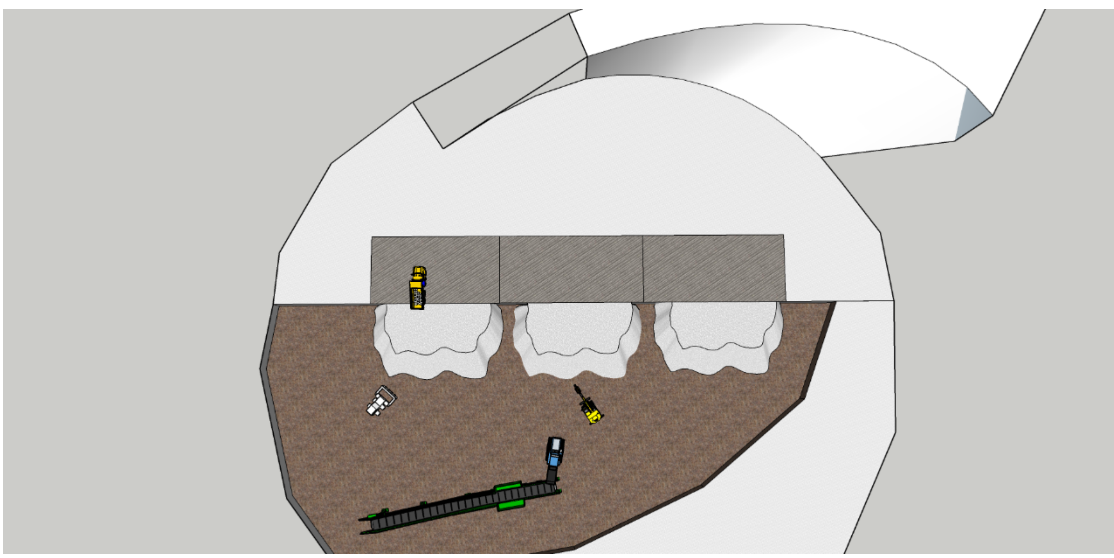

Figure 1. The layout of the near-face stockpile open pit mining method.

In an NFS mine, the material handling cycle for the waste material is the same as in conventional open pit mining. However, the ore transportation cycle is modified in a way that instead of truck dumping ore directly into the crusher, as in either conventional truck and shovel open pit or IPCC open pit, it dumps its ore loads on the designated grade bin in the in-pit stockpile. Then the reclaiming shovel loads the ore from different grade bins into a mobile crusher. The crushed materials are then transported to the secondary crusher outside of the pit rim by the conveyor belt. Therefore, the essential difference between the NFS mining method and traditional open-pit mining methods is that the discrete and continuous subsystems are connected through the shovel-crusher interaction instead of the truck-crusher interaction. As the discrete shovel cycle time is far less than the discrete truck cycle time, the coupling of the two systems will be stronger in comparison.

According to Jupp et al. (2013), a near crusher stockpile plays four roles at the same time, which are storing, buffering, blending and grade separation. Obviously, the NFS mining method inherits all advantages from the near crusher stockpile. The benefit of two weakly coupled subsystems is that the whole system is more likely to have higher production and generate more profits since the stockpile could act as a buffer and avoid unnecessary production loss due to equipment failure or maintenance. Meanwhile, the existence of a near-face stockpile will lead to a more stable grade feed to the crusher since, in traditional mining methods, the materials are truck-by-truck blended while the NFS method allows batch blending. Nevertheless, another apparent benefit of the near face stockpile is that it could shorten the hauling time significantly and reduce the costs from three aspects. Firstly, it requires a smaller number of trucks in the fleet. Currently, most of the mines in the world hire more trucks to avoid the idle of the mining shovels, while with NFS, the truck cycle time will be reduced dramatically. Therefore, some investment on equipment, especially on trucks, could be saved. Secondly, as mentioned in (Alarie & Gamache, 2002; Moradi Afrapoli & Askari-Nasab, 2019) truck and shovel operating cost make up to 50 percent or even more in overall operation cost in open-pit mines, which means even a small increase of utilizations of those equipment will yield significant benefits for mining enterprises. Thirdly, shortening the haulage distance could lower the possibility of traffic jams, and make the autonomous haulage system more practical.

Given that NFS mining method has so many theoretical advantages against normal open-pit mining method, how to quantitatively measure and verify the performance of the NFS method is a scientific question worth studying. Thus, in this paper, we develop a long-term production planning model for the NFS mining method to investigate its performance on the plant throughput quality and the net present value of the whole project.

2. Literature Review

Undoubtedly, with no solid mining plan, no matter how good the mining method is, it may lead to poor decisions with possible serious losses (Badiozamani et al., 2019; Ben-Awuah & Askari-Nasab, 2013). Therefore, to better understand the performance of the NFS mining method, an efficient strategic plan is needed. Usually, an optimized strategic plan consists of two main parts. The first part is the pit limit optimization, which defines the final shape of the open pit and it is the basis for the following part and affects the value of a mine to the most. Although different mathematical methods and models are published in past years, Lerchs-Grossman (LG) algorithm is still the dominant method that has been adopted by most researchers (Askari-Nasab et al., 2007; Dimitrakopoulos et al., 2007; Lerchs & Grossmann, 1965). In the second part of the strategic plan, a production schedule optimization model makes decisions on the sequence of blocks to be mined annually and addresses two main problems – when the blocks should be mined and where the materials from those blocks should be sent to. One of the most important objectives of this part is to maximize the NPV while meeting mining requirements like grade blending, plant capacity and other constraints (Askari-Nasab et al., 2008, 2011; Askari-Nasab & Awuah-Offei, 2009; Ben-Awuah et al., 2015; Lamghari, 2017). Due to the inherent complexity of the entire mining planning, time horizons are divided into three different phases: short-term, medium-term, and long-term (Tabesh et al., 2014). Then, the mine planning process aim at optimizing each time horizon separately to obtain a near-optimal results in a reasonable computer run-time (Badiozamani & Askari-Nasab, 2013; Dagdelen, 2001; Hustrulid et al., 2013). Since we want to investigate the NFS method performance on NPV and the grade blend and these two are directly involved in the strategic long-term production planning, herein we briefly survey the associated literature.

The long-term production plans of open pit mines are generated by implementing operations research techniques. Among those techniques, linear programming, and its mutant mixed integer linear programming (MILP) and mixed integer linear goal programming (MILGP) are the most popular and widely applied algorithm (Maremi et al., 2021; Upadhyay & Askari-Nasab, 2016).

The long-term planning algorithms take block models of the deposit as an input and as the number of blocks in the deposit increases the computing time for generating the plan increases. One way to reduce this processing time is to decrease the number of blocks in the block model. Tabesh and Askari-Nasab (Tabesh & Askari-Nasab, 2013) developed a two-stage clustering approach for block aggregation which has a significant impact on CPU time and the long-term production plan (LTPP) optimization and leads to a 10% higher NPV. The ore grade, block distance, and rock types are included in their clustering model but only one element was considered and many of explicit parameters have to be defined to get reasonable results. Shishvan and Sattarvand (Shishvan & Sattarvand, 2015) applied one metaheuristic algorithm - ant colony optimization (ACO) model to solve LTPP problem and tested the model in a real size copper -gold deposit. However, there is no guarantee that a global optimum schedule is generated, and the model is very sensitive to ACO parameters. Ramazan and Dimitrakopoulos (Ramazan & Dimitrakopoulos, 2018) proposed a stochastic integer programming (SIP) model for LTPP optimization while capturing the uncertainty of orebody. However, only hypothetical data are tested, and the results showed no significant difference with traditional model results. Although stockpiles are indispensable parts of mining operations these days as they can be helpful in achieving mine operation's economic goals such as minimizing the deviation of the tonnage and grade feed to the crusher compared against the target production, the abovementioned models do not incorporate stockpile into the modelling process.

In another stream of the literature of LTPP for open pit mines, Gholamnejad and Kasmaee(Gholamnejad & Kasmaee, 2012) proposed a linear goal programming model for open pit mining where they incorporated the role of stockpiles in the formulation. In their proposed model, the focus is dedicated to the reclamation of the material from the stockpile and ore delivery to it is totally ignored. Later on, a mixed integer linear programming (MILP) model for LTPP problems that considers grade uncertainty and a stockpile was proposed by Koushavand et al. (Koushavand et al., 2014). The objective function of their model is to maximize profit while including the cost of uncertainty. Mousavi et al. (Mousavi et al., 2016) and Kumar and Chatterjee (Kumar & Chatterjee, 2017) proposed similar formulations for LTPP in open pit mines. These two models have predetermined stockpile grades that force their models to perform far from reality. Instead of using classical linear programming, a goal programming model that aiming at reducing stockpile fluctuation was purposed in Souza et al. (Souza et al., 2018). In their model, Souza et al. minimized operating costs and deviation from head grade. The model has limitations in test dataset. For those models listed above, although stockpile is incorporated, an automatic perfect blending assumption is adopted. The main drawback of perfect blending is that the stockpile in traditional open-pit mining will not be fully reclaimed, so there will be a difference between real reclaimed material grade and hypothesized reclaimed grade, which would definitely introduce errors into the result and make it not credible.

There are also non-linear models proposed for LTPP optimization which incorporate stockpiles. Bley et al. (Bley et al., 2012) added a non-convex quadratic constraint for stockpile in each period and used s primal heuristic method to find feasible solutions for a specific problem. Ramazan and Dimitrakopoulos (Ramazan & Dimitrakopoulos, 2013) proposed a non-linear SIP model and applied it in a gold mine in Australia. That model is based on conditionally simulated deposit which captures more uncertainty compared to normal predetermined deposit. Tabesh et al. (Tabesh et al., 2015) suggested to model stockpiles nonlinearly. Then they linearized the nonlinear model by defining fixed tight grade intervals for different stockpiling bins. Paithankar and Chatterjee (Paithankar & Chatterjee, 2019) proposed a mathematical model based on genetic algorithm to simultaneously optimize production sequence and dynamic cut-off grades. The final goal is set to generate the highest NPV. The model assumes that stockpile has infinite capacity and no fluctuation on yearly mining capacity, which is not realistic in real operation. However, although most of the proposed non-linear models claimed a higher NPV under a specific case study, these types of models require more variables than linear models, especially for stockpiles which causes inefficiency issues. Besides, overall optimal results or near optimal results are not guaranteed and the time consumption is much higher than linear models.

3. Material and Methods

As the first step of our study, we implemented clustering algorithm developed by (Tabesh & Askari-Nasab, 2019) to aggregate mining blocks into mining-cuts and panels in an iron ore open pit mine. Then we used the LTPP model developed by Tabesh and Askari-Nasab (Tabesh et al., 2015) as our benchmark LTPP model and generated long-term production plan for the case study considering traditional open pit mining method with stockpile located outside of the pit rim. Then, we improved their model to develop our new LTPP model that can generate long-term production plan for the mine considering the NFS open pit mining method. In this section we are presenting the formulation of our LTPP model for the NFS open pit mining method. Various optimization mathematical models for long-term mining schedule that contain stockpiles were developed in the past decades and the typical ones are reviewed in literature review section of this paper. In order to have a feasible near-optimal solution within reasonable time periods, we selected a mixed integer linear programming approach for our LTPP model. Following, we first define indices, sets, parameters, and variables we used in the model. Then, we present the objective function and the constraints.

Indices

k	index for mining cuts ($k \in \{1, 2, \ldots K\}$)
p	index for panels ($p \in \{1, 2, \ldots P\}$)
t	index for scheduled periods ($t \in \{1, 2, \ldots T\}$)
d	index for destinations (stockpile or waste dump)
s	index for stockpiles zones ($s \in \{1, 2, \ldots S\}$)

Sets

C_p	set of the panels that must be extracted prior to mine panel p
K_p	set of the mining-cuts within panel p

Parameters

r_s^t	discounted revenue generated by sending 1 unit of material from stockpile zone s in period t to crusher minus the dozing, reclaiming cost and processing cost
q_p^t	discounted cost of mining all the material in panel p as waste in period t
o_k	ore tonnage in mining-cut k
o_p	ore tonnage in panel p
w_p	waste tonnage in panel p
o_r	ore tonnage in reserve

w_r	waste tonnage in reserve
c_{sp}	total capacity of stockpile
c_s	capacity of stockpile zone s
g_k^e	average grade of element e in ore portion of mining-cut k in percent
g_s^e	average grade of element e reclaimed from stockpile zone s in percent
gsu_e^t	upper bound of stockpiled head grade of element e in period t in percent
gsl_e^t	lower bound of stockpiled head grade of element e in period t in percent
gcu_e^t	upper bound of crusher acceptable grade of element e in period t in percent
gcl_e^t	lower bound of crusher acceptable grade of element e in period t in percent
pu^t	upper bound on ore processing capacity in period t in tonnes
pl^t	lower bound on ore processing capacity in period t in tonnes
mu^t	upper bound on mining capacity in period t in tonnes
ml^t	lower bound on mining capacity in period t in tonnes

Decision variables

$x_k^t \in [0,1]$	continuous variable, representing the portion of mining-cut k to be extracted as ore and send to stockpile in period t
$y_p^t \in [0,1]$	continuous variable, representing the portion of panel p to be mined in period t, fraction of y characterizes both ore and waste included in the panel
$b_p^t \in \{0,1\}$	binary integer variable controlling the precedence of extraction of panels. b_p^t is equal to one if extraction of panel p has started by or in period t, otherwise it is zero
$f_s^t \geq 0$	continuous variable, representing the tonnage of material sent from stockpile zone s to crusher in period t

Objective function and constraints

$$\max \sum_{t=1}^{T} \left\{ \underbrace{\sum_{s=1}^{S} (r_s^t \times f_s^t)}_{\text{Discounted revenue}} - \underbrace{\sum_{p=1}^{P} (q_p^t \times y_p^t)}_{\text{Discounted cost}} \right\} \tag{1}$$

$$ml^t \le \sum_{p=1}^{P} (o_p + w_p) \times y_p^t \le mu^t \qquad \forall t \in \{1,\dots,T\} \tag{2}$$

$$\sum_{t=1}^{T} \sum_{p=1}^{P} o_p \times y_p^t \le o_r \qquad \forall p \in \{1,\dots,P\}, \quad t \in \{1,\dots,T\} \tag{3}$$

$$\sum_{t=1}^{T} \sum_{p=1}^{P} w_p \times y_p^t \le w_r \qquad \forall p \in \{1,\dots,P\}, \quad t \in \{1,\dots,T\} \tag{4}$$

$$pl^t \le \sum_{s=1}^{S} f_s^t \le pu^t \qquad \forall t \in \{1,\dots,T\} \tag{5}$$

$$\sum_{k=1}^{K} o_k \times x_k^t - c_{sp} \le \sum_{s=1}^{S} f_s^t \le \sum_{k=1}^{K} o_k \times x_k^t + c_{sp} \qquad \forall t \in \{1,\dots,T\} \tag{6}$$

$$\sum_{s=1}^{S} \left(g_s^e - gcl_e^t \right) \times f_s^t \ge 0 \qquad \forall t \in \{1,\dots,T\}, \quad e \in \{1,\dots,E\} \tag{7}$$

$$\sum_{s=1}^{S} \left(g_s^e - gcu_e^t \right) \times f_s^t \le 0 \qquad \forall t \in \{1,\dots,T\}, \quad e \in \{1,\dots,E\} \tag{8}$$

$$gsl_e^t \le (\sum_{k=1}^{K} g_k^e \times o_k \times x_k^t) / (\sum_{k=1}^{K} o_k \times x_k^t) \le gsu_e^t \qquad \forall t \in \{1,\dots,T\}, \quad e \in \{1,\dots,E\} \tag{9}$$

$$\sum_{t=1}^{T} y_p^t = 1 \qquad \forall p \in \{1,\dots,P\} \tag{10}$$

$$b_p^t - \sum_{i=1}^{t} y_{\mathrm{b}}^i \le 0 \qquad \forall p \in \{1,\dots,P\}, \quad t \in \{1,\dots,T\}, \quad \mathrm{b} \in C_p \tag{11}$$

$$\sum_{i=1}^{t} y_p^i - b_p^t \le 0 \qquad \forall p \in \{1,\dots,P\}, \quad t \in \{1,\dots,T\} \tag{12}$$

Equation (1) is the objective function that aims at generating the highest discounted net present value of the project. Equation (2) ensures that the tonnage of total material mined in each period does not exit the mining capacity. Equation and Equation enforce the mining of ore and waste to not exit the available reserve. Equation (3) ensures that the total tonnage of material reclaimed from different stockpile zones matches the required processing capacity. Equation (4) limits reclaiming the material from different stockpile zones in each period. The reclaimed tonnage should not be less than ore material mined in that period minus stockpile capacity and more than ore material mined in that period plus stockpile capacity. We defined equations (5) and (6) for stockpile grade control. Constraint (7) ensures that the average grade of material being reclaimed from the stockpile in each period does not fall below the lowest acceptable head grade for the processing. Moreover, the constraint (8) ensures that the average grade reclaimed from stockpile does not exceed the upper bound of required processing head grade. Equation (9) limits the average ore grade mined from mining-cuts. Equation (10) puts a limit on all panels to be fully extracted within the mine life. Equation (11) ensures that all predecessor panels of the current active panel are fully extracted before mining the current panel. Constraint (12) limits mining of each panel to its maximum available reserve.

4. Results

To verify the performance of the NFS open pit mining method, we implemented it in an iron mine case study with 19,561 blocks in the deposit's block model and a total of 430 million tons of material in its final pit after performing pit optimization process. The dimension of each block in the block model is 25m (length)×25m (width)×15m (height) and the main element of interest is iron which is tracked by magnetic weight recovery (MWT) and the accompanying impurity contents (sulfur and phosphor) are tracked by percent mass units (%). The target processing head grade for MWT is 78% and maximum acceptable content for sulfur and phosphor are 1.7% and 0.14%, respectively.

The pit optimization resulted in four pushbacks and 40 panels in its optimal case. Meanwhile, the mining capacity is 32 million ton in early years which decreases to 9 million ton in the last year while processing capacity is 7.5 million ton from year five to the end of the mine life. We then implemented an adopted version of hierarchical clustering method proposed by (Tabesh & Askari-Nasab, 2013) to create mining polygons, resulting in 1883 mining-cuts. The clustering algorithm takes approximately 75 seconds to finish the block aggregation process in an Intel Core i7-7700HQ CPU at 2.80GHz, and 16 GB of RAM computer.

After the block aggregation stage, we generated LTPP for the conventional open pit mining and LTPP for the NFS open pit mining for the case study. We formulated both LTPP models in MATLAB (The MathWorks Inc., 2018) and solved them using the CPLEX (CPLEX, 2014). The following we first present results of implementing the NFS open pit mining method and then present a comparison against conventional open pit mining. It worth noting that the near face stockpile is considered during mine life consists of three zones representing low-grade, medium-grade and high-grade ore.

By the implementation of the NFS method in the case study, the project will generate a net present value of $2355 million dollars in the 20 years of mine life following the life of mine production schedule/plan presented in Figure 2. Meanwhile, the amount of materials processed each year is fairly stable with the average deviation of 2.7% from the capacity of the plant (Table 1).

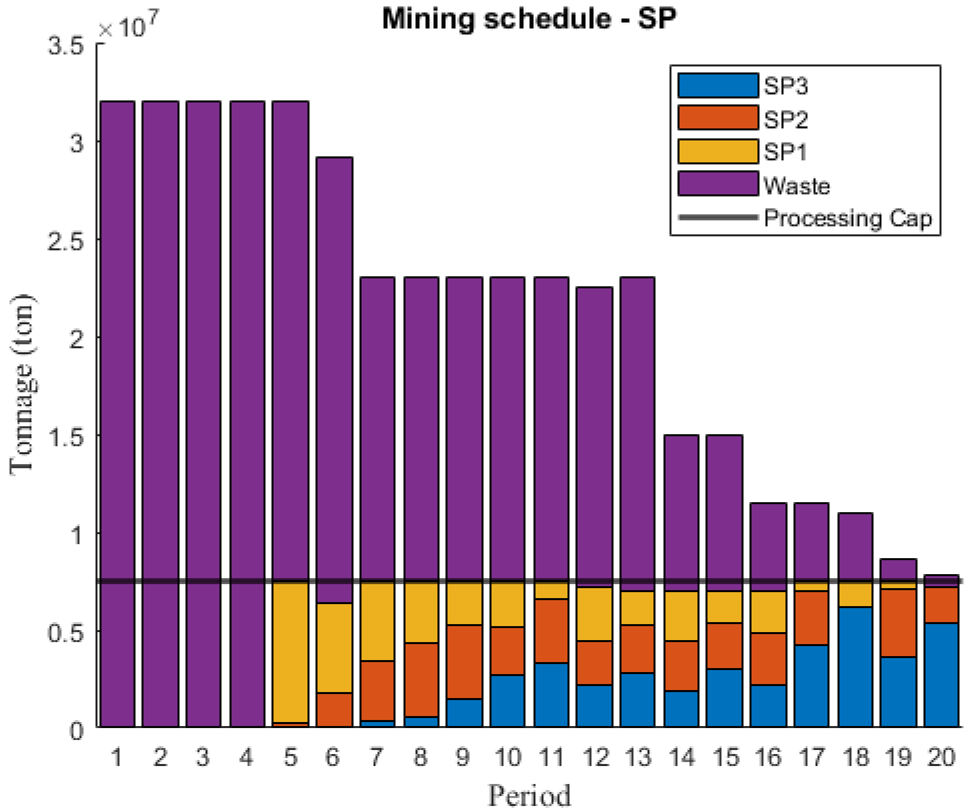

Figure 2. Long-term production schedule of the case study extracted using the NFS open pit mining method.

Table 1. Yearly tonnage of ore delivered to the processing plant using the NFS open pit mining method.

Year	5	6	7	8	9	10	11	12
Processed (Mt)	7.5	6.4	7.5	7.5	7.5	7.5	7.5	7.2
Difference (%)	0.0	-14.5	0.0	0.0	0.0	0.0	0.0	-3.9
Year	13	14	15	16	17	18	19	20
Processed (Mt)	7.0	7.0	7.0	7.0	7.5	7.5	7.5	7.2
Difference (%)	-6.7	-6.7	-6.7	-6.7	0.0	0.0	0.0	-4.3

Due to the particularity of the NFS mining method, all target minerals excavated from mining faces will be sent to the stockpile prior to be reclaimed by a shovel and delivered to the plant through the mobile IPCC system. The associated cost of reclaiming one ton of blended ore from the NFS in the case study is $0.5/ton. As mentioned before, the NFS has three zones in its stockpile. In order to equally utilize these zones as much as possible, we calculated the material tonnage and grade in each block, and selected two interim MWT grade values of 76.65% as the transition point from low-grade to medium-grade and 80.23% as the transition point from medium-grade to high-grade. The grade of iron in the deposit varies between the minimum MWT grade of 41.22% and the maximum MWT grade of 84.52% (Table 2). Figure 3 shows the yearly average MWT grade of each zone in stockpile and the MWT grade of the final blend reclaimed and processed each year, and Figure 4 and Figure 5 show the yearly average grade of phosphor and sulfur in each stockpile zone and the overall phosphor and sulfur grade of the blended material processed in each year of the mine life.

Table 2. Stockpile zoning parameters for the NFS method.

	Lower MWT (%)	Upper MWT (%)	Avg MWT (%)	Avg P (%)	Avg S (%)	Tonnage (Mt)
Zone1	41.22	76.65	70.02	0.14	1.31	37.56
Zone2	76.65	80.23	78.68	0.13	1.69	38.72
Zone3	80.23	84.52	81.26	0.14	1.60	40.01

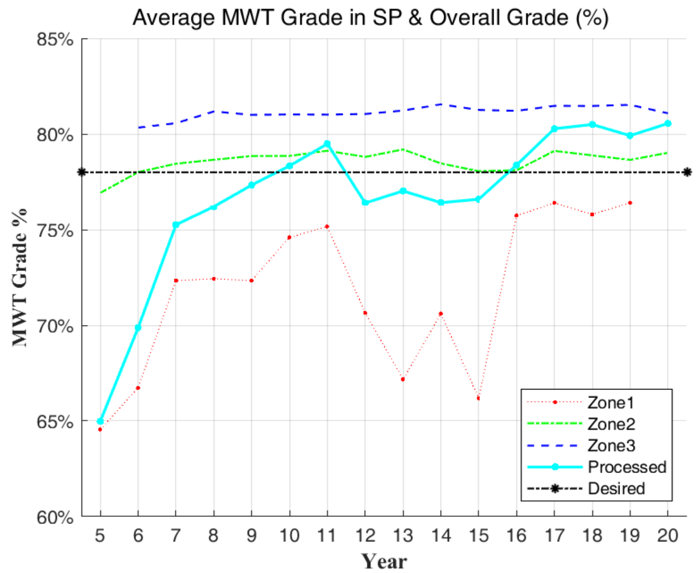

Figure 3. MWT grade delivered to each zone of the stockpile and the MWT grade of final blend reclaimed from the stockpile by year of the mine life.

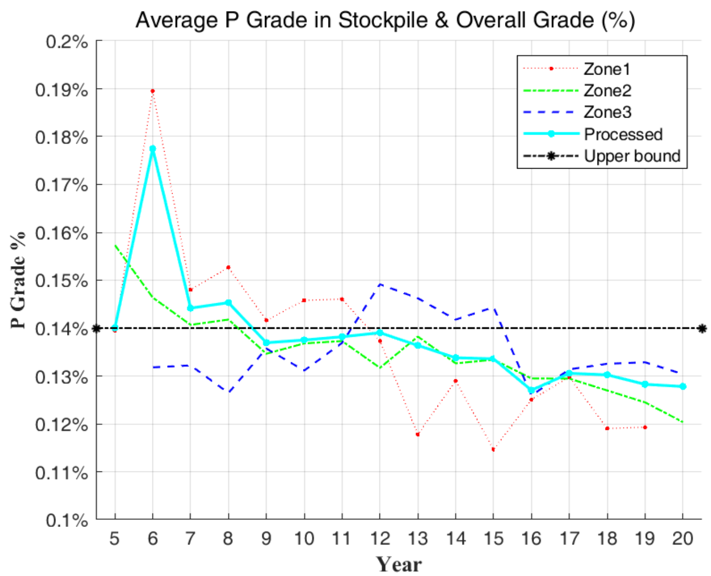

Figure 4. Phosphor grade delivered to each zone of the stockpile and the phosphor grade of final blend reclaimed from the stockpile by year of the mine life.

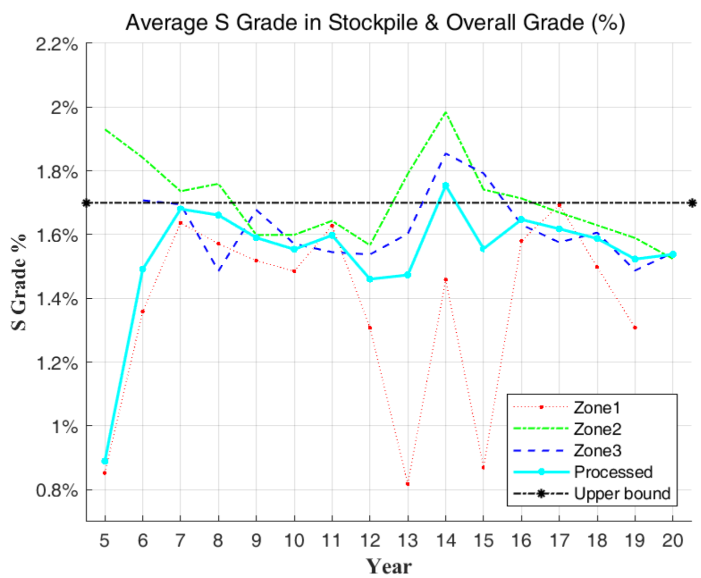

Figure 5. Sulfur grade delivered to each zone of the stockpile and the sulfur grade of final blend reclaimed from the stockpile by year of the mine life.

In Table 3, we present the average yearly deviation of blended grade processed from the target head grade.

Table 3. Deviation of the blended material grade from the desired head grade.

Year	5	6	7	8	9	10	11	12
S grade	0.89	1.49	1.68	1.66	1.59	1.55	1.60	1.46
Difference (%)	-	-	-	-	-	-	-	-
P grade	0.14	0.18	0.14	0.15	0.14	0.14	0.14	0.14
Difference (%)	0.05	26.8	2.99	3.8	-	-	-	-
MWT grade	65.0	69.9	75.3	76.2	77.3	78.3	79.5	76.4
Difference (%)	-17	-10	-4	-2	-1	0	2	-2
Year	13	14	15	16	17	18	19	20
S grade	1.47	1.75	1.56	1.65	1.62	1.59	1.52	1.54
Difference (%)	-	3.2	-	-	-	-	-	-
P grade	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Difference (%)	-	-	-	-	-	-	-	-
MWT grade	77.0	76.4	76.6	78.4	80.3	80.5	79.9	80.6
Difference (%)	-1	-2	-2	0	3	3	2	3

Table 2 and Table 3 show that inside the near face stockpile, zone 1 has widest grade range for both MWT and phosphor and is the dominant zone to be reclaimed and processed in the first two years after processing starts, leading to a higher grade deviation in early years. However, with the development of pit limit, more material are sent to the zone 3 of the NFS improving the reclamation grade in the later years of the mine life.

To evaluate the performance of the NFS open pit mining method, we compared results of our proposed LTPP with the results of the benchmark LTPP that was developed for mining the same case study using conventional mining method in two important KPIs (the NPV and the head grade deviation). In the benchmark model, the case study generates $2155 million dollar of NPV with an average grade deviation of 3% for MWT. This means that by switching from conventional open pit mining to the NFS open pit mining method the NPV generated by the case study will increase for 9.3% and the average head grade deviation will reduce for 58.3%. This is mainly due to the higher turnover rate of near face stockpile since material in different zones are fully reclaimed in a predetermined time range while in traditional mining method, stockpile is only reclaimed when material mined in that period is not enough and rarely does stockpile realize a fully turnover in life of mine. To be more specific, high stockpile turnover rate has a strong positive effect on the blending results since with higher turnover rate, the tolerance for ore grade fluctuations will increase, and some relatively extreme high-grade and low-grade ore material will become acceptable. This is particularly beneficial to those mining companies whose material of interest comes with associated impurities – just as the iron mine used in the case study. Moreover, with more materials becoming acceptable for processing, a higher production is expected which will eventually bring higher revenues and profits to the company.

5. Conclusions

To scientifically understand the performance of the near face stockpile open pit mining method under life of mine schedule, especially the blending process, this article proposed a mixed integer linear programming model to generate a near-optimal long-term production schedule. The proposed mathematical model was implemented in a real mining case study and the results were presented in this paper. Then, the impact of the near face stockpiling open pit mining method on the NPV and the head grade has been compared with the conventional open pit mining method. The results of this comparison show that the near face stockpile open pit mining method outperforms the conventional open pit mining method in the NPV with 9.3% improvement and the head grade deviation with 58.3% improvement in the quality of blended material delivered to the plant.

However, there are many theoretical advantages of the near face stockpile open pit mining method and only two aspects were verified in this paper. Some unnecessary losses due to uncertainties like equipment failure and saved cost for shorter haul which may lead to higher NPV are not included in our investigations. The authors will investigate the operational performance of the near face stockpile open pit mining method by simulating the daily operation of the case study in the next step of the research.

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