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Estimating mining time-span to improve the solution time in long-term production planning

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ABSTRACT

Long-term production planning in open-pit mines is a precedence-constraint knapsack problem. A spatial representation of the mining region (called the block-model) is the primary input of mine planning models. One should note that as the number of blocks and periods to be planned increases, the number of decision variables increases. This paper presents a fast yet straightforward algorithm to reduce binary variables in open-pit mine production planning models. The algorithm considers mining capacity, processing capacity, and pit deepening rate to estimate the time span within which a block is mineable. This paper applies the algorithm in 12 different cases. The number of blocks varies from 1000 to 240000, and the mining periods range from 6 to 30 years. According to the results, this algorithm is helpful for problem size reduction.

Keywords: *Production planning; Open-pit mining; Long-term planning; Mining time-span*

1. Introduction

Production planning of open-pit mines is a type of multi-period precedence-constraint knapsack problem. It can be modeled using Mixed Integer Linear Programming (MILP) framework [1-3]. Mine planning aims to guide the mining operation to the highest Net Present Value (NPV) by developing annual extraction plans [4-5]. It must consider the changing and uncertain conditions of operational constraints and actuates the economy and the payback period. These constraints involve the following [6]:

1- mill throughput (mill feed and mill capacity)
2- the volume of material extracted per period (mining capacity)
3- blending constraints (quality of the feed)
4- stockpile related constraints (dynamic cut off grades)
5- logistic constraints (slope constraint, pit bottom constraint, Pit Deepening Rate (PDR))

Since 1976, many researchers study production planning in open-pit mines, and they developed different models to optimize the production plan [7-18]. These models require a spatial representation of the mining area called the block model. To generate a block model for a deposit understudy, one should divide the deposit into fixed-sized cubic cells (i.e., blocks). The block size depends on both exploration and mining conditions including the exploration drilling pattern, geological condition, mining system, and the available mining equipment size. After determining block dimensions, a procedure assigns the geological characteristics of blocks using inverse distance, geostatistical methods, conditional simulation, or any other available technique [19]. After that, considering some economic and technical data such as selling price, operating costs, and overall recovery, one could calculate block economic values. In this step, the generated block model is fed into a production-planning model to optimize the mine output.

Typically, a block model may contain more than millions of blocks, but there is a limitation on the number of blocks that optimization tools could handle [20]. Thus, solving a production-planning model is a challenging and time-consuming task. Typically, in any mining operation, the mine life is more than 15 years, and the number of blocks is more than 1 Million blocks. Hence, there will be about 15 Million binary decision variables that the mathematical models should handle. However, the open-pit mining structure makes it possible to develop some strategies to reduce binary decision variables. This issue is the motivation of the current paper.

A decrease in the number of blocks (or increase of block size) seems to be the easiest way to improve the problem's tractability. As the number of blocks decreases (or block size increases), the geologic details are becoming hard to be modeled using large blocks. This fact will assuredly affect the preciseness and complexity of production planning models.

There are many works related to size reduction in the case of open-pit mine planning. Among them, the simplest is the bounding algorithm [22]. This algorithm starts with identifying all the ore blocks (i.e., the black cells in Figure 1). Then, considering the overall pit slope, it determines the preceding blocks of all the ore blocks regardless of economic issues (i.e., the gray cells in Figure 1). Finally, those blocks, which are neither an ore block nor a preceding block, are removed from the block model (the white cells in Figure 1a). This simple modification reduces the number of blocks significantly.

The bounding algorithm removes unnecessary blocks regardless of economic issues. If economic issue matters, one should determine the Ultimate Pit Limit (UPL). UPL determination is similar to bounding, but the difference is that it deems economic issues. Determining a UPL fits into a single-period precedence-constraint knapsack problem, and it is equal to finding the maximal closure of the representing network [23]. The blocks inside the UPL will then feed into the mine planning optimizers. Notably, the pit limit resulting from production planning

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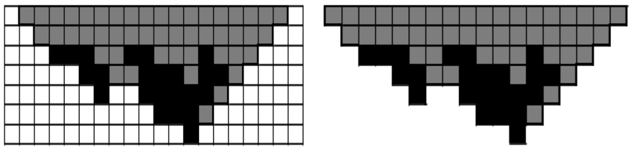
models is always contained within the UPL due to discounting of block values [6, 24, and 25].



(a) (b)

Figure 1. Removing the unnecessary blocks using the bounding algorithm

Another most widely used method is the aggregating of blocks. Aggregation can reduce the number of variables, constraints, or both, based on some criteria. In that regard, Ramazan et al. [26] presented the concept of Fundamental-Tree (FT). In this algorithm, an FT is a set of blocks such that (1) they can be mined without violating slope constraints; (2) the economic value of each FT is positive; (3) and each FT cannot be partitioned into smaller trees without violating (1) and (2). In this method, both the extraction and the processing decisions are made on the aggregate scale. This algorithm requires solving a series of linear models that seem to be relatively computationally expensive. Boland et al. [27] developed an iterative approach. In this approach, they use block aggregation to schedule the extraction sequence. Then, they disaggregate their data back into the block scale to make the processing decisions. In this method, the number of aggregates is adapted as the algorithm proceeds.

Askari-nasab et al. [28] presented a hieratical clustering algorithm to aggregate blocks into some mining cuts. The mining cuts are generated based on some similarity indexes. The rock types, ore grade, spatial location, and the preceding-constraint requirements are the bases for defining the similarity of blocks in a cut. Jelvez et al. [29] introduced a heuristic method for open pit mine planning where they use block aggregation to schedule the extraction sequence. They separate the aggregated blocks into the inner and borders blocks according to scheduling results. Then, they disaggregate their data back into the initial block scale and correct the blocks located at the borders.

Some researchers take advantage of panels and parcels to reduce decision variables [30-32]. In their method, each panel is the intersection of pushbacks and benches. Lotfian et al. [33] applied a genetic algorithm to solve the clustering problem. The generated cluster are not practical because they did not consider the pit slope restrictions. Thus, an iterative algorithm based on a simple mathematical model is applied to modify the non-practical clusters.

Apart from aggregating blocks, some researchers have worked on heuristics to reduce the number of decision variables. Goodwin et al. [34] applied the concept of receding horizon planning to reduce planning periods and the number of decision variables. Topal [35] presents an algorithm to estimate early and late extraction times of blocks in the case of underground mining operations. Gaupp [36] developed the same idea in open-pit mining. The algorithm is time-consuming, and it requires about 1150 seconds for a block model containing 10800 blocks. Chicoisne et al. [37] applied this concept in their models. However, they did not report how these times are calculated.

The present paper introduces a fast yet simple algorithm for problem size reduction. This algorithm estimates the early and late extraction times of blocks. The period between the early and late time is referred to as the Mining Time-Span (MTS). The efficiency of the proposed algorithm is evaluated in several cases and the results are reported.

2. Methodology

Consider the integer linear model for long-term production planning given in Equation 1. This model determines the extraction time of blocks. Also, it determines the processing method of each block, such that the NPV of the operation is maximized. The notations used in the model are as follows:

Decision variable:

x_{bmt}	is the decision variable. It is equal to 1 if the block b is mined at the time t and sent to the destination m ; otherwise, it is equal to 0.

Model parameters:

B	is the set of blocks in the block model
P_b	is the set of blocks that overlays or precedes block b
t,t'	are the time indexes
T	is the mine life or the number of planning periods
M	is the number of possible destinations or processing alternatives
c_{bmt}	is the discounted economic value of block b mined at the time t and sent to the destination m
$MC_t, \overline{MC_t}$	are the minimum and maximum mining rates at the time t , respectively
X_b	is the amount of rock in the block b
g_b	is the grade of the commodity in the block b (it is usually presented in percentage of the total tonnage in each block)
$G_{\min}^{t,m}, G_{\max}^{t,m}$	are the minimum and maximum acceptable grades at the destination m at the time t , respectively
$PC_{mt}, \overline{PC_{mt}}$	are the minimum and maximum processing capacities at the destination m at the time t , respectively

$$\text{Max} \sum_{b\in B}\sum_{t\in T}\sum_{m\in M} c_{bmt}\, x_{bmt} \tag{1a}$$

Subject to :

$$\sum_{t\in T}\sum_{m\in M} x_{bmt} \le 1, \ \forall b \tag{1b}$$

$$x_{bmt} \le x_{b'mt}, \ \forall b\in B, \forall t'\in\{1,\ldots,T\}, \forall b'\in P_b \tag{1c}$$

$$MC_t \le \sum_{b\in B}\sum_{m\in M} X_b\, x_{bmt} \le \overline{MC_t}, \ \forall t \tag{1d}$$

$$PC_{mt} \le \sum_{b\in B} X_b\, x_{bmt} \le \overline{PC_{mt}}, \ \forall t,m \tag{1e}$$

$$\sum_{b\in B} (g_b - G_{\max}^{t,m}) x_{bmt} \le 0, \forall t,m \tag{1f}$$

$$\sum_{b\in B} (g_b - G_{\min}^{t,m}) x_{bmt} \ge 0, \forall t,m \tag{1g}$$

$$x_{bmt} = 0\, or\, 1, \ \forall b,t,m \tag{1h}$$

Equation 1a is the objective function of the model. The model aims to maximize the discounted economic value or NPV of the mining operation. Constraint 1b ensures that if the block b is to be mined, it could only be mined once and sent to the destination m at time t. Constraint 1c is known as slope or proceeding constraint. This constraint ensures that wall slope restrictions are obeyed. Moreover, the block b can only be mined if all its overlaying blocks are removed beforehand. Constraint 1d and 1e ensure that the total amount of rock mined at the time t and processed in the destination m do not exceed the prescribed lower and upper bounds on mining and processing capacities. Constraints 1f and 1g ensure that the average grade of material sent to each destination is within the prescribed lower and upper bounds.

Solving the production-planning model (given in Equation 1) is a challenging and time-consuming task. This model contains B*T binary variables. Typically, T is around 15 years in a mining operation, and the number of blocks reaches more than 1000000 blocks. However, the open-pit mine structure makes it possible to reduce the number of binary variables. In this paper, Mining Time-Span (MTS) is introduced for problem size reduction.

The MTS of a block is equal to the difference between the earliest and the latest mining times. The earliest possible time of extracting a block is equal to the time required to remove the entire blocks that overlay the block. The overlay blocks (or precedence constraints) are identified based on a pit slope angle. On the other hand, the latest possible time of extracting a block is equal to the time required to remove the entire blocks inside the pit limit except the blocks located spatially under (i.e., the underlying blocks) that particular block. Thus, the primary step is to determine the underlying and overlay blocks for each block in a block model. Underlie blocks are called Downstream Blocks (DB), and the overlay blocks are called Preceding Blocks (PB). The cone containing the OB is named Preceding Cone (PC), and the cone containing the DB is named Downstream Cone (DC). These terms are shown in Figure 2.

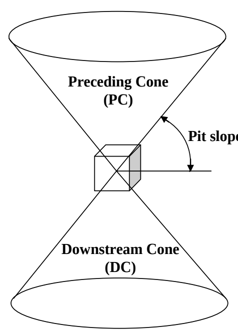


Figure 2. Preceding and Downstream cones

To generate PC and DC cones (and, PB and DB in the next level) is to use a cone generating pattern. Figure 3 depicts the pattern (1-5) that determines PB and DB. The most efficient way to create a pattern is to use the Minimum Search Pattern (MSP) [25, 38]. The MSP algorithm identifies the minimum number of blocks that generate a truncated cone. The MSP is related to block dimensions and the preciseness of the pit slope model. The MSP algorithm applies the pattern on a particular block to determine its preceding blocks. It tags the overlaying block according to the pattern. Then the algorithm uses the same pattern on every tagged block inside the block model. In the end, all of the tagged blocks represent the preceding blocks and the corresponding preceding cone. The same procedure is applied to determine the downstream blocks. As each blocks' preceding and downstream blocks are determined, estimating the earliest and latest mining time is possible. The results of the MSP algorithm will reduce the number of arcs in the network, hence, decrease the solution time.

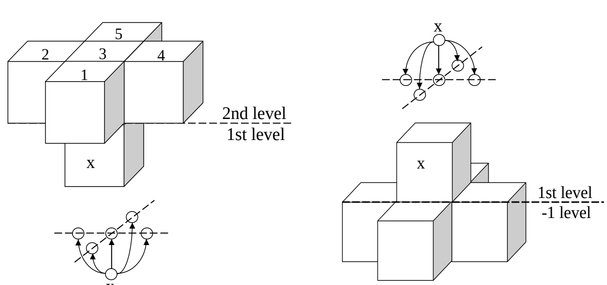


Figure 3. Pattern 1-5 for pit slope generation and identification of preceding and downstream blocks and their network representation

2.1. Earliest possible time to mine a block

In order to mine a block, its overlaying blocks should be removed in advance. Thus, the earliest possible time to mine a block is equal to the time required to mine its overlaying blocks. The constraints include mining capacity, processing capacity, and PDR are controlling the earliest possible time. The PDR is the rate at which the depth of the pit increases. This fact restricts the mining operation from going deep before mining enough waste from the upper benches. These constraints cause some delays at the earliest time that a block could be mined. PDR depends on the mine condition, mine size, depth of the ore deposit, and the number of ore blocks on each bench. It affects the amount of waste removal (stripping strategy) in open-pit mines. Therefore, the earliest possible time to mine a block is calculated using equation 2.

$$E_1 = \left\lfloor \frac{OT_{PrC}}{\overline{PC}} \right\rfloor + 1 \tag{2a}$$

$$E_2 = \left\lfloor \frac{RT_{PrC}}{\overline{MC}} \right\rfloor + 1 \tag{2b}$$

$$E_3 = \left\lfloor \frac{D}{PDR} \right\rfloor + 1 \tag{2c}$$

$$EPTM = Max\left(E_1, E_2, E_3\right) \tag{2d}$$

In this equation, $EPTM$ is the earliest possible time to mine a block, OT_{PrC} , RT_{PrC} is the total tonnage of ore and rock in the preceding cone, respectively. The total tonnage of rock is the summation of ore and waste tonnage in the preceding cone. The maximum processing and mining capacities are represented by $\overline{PC}$ and $\overline{MC}$ respectively. D stands for depth of the block and PDR is the pit-deepening rate. The symbol $\lfloor\ \rfloor$ represents the floor function. It returns the largest integer number less than or equal to the number inside the $\lfloor\ \rfloor$.

Equation 2a calculates the earliest time to process the block at the mill according to the maximum available processing capacity (E_1). Equation 2b calculates the earliest time to mine the block according to the maximum available mining capacity (E_2). Equation 2c calculates the earliest time to mine the block according to the maximum pit-deepening rate (E_3). The maximum of E_1, E_2, and E_3 indicates the limiting constraint on mining a block. Thus, the earliest possible time to mine a block ($EPTM$) is equal to the mining time considering the primary limiting constraint.

2.2. Latest possible time to mine a block

The latest possible time to mine a block is the time that a block could remain un-mined. In other words, a block can remain un-mined until the entire block other than its downstream blocks are mined. The constraints controlling the latest time to mine a block are mining capacity and processing capacity. Thus, the latest possible time to mine a block is calculated using equation 3.

$$L_1 = \left\lfloor \frac{O_{TOT} - OT_{DoC}}{PC} \right\rfloor + 1 \tag{3a}$$

$$L_2 = \left\lfloor \frac{R_{TOT} - RT_{DoC}}{MC} \right\rfloor + 1 \tag{3b}$$

$$LPTM = Min\left(L_1, L_2\right) \tag{3c}$$

In equation 3, $LPTM$ is the latest possible time to mine a block, O_{TOT} and R_{TOT} is the total tonnage of ore and rock inside the pit limit, OT_{DoC} , RT_{DoC} is the total tonnage of ore and rock in the downstream cone, respectively. The minimum processing and mining capacities are represented by PC and MC respectively.

Equation 3a calculates the latest time to mine a block according to the minimum processing capacity (L_1). Equation 3b calculates the latest time to mine the block according to the minimum mining capacity (L_2). The minimum of L_1 and L_2 indicates the limiting constraint on mining a block. Thus, the latest possible time to mine a block ($LPTM$) is equal to the minimum of L_1 and L_2.

As soon as $LPTM$ and $EPTM$ are calculated, the time-span (TS) for each block is determined using Equation 4.

$$TS = (EPTM, LPTM) \tag{4}$$

Figure 4 shows the algorithm for calculating the time span. The input is a block model. Each block contains information about its spatial location and the type and amount of material in it. At first, these data are sorted according to their z coordination. Based on the predetermined minimum search pattern, the preceding and downstream blocks are identified. The corresponding forward and reveres arcs are generated. A FIFO approach is then conducted to determine the preceding and downstream cones and calculate ore and rock tonnage in each cone. Afterward, according to Eq. 2 and 3, $LPTM$ and $EPTM$, the time span of each block is calculated. The worst-case complexity of this algorithm is O(nm), where n is the number of blocks, and m is the number of arcs in the network, which is controlled by the minimum search pattern.

```
int main ()
{
        Sort input data according to its z coordination in ascending order;
        Apply minimum search pattern to identify forward and reverse arcs;

        for (i=1;i<n+1;i++){
                LABEL_P B[i];
                Add B[i] to LIST_P;
                LABEL_D B[i];
                Add B[i] to LIST_D;

                for (j=1;j<n+1;j++){
                        Select block B[j] from LIST_P;
                        if (LIST_P=Ø) GOTO L10;
                        // determine the preceding blocks based on forward arcs
                        for (k=1;k<d+1;k++){
                                if (B[k] is not labelled){
                                        LABEL_P B[k];
                                        Add B[k] to LIST_P;
                                        if (B[k] is an ore block) ore_ton_P= ore_ton_P +(ton of B[k]);
                                        rock_ton_P = rock _ton_P +(ton of B[k]) ;
                                }
                        }

                        // determine the downstream blocks based on reverse arcs
                        L10: Select block B[j] from LIST_D;
                        if (LIST_D =Ø) BREAK;
                        for (k=1;k<d+1;k++){
                                if (B[k] is not labelled){
                                        LABEL_D B[k];
                                        Add B[k] to LIST_D;
                                        if (B[k] is an ore block) ore_ton_D = ore_ton_D +(ton of B[k]);
                                        rock_ton_D = rock _ton_D +(ton of B[k]);
                                }
                        }
                }
                Calculate TS of B[i];
        }
}
```

Figure 4. The time-span estimation algorithm

3. Results

The algorithm is tested in some sample block models available at MinLib [39]. Test data contains a variety of instances. Newman is the smallest case in the dataset. Zuck small, Zuck medium, and Zuck large are fictitious mines (Figure 5a, 5b, and 5e). D is a copper deposit, P4HD is a gold and copper mine (Figure 5c), and W23 consists of phases 2 and 3 of a gold mine (Figure 5d). All of them are located in North America. Marvin is a well-known test mine that is provided with the Whittle optimizing software. SM2 is a fictional nickel mine located in Brazil. McLaughlin is a gold mine in California, and its final pit limit is named McLaughlin-limit (Figure 5f) in the dataset. McLaughlin is the largest block model in the dataset, and it contains about 2140342 blocks. Therefore, before the application of the time-span algorithm, the block model of McLaughlin is bounded using the method described in figure 1. Thus, the number of blocks reduces to 237470. Apart from these data, the algorithm is tested on the block model of Gol-e-Gohar mine number 2. Gol-e-Gohar iron ore mine is located in Kerman province in the southeast of Iran.

The first step is to generate PC and DC cones using the MSP algorithm. As stated, the resulting MSP is related to block dimensions and the preciseness of the pit slope model. According to the dataset, the block dimensions are the same along the x, y, and z-axis, thus, the block is cubic. For the case of Gol-e-Gohar mine number 2, the block dimensions are 10×10×15 meters. The pit slope is assumed to be 45 degrees in every direction for all the cases. The preciseness of the pit slope model is 1 degree.

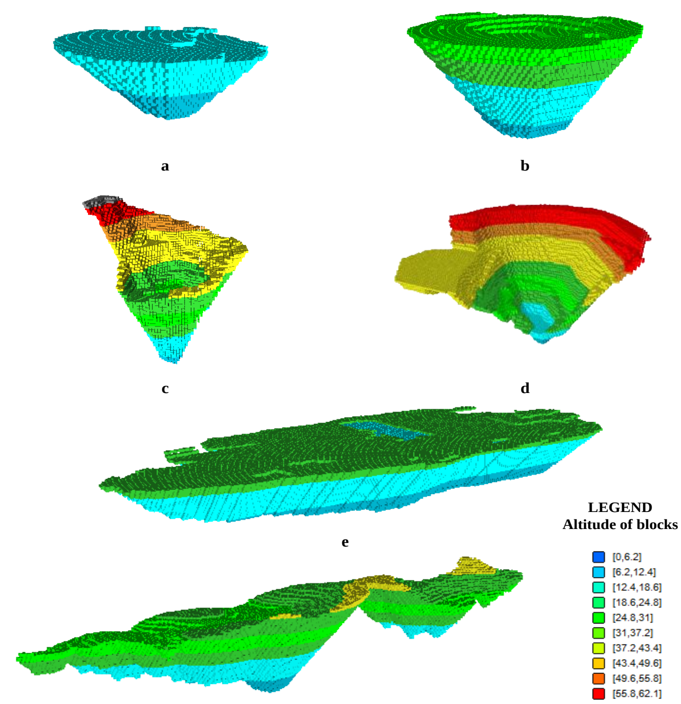


Figure 5. 3D view of data set - (a) Zuck small, (b) Zuck medium, (c) P4HD, (d) W23, (e) Zuck large, and (f) McLaughlin-limit

Based on the data, the MSP algorithm suggests the 1-5-9 pattern (also known as Knight-Move in the literature) to generate the preceding and downstream cones for the MinLib dataset. While, for Gol-e-Gohar mine number 2, the MSP contains 53 blocks in this case. Figure 6 shows the pattern 1-53 and the corresponding preceding and downstream cones. In Figure 6(a) the highlighted blocks indicate the blocks selected by the pattern 1-53. The number inside each block indicates the level that the block is located spatially relative to block x.

The algorithm of determining the preceding and downstream cones and calculation of LPTM and EPTM is coded in C++. Table 1 summarizes the number of blocks and the time spent calculating the LPTM and EPTM in each case. The algorithm, first, determines the preceding blocks and calculates the EPTM, and then it starts with the determination of downstream blocks and LPTM. According to the results (Figure 7), as the number of blocks increases, the total time spent determining the time-span increases. However, this is a fast algorithm, and it requires 1210 seconds to assess the time-span of a block model of a size of 112000 blocks.

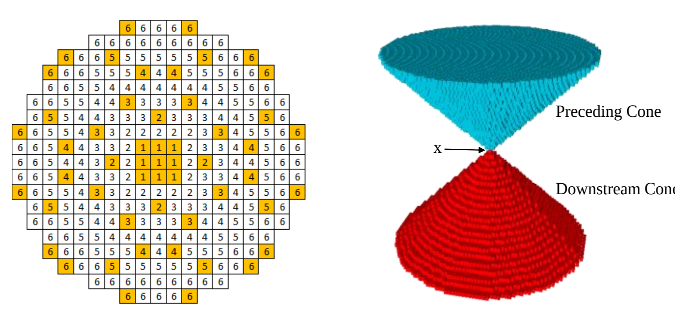


Figure 6. Pattern 1-53 and the preceding and downstream cones generated using the pattern

Table 1. Running time in different data sets

Problem instance	Block count	EPTM (Sec.)*	LPTM (Sec.)*
Newman	1060	<1	<1
Zuck-small	9400	4	4
D	14153	11	11
Zuck-medium	29277	39	40
P4HD	40947	93	94
Marvin	53271	158	158
Gol-e-Gohar2	65797	393	390
W23	74260	305	307
Zuck-large	96821	475	449
SM2	99014	538	543
McLaughlin -limit	112687	603	608
McLaughlin	238470	2956	2970

* The problems are solved on an "hp EliteBook 8540p" laptop set.

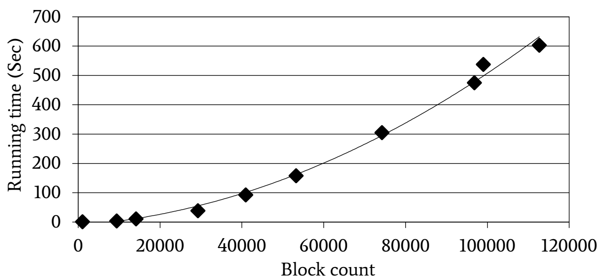


Figure 7. The relation between running time and the number of blocks

Table 2 represents the number of blocks, the corresponding mine-life, and the number of binary variables in each instance according to the model given in Equation 1. After implementing the algorithm and calculating time-spans, it is possible to calculate the number of reduced binary variables. The percentage of reduction in the number of binary variables varies from 1% to 74%. As presented in table 2, there is no trend in the number of variables after removing the unnecessary variables. However, the number of ore blocks and their spatial location in the block model affect the algorithm's efficiency. According to the results, in vertically oriented ore deposits and deep pits (for example, SM2), the algorithm's efficiency on the number of reduced binary variables becomes significant. However, in the case of large deposits that oriented horizontally (for example, Gol-e-Gohar2, Zuck-large, McLaughlin, McLaughlin-limit, and D), the percentage of reduction for binary variables is lower than 7%.

Table 2. Reduction in the number of binary variables

Problem instance	Block count	Mine life	Num. of benches	Total number of binary variables	Number of reduced variables	Reduction percentage
Newman	1060	6	23	6360	4240	33%
Zuck-small	9400	20	14	188000	169362	10%
D	14153	12	19	169836	166328	2%
Zuck-medium	29277	15	29	439155	351020	20%
P4HD	40947	10	64	409470	293317	28%
Marvin	53271	20	16	1065420	1034396	3%
Gol-e-Gohar2	65797	17	23	1118549	1036078	7%
W23	74260	12	63	891120	678379	24%
Zuck-large	96821	30	21	2904630	2886140	1%
SM2	99014	30	98	2970420	758401	74%
McLaughlin -limit	112687	15	46	1690305	1659148	2%
McLaughlin	238470	20	49	4769400	4709075	1%

4. Discussions

Long-term production planning in open-pit mines is a precedence constraint knapsack problem. A long-term plan is a plan for the specific portion of a mineable reserve or whole life of the mine, or for a period of significant income (which one is smaller). Long-term plans are based on the geological block model. Typically, a geological block model contains more than 1 Million blocks, and the number of planning periods varies from 15 to 25 years. Thus, a production-planning model (as the model given in equation 1) contains about two million binary variables. Solving such a production-planning model is a challenging and time-consuming task.

Moreover, predictions in the mineral industry indicate that future mines are giant mines that exploit low-grade material. Therefore, mining engineers must deal with a large number of blocks in block models. The deal with large block models highlights the need for new algorithms that increase the tractability of production-planning models.

However, the structure of open-pit mining provides some strategies to reduce the number of binary variables. This paper deals with some issues that could reduce the complexity of the production-planning problem in open-pit mines. The paper's core concept introduces a fast and simple algorithm to estimate blocks' early and late extraction time. The period between the early and late time is referred to as mining time-span or briefly time-span.

The algorithm of estimating time-span applies the minimum search pattern to recognize the preceding and downstream cones. The mining time-span algorithm considers the constraints on mining capacity, processing capacity, and pit-deepening rate. These time-spans will lead to an efficient formulating of production planning.

The algorithm is tested on 12 cases with various block numbers and spatial distribution of blocks to reveal the improvements in running time. The number of blocks varies from 1000 to 240000 and the planning periods (mine life) range from 6 to 30 years. According to the results (Table 1 and Figure 7), as the number of blocks increases, the running time increases. The running time varies from less than a second to about 3000 seconds in the most extensive data instance. It shows that the procedure is applicable in large block models with even more blocks than presented in this paper. The test case of Gol-e-Gohar2 is not included in Figure 7 because the size of blocks in this model and the corresponding search pattern are different from the other samples. However, the algorithm can handle various block models with varying block counts, block sizes, and variable pit slopes.

The proposed method is a fast algorithm, and it estimates the earliest and the latest possible time of mining a block and its time-span in a reasonable amount of time. Estimating the time span is assuredly the preliminary step in production planning, and it reduces the number of binary decision variables. The algorithm's efficiency depends on the shape, orientation, depth of the ore deposit, the number of ore blocks and their spatial location in a block model, and the number of planning periods or mine life. In large and horizontally oriented deposits (for example, Zuck-large and McLaughlin-limit), the reduction of binary variables is less than 10%. While in the case of vertically oriented ore deposits (W23, Zuck-small, Zuck-medium, and P4HD, for instance), the reduction in the number of binary variables is significant. Furthermore, the algorithm could improve the solution time effectively. A reduced number of decision variables will remove unnecessary branching and bounding and reduce the solution time.

5. Conclusions

The paper presents a heuristic algorithm to tackle the open-pit mine scheduling problem by reducing the size of the binary variables in the formulation. The algorithm considers mining capacity, processing capacity, and pit deepening rate to estimate the time span within which a block is available for mining. This paper applies the algorithm in 12 different cases. The number of blocks varies from 1000 to 240000, and the mining periods range from 6 to 30 years. According to the results, the algorithm's efficiency depends on the deposit orientation, depth, and spatial location of blocks in a block model, and the number of planning periods or mine life.

REFERENCES

[1] Goodwin, G. C., Seron, M. M., and Mayne, D. Q., (2008), Optimization opportunities in mining, metal and mineral

processing, Annual Reviews in Control, 32, 17-32, doi:10.1016/j.arcontrol.2008.02.002

[2] Osanloo, M., Gholamnejad, J., and Karimi, B., (2008), Long-term open pit mine production planning: a review of models and algorithms, International Journal of Mining, Reclamation and Environment, 22(1), 3-35, doi:10.1080/17480930601118947

[3] Newman, A. M., Rubio, E., Caro, R., Weintraub, A., and Eurek, K., (2010), A review of operations research in mine planning, Interfaces, 40(3), 222-245, doi:10.1287/inte.1090.0492

[4] Dagdelen, K., (2007), Open pit optimization — strategies for improving economics of mining projects through mine planning, in Dimitrakopoulos, R., (Ed.), Orebody modelling and stochastic mine planning, 2nd Ed., Spectrum Series No 14, AusIMM, 145-148

[5] Rahmanpour, M., Osanloo, M., (2016), Determination of value at risk for long-term production planning in open pit mines in the presence of price uncertainty, Journal of the Southern African Institute of Mining and Metallurgy, 116(03), 229-236

[6] Caccetta, L., Hill, S. P., (2003), An application of branch and cut to open pit mine scheduling, J. Global Optimization, 27, 349–365, doi:10.1023/A:1024835022186

[7] Albach, H., (1976), Long range planning in open pit mining, Management science, 13(10), B549-B568

[8] Gangwar, A., (1982), Using geostatistical ore block variance in production planning by integer programming, 17th APCOM, New York: SME, 443-460

[9] Tolwinski, B., and Underwood, R., (1996), A scheduling algorithm for open pit mines, Journal of Mathematics Applied in Business & Industry, 247-270, doi:10.1093/imaman/7.3.247

[10] Kumral, M., (2003), Application of chance-constrained programming based on multi-objective simulated annealing to solve a mineral blending problem, Engineering Optimization, 35(6), 661-673, doi:10.1080/03052150310001614837

[11] Gholamnejad, J., Osanloo, M., and Karimi, B., (2006), A chance-constrained programming approach for open pit long-term production scheduling in stochastic environments, The Journal of The Southern African Institute of Mining and Metallurgy, Vol. 106 (Feb. issue), 105-114, ISSN 0038–223X/3.00 +0.00.

[12] Boland, N., Dumitrescu, I., and Froyland, G., (2008), A multistage stochastic programming approach to open pit mine production scheduling with uncertain geology, Optimization, online, 33 pages, available at: http://www.optimization-online.org/DB_FILE/2008/10/ 2123.pdf

[13] Dimitrakopoulos, R., and Ramazan, S., (2008), Stochastic integer programming for optimizing long term production schedules of open pit mines, methods, application and value of stochastic solutions, Mining Technology, 117(4), 155-160, doi:http://dx.doi.org/10.1179/174328609X417279

[14] Bley, A., Boland, N., Fricke, C., and Froyland, G., (2010), A strengthened formulation and cutting planes for the open pit mine production scheduling problem, Computers and Operation Research, 37(9), 1641-1647, doi:http://dx.doi.org/10.1016/j.cor.2009.12.008

[15] Kumral, M., (2010), Robust stochastic mine production scheduling, Engineering Optimization, 42(6), 567-579, doi:10.1080/03052150903353336

[16] Liu SQ, Kozan E (2016), New graph-based algorithms to efficiently solve large scale open pit mining optimisation problems. Expert Systems Appl. 43(1):59–65

[17] Muñoz G, Espinoza D, Goycoolea M, Moreno E, Queyranne M, Rivera O (2018), A study of the Bienstock-Zuckerberg algorithm, Applications in mining and resource constrained project scheduling. Comput. Optim. Appl. 69(2):501–534

[18] Vossen TWM, Wood KRK, Newman AM (2016), Hierarchical benders decomposition for open-pit mine block sequencing. Oper. Res. 64(4):771–793

[19] Journel, A., and Kyriakidis, P.C., (2004), Evaluation of mineral reserves: a simulation approach, Oxford University Press, 215 pages

[20] Rojas, C.R., Goodwin, G.C., Seron, M.M., and Zhang, M., (2007), Open-cut mine planning via closed-loop receding-horizon optimal control, in Ricardo S., and Joseba, Q., (eds.), Identification and Control, Springer, 43- 60, doi:10.1007/978-1-84628-899-9_2

[21] Noble, A. C., (2011), Mineral Resource Estimation, in Darling, P. (Editor), SME mining engineering handbook, 3rd edition, CHAPTER 4.5, 203-217, Society for Mining, Metallurgy, and Exploration Inc. (SME)

[22] Caccetta, L., and Giannini, L. M., (1985), On bounding techniques for the optimum pit limit problem, The AusIMM Bulletin, 290(4): 87-89

[23] Picard, J. C., Smith, B. T., (2004), Parametric maximum flows and the calculation of optimal intermediate contours in open pit mine design, INFOR, 42(2), 143-153, ISSN 0315-5986

[24] Askari-nasab, H., Awuah-Offei, K., (2009), Open pit optimization using discounted economic block values, Mining Technology, 118 (1), 1-12, http://dx.doi.org/10.1179/037178409X12450752943243

[25] Osanloo, M., Rahmanpour, M., Sadri, A., (2010), Ultimate pit limit of iron ore mines using maximum, proceeding of MPES 2010, Fremantle, AusIMM, pp. 81-87

[26] Ramazan, S., Dagdelen, K., Johnson, T. B., (2005), Fundamental tree algorithm in optimizing production scheduling for open pit mine design, Mining Technology, 114(March), pp. 45-54, http://dx.doi.org/10.1179/037178405X44511

[27] Boland, N., Dumitrescu, I., Froyland, G., Gleixner, A. M., (2009), LP-based disaggregation approaches to solving the open pit mining production scheduling problem with block processing selectivity, Computers & Operations Research, 36, pp. 1064 - 1089, doi:10.1016/j.cor.2007.12.006

[28] Askari-nasab, H., Tabesh, M., Badiozamani, M. M., Eivazy, H., (2010), Hierarchical clustering algorithm for block aggregation in open pit mines, MPES, pp. 469-479

[29] Jelvez, E., Morales, N., Nancel-Penard, P., Peypouquetd, J., Reyes, P., (2016), Aggregation heuristic for the open-pit block scheduling problem, European Journal of Operational Research, 249, 1169–1177

[30] Elkington, T., Durham, R., (2011), Integrated open pit pushback selection and production capacity optimization, Journal of Mining Science, 47(2), pp. 177-190, doi: 10.1134/S1062739147020055

[31] Whittle, J., (2011), Long-Term Scheduling, In E. Y. Baafi, R. J. Kininmonth, I. Porter (Eds.), 35th APCOM, Wollongong: AusIMM, 75-80

[32] Letelier, O.R., Espinoza, D., Goycoolea, M., Moreno, E., Muñoz, G., (2020), Production scheduling for strategic open pit mine planning: a mixed-integer programming approach, Operations Research, INFORMS, DOI: 10.1287/opre.2019.1965

[33] Lotfian, R., Gholamnejad, J., and Mirzaeian, Y.L., (2020), Effective solution of the long-term open pit production planning problem using block clustering, Engineering Optimization, DOI: 10.1080/0305215X.2020.1771703

[34] Goodwin, G.C., Seron, M.M., Middleton, R.H., Mayne, D.Q., (2006), Receding horizon control applied to optimal mine planning, Automatica, vol. 42, pp. 1337 – 1342, doi:10.1016/j.automatica.2006.01.016

[35] Topal, E., (2008), Early start and late start algorithms to improve the solution time for long-term underground mine production scheduling, The Journal of the Southern African Institute of Mining and Metallurgy, 108(February), 99-107

[36] Gaupp, M P., (2008), Methods for improving the tractability of the block sequencing problem for open pit mining, Ph.D. thesis, Colorado School of Mines, Golden, CO, 159 pages

[37] Chicoisne, R., Espinoza, D., Goycoolea, M., Moreno, E., and Rubio, E., (2012), A new algorithm for the open-pit mine scheduling problem, Operations Research, 60(3), 517–528, doi: http://dx.doi.org/10.1287/opre.1120.1050

[38] Caccetta, L., and Giannini, L. M., (1988), The generation of minimum search pattern in the optimum design of open pit mines, The AusIMM Bulletin, 293(5):57-61

[39] Espinoza, D., Goycoolea, M., Moreno, E., Newman, A., (2012), MinLib: a library of open pit mining problems, Ann Oper Res, 22 pages, doi: 10.1007/s10479-012-1258-3.