Chapter 8: Advanced Analytics and Surface Extraction

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Abstract

Nowadays, approximately 90% of the minerals are extracted using surface mining methods. Surface mining is the process of extracting minerals located at the surface or near the surface. Although at least nine different surface mining methods have been introduced thus far, open pit and strip mining have the highest contribution in raw material extraction from Earth. Deposits that are being mined using these two methods are substantially expensive, both in the capital and operational costs requiring several managerial decisions to be made for the sake of lowering proportions of the total costs. Analytics has had an inevitable role in this matter. It has been involved in the decision-making procedures from method selection to finding the best location for in-pit crushers in surface mines. This chapter elaborates on how analytics contribute to different steps of extracting material using surface mining methods.

Keywords: Surface mining, open-pit mining, mine planning, decision making, In-pit crushing, Equipment selection

Introduction to Surface Mining

Surface mining is defined as the exploitation of ore from the ground's surface with no exposure of operation crew to underground spaces. The surface mining operation is performed using nine different methods categorized under two main classes of mechanical methods and aqueous methods (Table 8. 1). The mechanical methods class responsible for 90% of total surface mining production is defined as a class of ore extraction that applies mechanical processes to mine material from the Earth in a dry environment [1].

Table 8. 1: Surface mining methods

Class	Method
Mechanical	Open-pit
	Strip
	Quarry
	Auger (High-wall)
Aqueous	Dredging
	In-situ
	Hydraulic
	Surface Techniques
	Evaporate

From all nine surface mining methods listed in Figure 8. 1, 90% of tonnages mined using surface mining methods are mined by open-pit and strip mining [2]. Strip mining is more common in tabular near the surface flat-lying deposits like coals, whereas open-pit mining is more common in vertically aliened deposits. A literature survey shows that more than 52% of total industrial-scale mining operations in the world are open-pit metal mines [3]. Based on the importance of open-pit mining across the different surface mining methods, this chapter will focus on elaborating the application of advanced analytics in different planning and design stages of the open-pit mining method.

As defined in [3], open-pit mining is the process of mining near-surface deposits using horizontal benches. It has two main differences comparing to strip mining and quarrying. In open-pit mining, the overburden must be moved out of the pit rim and been disposed in an external disposal area, whereas in the strip mining, the overburden can be disposed inside the mined area. Compared to the quarrying, the open-pit mining method selectively mines the ore, whereas, in quarrying, an aggregate or a dimensional stone is produced.

All open-pit mines have at least three main infrastructures: benches, haul road networks and dumps. Material is excavated on a series of layers with a uniform thickness called a bench [4]. AS depicted in Figure 8. 1, an open-pit consists of three types of benches. Active (working) benches are benches where shovels are mining material. Inactive benches where no production activity is taking place at the moment but has the potential to be activated in the future, and catch benches where material falling from the top benches are caught and stopped from falling onto the active areas.

Haul road networks are a series of haul roads connecting different loading points to different dumping points and providing connections to other service areas inside and outside of the open-pit. Haul roads in open-pit mines are constructed by either cutting or filling the floor of mining benches in deep hard rock mines and paving the pit floor in shallow soft rock mines. A typical haul road in an open-pit mines consists of three major components: travel lane, safety berm, and drainage ditch. As a rule of thumb, road width for two-way traffic, which is the most common road in open-pit mines, must be greater than four times the largest truck's width [4].

The third major infrastructure of an open-pit mine is its waste dump. The waste dump refers to the dump of mined material with no to little economic value at the time of its placement [5].

The mining production fleet works within the three above-mentioned infrastructures to produce economic value for shareholders. This brief introduction being said, the following subsections in this chapter present the application of advanced analytics in each stage of planning, design, and production from surface mines and, more specifically, open-pit mining methods.

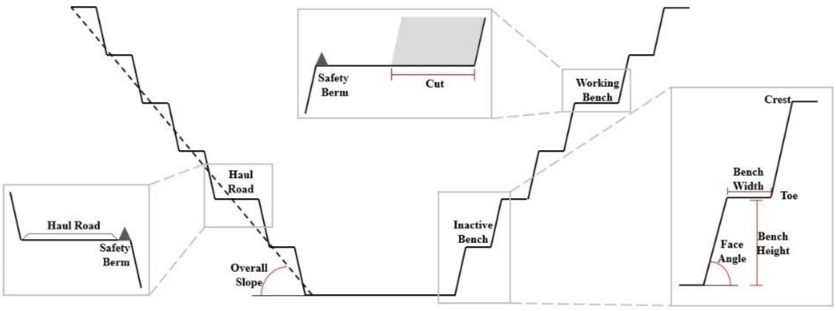

Figure 8. 1: Open-pit Geometry [5].

Open-Pit Planning and Design

Before starting extraction of raw material from the ground, the business needs a step-by-step actionable plan that provides a detailed guideline for the production to maximize the net present value of the deposit. The open-pit planning and design is a decision-making process that provides a detailed, actionable plan for profitably producing the raw material from the area of interest [6].

Open-pit planning and design are generally outlined for three different time frames. Short-range plans are providing information for a time frame between a shift to a week. Medium-range plans range between a week to a year of operation, and the long-range plans provide production schedule and design for a year of operation to the life of mine. In this chapter, our focus is on long-range open-pit planning and design.

There are seven main steps in generating the long-range mine plan for an open-pit mine. Initially, a resource model is needed to be prepared for the area of interest.

Then, in the second step of the open-pit planning and design, we apply a pit optimization algorithm to generate a set of pit shells. After laying out the set of possible pit shells, the planner needs to choose the final pit. The final pit is the pit in the set of possible pit shells that maximizes the mine's net present value. When the final pit is selected, we need to establish the desired production rate and generate a plan for material production within the final pit. In the last two steps of the long-range open-pit planning and design, the number of desired pushbacks and their basic designs are chosen, and finally, the production schedule is optimized. A detailed step by step open-pit mine planning and design can be found in [4].

Optimization is the branch of advanced analytics that is of the highest demand in the open-pit mining planning and design stage. Determination of ultimate pit limit and production schedulings are two main steps in the open pit mine planning and design where optimization algorithms are required to make optimal decisions.

The final pit limit is defined as the extent of the mineable reserve and the waste material that is economically and technically viable and safe to be mined for extracting the ore [7]. The optimum final pit limit is determined by maximizing net present value (NPV) from mining a set of blocks concerning slope constraints. In equation (8.1) and equation (8.2), we present the formula for calculating the block economic value for each block in the block model and the basic formula for NPV calculation.

$$\begin{aligned} BEV_{ijk} = \ & Ore_{ijk} \times g_{ijk} \times Recovery \\ & \times (Price - Cost\ of\ Selling) \\ & -\ Ore_{ijk} \times Cost\ of\ Processing \\ & - Total\ Rocks\ _{ijk} \times Cost\ of\ Mining \end{aligned} \tag{8.1}$$

$$Max\ P = \sum_{ijk} BEV_{ijk} \tag{8.2}$$

Subject to pit slope constraints.

Where BEV_{ijk} is the block economic value of the block located in the orebody with index i, j, and k. Ore_{ijk} is the content of ore in the same block with an average grade of g_{ijk}.

Two major steps must be taken. At first, the block economic value (BEV) must be calculated using stochastic parameters in nature, such as tonnage of ore, grade, recovery, price, cost, etc. Then in the second step, the pit limit must be determined using a set of uncertain BEVs inputs. Analytics is to the rescue here. It all started with Dowd's risk-based algorithm [8]. In the risked base mine planning algorithm developed by Dowd (Figure 8. 2), all the input parameters with the stochastic behavior are imported as the distributions fitted on the data. In each step of the algorithm, it randomly samples from the distributions instead of using a deterministic value for each input parameter.

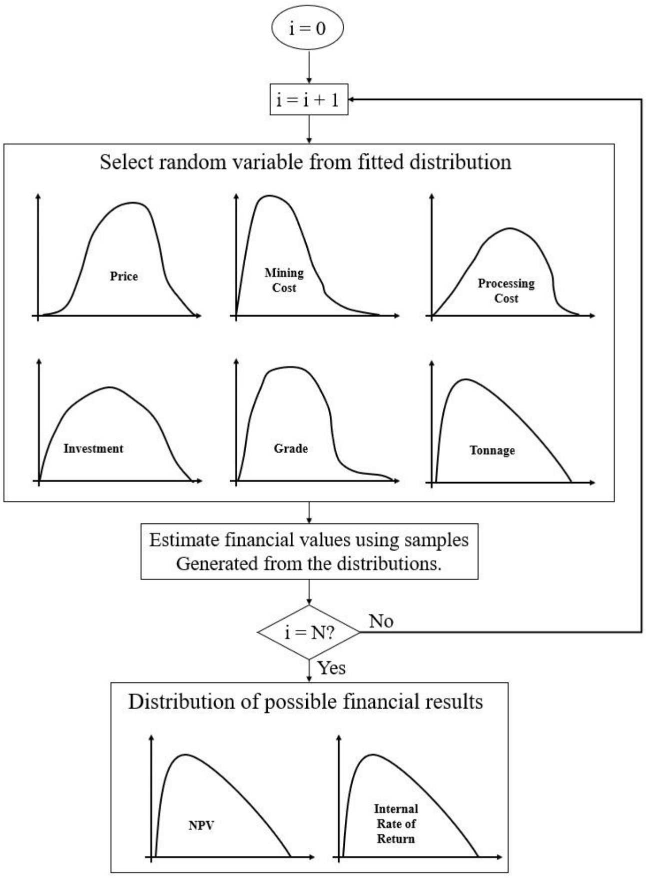

Figure 8. 2: Risked based mine planning [8, 9]

After the risked base algorithm developed by Dowd, several other algorithms have been developed by researchers to schedule open-pit production incorporating uncertainties in the procedure. Godoy and Dimitrakopoulos [10] proposed a five-step algorithm that provides an open-pit mine production schedule under uncertain conditions. Osanloo and Gholamnejad [9] brief the proposed five steps as follows:

1. Generate a series of simulated ore body;
2. Design final pit and push backs for the simulated ore body;
3. Find the optimal production rate for the life of mine;
4. Generate a production plan for each simulated ore body;
5. Combine obtained mining sequences to a single production schedule.

To accommodate grade uncertainty in open-pit mine production planning, Ramazan and Dimitrakopoulos [11, 12] proposed another algorithm. Here, after receiving the simulated orebody, the MIP generates a production scheduling pattern. This pattern is used as a guideline to calculate the probability of mining each block in a given period. Then any block with a chance between zero and one is considered in a new optimization model with the objective function presented in equation (8.3).

$$Maximize \sum_{t=1}^{T}\sum_{n=1}^{N} v_n^t \times x_n^t \tag{8.3}$$

Where T and N are the total number of periods and blocks in the model. v_n^t is the NPV that will be generated by mining block n in period t. x_n^t is one if the block n is scheduled to be mined in period t and zero otherwise.

The stochastic open-pit production schedule model is, however, limited with the following constraints:

The material sent to the plant must meet the upper and lower bounds for the average grades, as presented in equation (8.4) and equation (8.5).

$$\sum_{n=1}^{N}(g_n - G_{min}) \times \ O_n \times x_n^t \geq 0 \tag{8.4}$$

$$\sum_{n=1}^{N}(g_n - G_{max}) \times \ O_n \times x_n^t \leq 0 \tag{8.5}$$

Where g_n is the grade of material in block n, G_{min} and G_{max} are lower and upper bounds of the average feed grade to the processing plant, and O_n is the tonnage of ore to be mined from block n.

The plant also has a capacity constraint that must be followed by the quantity of material being sent to it in each period. Equation (8.6) and equation (8.7) present an example of how the plant capacity is constrained in stochastic production planning.

$$\sum_{n=1}^{N} O_n \times x_n^t \geq \ PC_{min} \tag{8.6}$$

$$\sum_{n=1}^{N} O_n \times x_n^t \leq \ PC_{max} \tag{8.7}$$

Where PC_{min} and PC_{max} are the minimum production requirement and maximum production capacity of the plant.

The mining operation has its limitations. We cannot produce more than the available equipment capacity, and we need to maintain waste material production throughout the periods. These are met using equation (8.8) and equation (8.9).

$$\sum_{n=1}^{N}(O_n + W_n) \times x_n^t \geq MC_{min} \tag{8.8}$$

$$\sum_{n=1}^{N}(O_n + W_n) \times x_n^t \leq MC_{max} \tag{8.9}$$

Where W_n is the waste tonnage scheduled to be mined from block n.

We first need to mine a series of blocks located above the block based on slope requirements. The constraint provided in equation (8.10) is used to ensure that all blocks situated above the current block are mined ahead of the current block or at least at the same period.

$$Yx_k^t - \sum_{y=1}^{Y}\sum_{r=1}^{t} x_y^r \leq 0, t = 1, 2, 3, \ldots, T \tag{8.10}$$

Where Y is the total number of blocks to be mined before mining a given block. k is the index of the block to be mined in period t. y is the index for Y blocks to be excavated before the given block.

The optimization model is also a constraint to mine all the blocks in reserve only once. Equation (8.11) makes sure that all the blocks in reserve are mined only once.

$$\sum_{t=1}^{T} x_n^t = 1 \tag{8.11}$$

We use the scheduling model presented above on all the ore body realizations. By doing that, we can calculate the probability of each block being mined in a given period. The probability calculation generates three categories of blocks: blocks with zero chance to be mined in a given period meaning that they are not mined in the period of concern. Blocks with probability equal to one indicating that the entire block must be mined in the given period. And the third category is the category of blocks with the probability of being mined in a given period between zero and one. Blocks in the third category are considered in a second optimization model with an objective function presented in equation (8.12).

$$Maximize \sum_{t=1}^{T}\left[\sum_{n=1}^{N} c_n^t \times x_n^t - \sum_{m=1}^{M} w \times d_m^t\right] \tag{8.12}$$

Where M is the number of blocks in the smoothness constraints, as shown in Figure 8. 3 c_n^t is calculated as $(v_n^t \times p_n^t)$ where p_n^t is probability of mining block n in period t. w is cost of unit deviation caused by smoothing the schedule and d_m^t is the deviation from the smooth pattern when mining block m.

The model is constrained by the probability of blocks having the desired grade, equipment access, and mobility listed in equation (8.13) to (8.15).

$$\sum_{n=1}^{N}(P_n - 100) \times O_n \times x_n^t + Y_1^t \times TO = 0 \tag{8.13}$$

$$-\sum_{j=1}^{nb1} K1_j \times O_j \times x_j^t + K2_i \times OT_i^t - Y_{2i}^t \leq 0 \tag{8.14}$$

$$-\sum_{j=1}^{nb2} K1_j \times O_j \times x_j^t + K2_i \times OT_i^t - Y_{3i}^t \leq 0 \tag{8.15}$$

Where T and N are the total number of periods and blocks in the model. P_i is the probability of block i having a grade within the desired interval. OT_i^t is the tonnage of ore scheduled to be mined from block i in period t. TO is the total tonnage of ore to be mined in the period of concern. Y_1^t is a deviation from desired probability in period t. $K1_j = 1/TO_j$, $K2_i = nb1/TO_i$ for the inner window, and $K2_i = nb2/TO_i$ for the outer window is the coefficient to convert ore tonnage to percentage. TO_j is total ore available in mining block j. $nb1$ and $nb2$ are the total number of blocks within the inner and outer windows presented in Figure 8. 3. Y_{2i}^t and Y_{3i}^t are deviations from smoothness of the inner and outer windows, respectively.

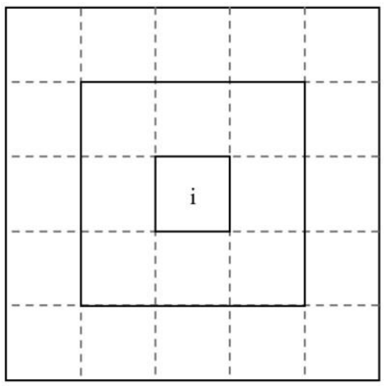

Figure 8. 3: Inner and outer windows for block i

Based on the same concept, the model can be solved using Genetic Algorithm (GA) [13]. The GA assumes p_n^t in above model as chromosome for block n to be mined in period t then estimates the p_n^t randomly in each stage of evolution using its mutation or crossover operation.

Mechanical Extraction, Loading, and Hauling

As presented in Table 8. 1, the five most common mechanical excavation methods are open-pit, stripping, quarry, and auger. These five mechanical methods account for 90% of the total surface mining productions all around the world. After deciding on using the mechanical surface mining method to excavate material from the deposit, step one is to choose between the above-mentioned four mechanical methods. Based on Hartman [1], selecting the proper method depends on four major factors, including the shape of the deposit, its depth, thickness, and size, as presented in Table 8. 2.

Table 8. 2: Mechanical extraction method selection factors

Mining Method	Shape of deposit	Depth of deposit	Thickness of deposit	Size of deposit
Open-pit	Any shape	Any depth	Thick	Large
Stripping	Tabular	Low depth	Thin	Large
Quarrying	Tabular or Massive	Any depth	Thick	Moderate size
Augering	Tabular	Flat	Thin	Remnant

Other mining method selection strategies exist in the literature. The mining method selection strategy developed by Nicholas [14] and its modified version known as UBC mining method selection [15] are two commonly used strategies. These two strategies also use qualitative ranking systems to select the best mining method for the deposit in hand.

The above-mentioned mining method selection techniques are manual methods. However, to make more precise decisions on the mining methods, one can employ a combination of different analytics techniques. Two of the main analytics techniques to select between several alternatives are the Analytic Hierarchy Process (AHP) and the Analytic Network Process (ANP). Thomas Saaty developed the AHP and ANP techniques at the University of Pittsburgh. Hierarchies of feedback networks are generated by AHP or ANP model developers considering criteria to derive ratio scales. These scales are then used to select the best alternative among the available choices. In a nutshell, AHP and ANP work based on developing priorities for available options and criteria used to judge the available choices [16]. An AHP model consists of three primary levels: goal, criteria, and alternative (Figure 8. 4).

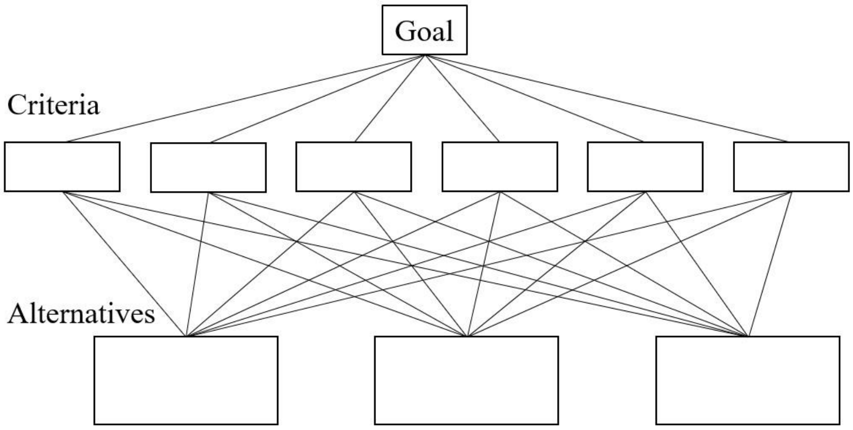

Figure 8. 4: AHP Diagram [16]

As depicted by Figure 8. 4, the first concept of the AHP is to structure the problem at hand as a hierarchy of goals, criteria, and alternatives. The second concept of the AHP is to perform a pair-wise comparison of elements at each hierarchy step. The third concept covering by AHP is to synthesize judgment on each piece over different levels of hierarchy. To solve an AHP structured problem, we first need to determine each criterion's importance compared to other criteria. Then we need to calculate the relative importance of each alternative to each criterion. And then, calculate the overall priority weight of each of the choices.

Following, we provide (Figure 8. 5) an example of selecting a mining method using the AHP technique based on [17].

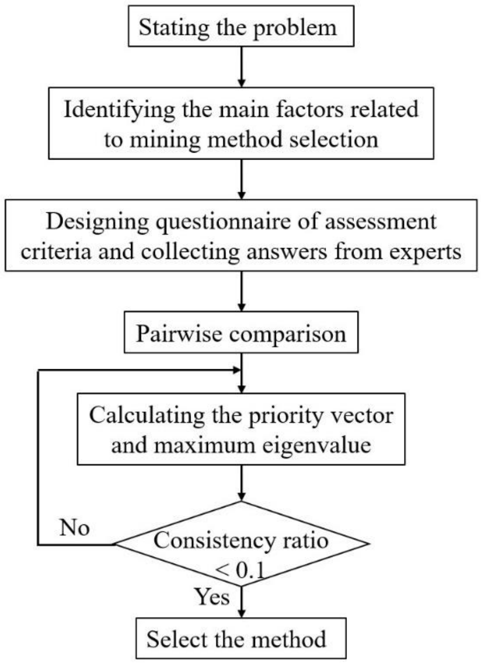

Figure 8. 5: Flowchart for selecting mining method using AHP technique [17].

A sample questionary to send to the experts to quantify critical criteria is provided in Table 8. 3. Based on the deposit you have in hand to select a mining method for, you prepare a list of important factors affecting the method selection procedure. Then, prepare a questionary like the one presented in Table 8. 3. Distribute the questionary among the area experts and ask them to fill it based on the information of your deposit. It is worth noting that Table 8. 3 is a simple example, and the questionary list can vary from one deposit to the other one.

Table 8. 3: A simple example of a questionary for assessing the importance of each factor

Criterion	Importance				
	None:1	Minor:2	Substantial:3	Fundamental:4	Highest:5
Shape of deposit					
Depth of deposit					
Thickness of deposit					
Size of deposit					

If you have listed many factors, using the questionary, you decide on which essential factors must be included in the method selection procedure as a criterion. After finding the most critical factors in the method selection, we construct the hierarchy as presented in Figure 8. 6.

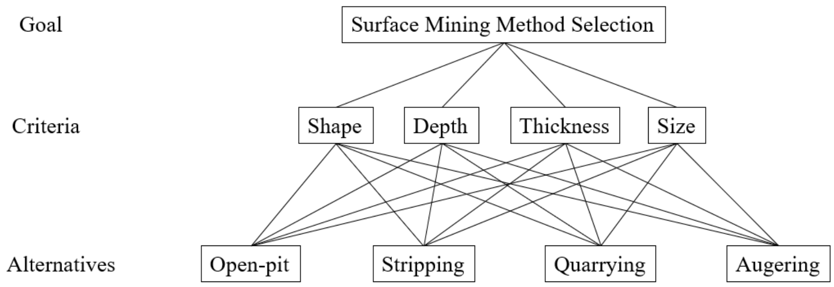

Figure 8. 6: AHP model structure for surface mining method selection

Now we need to determine the relative importance of criteria with respect to the goal. For that, we use the pair-wise comparison matrix. To create the pair-wise comparison matrix, we use the so-called fundamental scale provided in Table 8. 4.

Table 8. 4: the fundamental scale ore the scale of relative importance table to be used for filling up the pair-wise comparison table [16]

Definition	Intensity of importance
Equal	1
Weak	2
Moderate	3
Moderate plus	4
Strong	5
Strong plus	6
Very strong	7
Very, very strong	8
Extreme	9
Inverse comparison	1/2, 1/3, 1/4, …, 1/9

The pair-wise comparison matrix is an n-by-n matrix where n is the number of criteria associated with our problem. For our specific example, the pair-wise comparison matrix is constructed as presented in Table 8. 5.

Table 8. 5: Pair-wise comparison matrix of the surface mining method selection problem.

	Shape	Depth	Thickness	Size
Shape	1	5	4	7

Depth	1/5	1	1/2	3
Thickness	1/4	2	1	3
Size	1/7	1/3	1/3	1
Sum	1.59	8.33	5.83	14

The value in each cell of the pair-wise matrix presented in Table 8. 5 depends on the decision-maker. However, one criterion compared to itself has equal importance. Thus, the diagonal values of the pair-wise comparison matrix are always one. Another important note regarding the pair-wise comparison matrix is that if the importance of criterion A to criterion B is equal to x, then the importance of criterion B to criterion A is 1/x. We then calculate each column's sum and insert it in the last row of the pair-wise matrix.

In the next step, we create the normalized pair-wise comparison matrix by dividing each value in a column to the same column's cumulative value as depicted in Table 8. 6.

Table 8. 6: Normalized pair-wise comparison matrix

	Shape	Depth	Thickness	Size
Shape	1/1.59=0.6289	5/8.33=0.6002	4/7=0.6861	7/14=0.5000
Depth	0.2/1.59=0.1258	1/8.33=0.1200	0.5/7=0.0858	3/14=0.2143
Thickness	0.25/1.59=0.1572	2/8.33=0.2401	1/7=0.1715	3/14=0.2143
Size	0.14/1.59=0.0898	0.33/8.33=0.0400	0.33/7=0.0572	1/14=0.0714
Sum	1.59	8.33	5.83	14

After normalizing the importance, we calculate each criterion's weight by averaging values in each row of the normalized pair-wise comparison table (Table 8. 6). Each criterion's weight is now calculated by averaging each row's values (Table 8. 7).

Table 8. 7: Weight of criteria

	Shape	Depth	Thickness	Size	Criteria weight
Shape	0.6289	0.6002	0.6861	0.5000	0.6038
Depth	0.1258	0.1200	0.0858	0.2143	0.1365
Thickness	0.1572	0.2401	0.1715	0.2143	0.1958
Size	0.0898	0.0400	0.0572	0.0714	0.0646

Now we need to calculate the consistency of the criteria to check if the calculated values are correct. To calculate the model's consistency, we use the pair-wise comparison matrix values in Table 8. 5, which are not normalized. Then, we multiply each value in a column with the criterion weight of that column. In the next step, we calculate the weighted sum value for each criterion by summing all the values in each row. By dividing the weighted sum value by the criteria weight and averaging over all the criteria, we find λ_{max}.

Table 8. 8: Preparation for calculating λ_{max}.

	Shape	Depth	Thickness	Size	Weighted sum value	Weighted sum /Criteria weight
Shape	1×0.60	5×0.14	4×0.20	7×0.06	2.52	4.18
Depth	0.2×0.60	1×0.14	0.5×0.20	3×0.06	0.55	4.02
Thickness	0.25×0.60	2×0.14	1×0.20	3×0.06	0.81	4.16
Size	0.14×0.60	0.33×0.14	0.33×0.20	1×0.06	0.26	4.05

$$\lambda_{max} = \frac{4.1762 + 4.0225 + 4.1553 + 4.0488}{4} = 4.1007$$

Now that we have λ_{max} value, we can calculate the consistency index using equation (8.16).

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (8.16)$$

Where n is the number of criteria and CI is the consistency index. In our example, CI= (4.1007-4)/(4-1) = 0.03358. We now can calculate the consistency ratio using equation (8.17).

$$CR = \frac{CI}{RI} \qquad (8.17)$$

Where CR is consistency ratio, and RI is the random index, which is the consistency index of the randomly generated pair-wise matrix of the same size. Saaty [18] calculated RI for one to ten criteria that is presented in Table 8. 9.

Table 8. 9: RI values for up to ten criteria in AHP [18].

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Based on Table 8. 9 consistency ratio in our example is:

$$CR = \frac{CI}{RI} = \frac{0.03358}{0.90} = 0.0373$$

A pair-wise matrix is consistent if it's $CR < 0.10$. Based on that, the pair-wise matrix in our example is consistent.

Now that we are sure about the consistency of the pair-wise comparison matrix for the selected criteria, we follow the same steps but this time for the alternative methods and develop pair-wise comparison matrices for them based on each criterion to calculate the weights. Table 8. 10 presents the pair-wise comparison matrices for our example based on each criterion. In Table 8. 10, O, S, Q, and A stand for Open-pit, Stripping, Quarrying, and Augering, respectively.

Table 8. 10: generating pair-wise matrices for solution alternatives with respect to different criteria

Shape	O	S	Q	A	Weight	Weighted sum	Weighted sum/weight	CI&CR
O								
S								
Q								
A								
Depth	O	S	Q	A	Weight	Weighted sum	Weighted sum/weight	CI&CR
O								
S								
Q								
A								
Thickness	O	S	Q	A	Weight	Weighted sum	Weighted sum/weight	CI&CR
O								
S								
Q								
A								
Size	O	S	Q	A	Weight	Weighted sum	Weighted sum/weight	CI&CR
O								
S								
Q								
A								

In the final step of the AHP for surface mining method selection, using equation (8.18), we determine the best surface mining method to mine the deposit.

$$Max \left\{ \sum_{i=1}^{N} CW_i \times MW_j \quad | \; j \in \{1, \dots, M\} \right\} \tag{8.18}$$

Where CW_i is criterion weight for criterion i from N criteria and MW_j is the j alternative weight from M alternative solutions available. The equation (8.18) shows the solution alternative, which obtained the highest rank among all the methods.

Selection and Sizing of Excavating, Loading, and Hauling Equipment

In open-pit mining, equipment selection and sizing are critical problems to be solved by the mining engineers. This problem is divided into two main subproblems of loading equipment and transferring equipment. For the loading equipment, we need to follow three steps: 1) finding the bucket capacity, 2) determining the machine's geometry, and 3) finding the best match from the machines that are currently available in the market [19].

The bucket size is determined using equation (8.19) after finding the mine's required production rate using the long-term plan.

$$BC = (Pr \times Ct)/(Ff \times Ma \times Ef \times 3600) \tag{8.19}$$

In equation (8.19), BC is the bucket capacity for the loading equipment required to meet the production plan, Pr is the rate of the production based on the production plan, Ct is the nominal cycle time of the desired equipment, Ff is the bucket fill factor, Ma is the mechanical availability of the equipment, and Ef is the operational efficiency. In the next step, using multiple iterations, the loader geometry is determined based on the benches' geometry in the designed pit. Based on the loader's selected geometry and its bucket capacity, the decision maker compares available options from different OEMs and makes decisions on the make and model of the loading equipment. Analytics comes to operation in this stage with the AHP method to select the best loader. The steps detailed in the previous section are required to be taken to make the best decision. Then, based on the production rate and stripping ratio size of the loader fleet is determined.

In the next step of the equipment selection and sizing for open-pit mines, it is required to determine the size and number of trucks needed to transport material from the pit to the destinations. Mining engineers typically select trucks with enough capacity to be loaded with three to five passes by the mine's available loaders. Thus, based on the size of the loaders in the mine's production fleet, using the AHP method, the decision-maker decides on the mark and model of the required trucks among those that can be filled by the selected loaders in three to five passes. Again, the decision-maker follows the previous section's steps to select the mine's best truck types. A typical example of how different types of trucks match different load types is presented in Table 8. 11.

Table 8. 11: Number of passes required to load a truck with a loader [19]

Truck size (t)	Loader bucket size (m^3)				
	15	20	25	35	45
136	5	4	3		
181	6	5-6	4	3	

217		6	5	3-4	
290			6	4-5	3-4
360				6	4-5

Based on the selected loaders' bucket capacity and a table of truck options, as shown in Table 8. 11, three sets of truck fleets are chosen. A fleet of small trucks that can be loaded by five to six passes using the selected loaders. A fleet of large trucks that can be loaded by three to four passes using the selected loaders. And a fleet of trucks, including both small and large trucks. After that, we need to calculate the number of trucks required in the fleet to meet the scheduled production.

The common practice in mining is determining the number of trucks in the fleet using a deterministic formula presented by Burt and Caccetta [20] based on the match factor definition. The match factor (MF) is defined as presented in equation (8.20) for a homogeneous truck fleet and equation (8.21) for a heterogeneous truck fleet:

$$MF = \frac{trucks}{loaders} \times \frac{loading\ cycle}{truck\ cycle} \tag{8.20}$$

$$MF = \frac{1}{\left(\sum_j \frac{loaders_j}{\sum_i trucks_i \times (loading\ cycle)_{i,j}}\right) \times truck\ cycle} \tag{8.21}$$

Where i and j are the index of truck types and loader types, respectively. Based on the match factor as presented in equation (8.20) and (8.21), the mining production system falls into one of the three domains of the under-truck system (MF<1), balanced system (MF=1), and over-truck system (MF>1). The number of trucks of each type in the fleet is determined to keep the match factor of the production system at one.

Although the required number of the trucks in the fleet is determined using the MF method, the method has some drawbacks, one of which is that it does not account for the technical uncertainties in its calculations. Analytics comes to action here, and using descriptive analytics, simulation, and optimization help the mining industry to more precisely determine the number of trucks required to meet the production targets. It is worth noting that the analytics approach to determine the size of the truck fleet uses the MF method as its starting point [21].

At the first step of using analytics to determine the optimal truck fleet size, understanding the surface mine's material handling system is essential. The material handling system consists of the mining operation, processing, and decision-making systems, which in most cases are the fleet management systems. The analytic system that needs to be developed to solve the truck fleet sizing problem must include these components (Figure 8. 7).

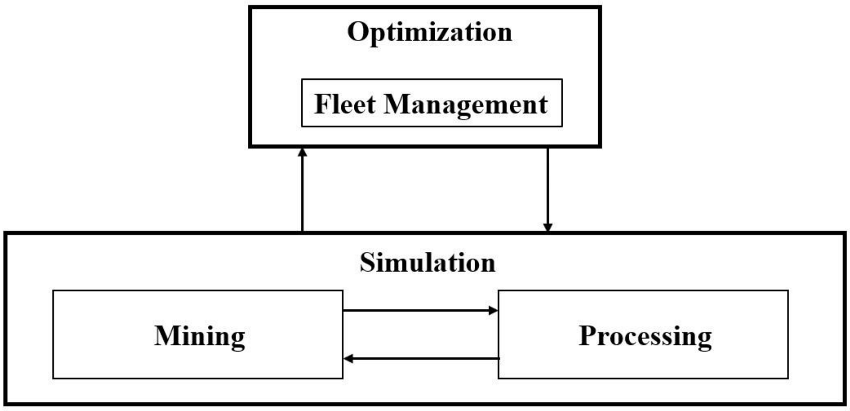

Figure 8. 7: Schematic of the analytics system to solve truck fleet sizing problem in surface mines [22].

As presented in Figure 8. 7, a simulation and optimization framework must be developed for the mine where the simulation part of the framework mimics the operations and the optimization part of the framework mimics decision-making tools. To develop the simulation and optimization framework, one requires three major software: a discrete event simulation software, an optimization software, and Microsoft Excel. These three software are needed to talk with each other, as presented in Figure 8. 8.

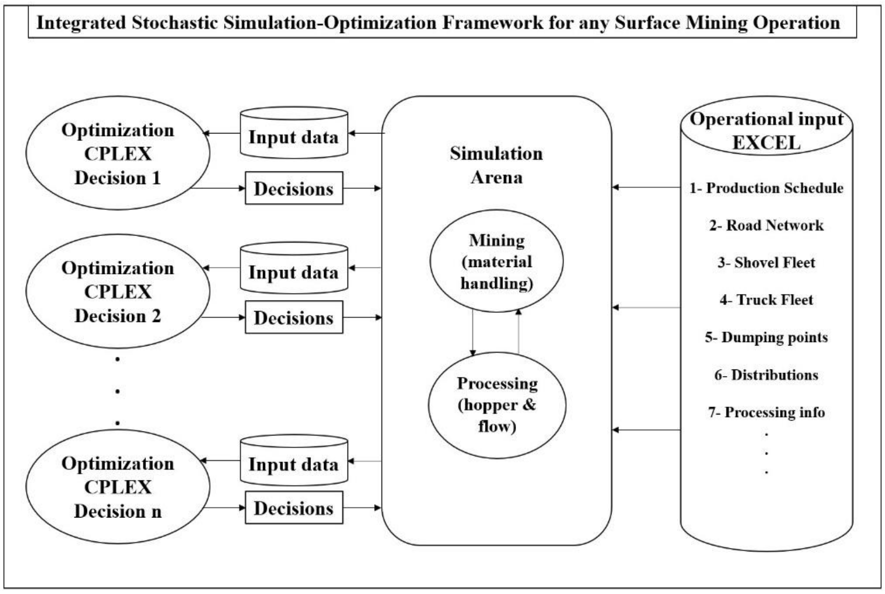

Figure 8. 8: A general layout of the simulation and optimization software to be used in the analytics system for determining truck fleet size in surface mines [23].

After selecting the proper software and setting up the framework in software, we need to prepare the required inputs. Thus, in a new mine, we collect historical data for our selected truck type and loader type from another mine. In the case of a currently active mine, we collect historical data from our mining operation. Using data analysis methods, we fit different distributions on the data and find the best distribution using testing methods such as Kolmogorov-Smirnov (KS).

A list of input parameters must be collected, preprocessed, analyzed and fitted with the proper distribution. After finding the fitted distribution for each input parameter, we store them in an excel file that is readable from the simulation software. The input parameters depend on how we develop our simulation and optimization framework and the level of detail we consider in the model development. However, for a truck and shovel surface mining operation, the major inputs are components of shovel loading time and truck cycle time, such as idling in the queue at the shovel, velocity, etc.

After setting up the input Excel file with the required input parameters stored in it, we develop the simulation model and connect it to an external optimization software such as IBM CPLEX [24]. In the optimization software, we need to set up all the decision-making models that the mine is or will be using in its operation. One of the essential decision-making models to be provided here is the fleet management system in use in the operation. Ali Moradi-Afrapoli, in [23], presents a comprehensive explanation of how to develop the framework.

The framework is ready to determine the optimal number of trucks required to meet the production schedule by connecting the simulation model to the optimization models and the data file. At this stage, one should define production scenarios based on the number of trucks in the fleet to test them and find the best possible combination of trucks and loaders fleet. Three sets of scenarios must be defined: a set of scenarios for the fleet of only small trucks, a set of scenarios for the fleet of large trucks, and scenarios for the fleet of small and large trucks. Here, to develop scenarios, one can start from a random number of trucks in the fleet add or deduct the number of trucks. This will increase the run time for the procedure. Thus, it is promising to start with the number of trucks determined by each category's MF method. Then develop ten scenarios in the under-truck system and ten scenarios in the over-truck system as presented in Table 8. 12.

Table 8. 12: Scenarios to be created for determining the optimal truck fleet size in surface mines.

Fleet type	Under truck	balanced	Over truck
Small trucks	$T_s - 10, \dots, T_s - 1$	T_s	$T_s + 1, \dots, T_s + 10$
Large trucks	$T_l - 10, \dots, T_l - 1$	T_l	$T_l + 1, \dots, T_l + 10$
Mixed fleet	$T_m - 10, \dots, T_m - 1$	T_m	$T_m + 1, \dots, T_m + 10$

In Table 8. 12, T_s, T_l, and T_m are the number of trucks required to meet the production in the small, large, and mixed truck fleet, respectively. These numbers are calculated using the MF method. Following the above-mentioned method, 63 scenarios are developed. The best fleet is then chosen by comparing their impacts on the key performance indicators of the operation, such as daily and hourly production, grade quality and quantity, etc.

In-Pit Crushing

The first in-pit crushing and conveying (IPCC) system was installed in a limestone quarry mine located east of Hanover in Germany [25]. Since then, three different IPCC systems have gained popularity in surface mining sectors: fixed, mobile, and semi-mobile crushers. The main reason for transferring the surface mining operations from the conventional truck and shovel operations to IPCC is that the mine gets deeper and the haul roads get longer, so transportation costs using conventional trucks get higher. This makes the implementation of IPCC economically viable. According to Utley [25], the major drawbacks of the IPCC systems are their short-term movement inflexibility, the dependency of their production to their loading process, inflexibility when different blending is required, etc. However, Osanloo and Paricheh [26] believe that the most reliable way to overcome trucking difficulties in surface mines is to implement IPCC. They also provide data on IPCC's economic advantage over conventional truck and shovel systems showing that by implementing IPCC in 25-year mine life, the system will produce 200% higher NPV than the truck and shovel system. The IPCC is also environmentally friendlier than a conventional truck and shovel mining systems as its total energy consumption and greenhouse gas emission are 20% and 5% less than the truck and shovel systems [26].

Accepting all the advantages of IPCC implementation in surface mines, it has a significant impact on the mine planning, which is not handleable using conventional mine planning tools as a significant change occurs by adding IPCC to the problem. Thus, new optimization models are needed to incorporate IPCC impacts into the mine plan. Conventional long-term production plans provide the time of mining of each block in the block model so that the mine's net present value is maximized. However, by adding IPCC to the equation, the long-term plans must provide the location of IPCC and time for the relocation of it along with the production plan. Paricheh et al. [27] proposed a two-step optimization model to incorporate IPCC in the long-term production plan by optimizing its location and finding the best relocation time. Their two-step model is presented here.

$$Minimize\ Z = \sum_{k=1}^{r}\sum_{j=1}^{p}\sum_{i=1}^{m_k+1} F_{kij}x_{kij} + \sum_{k=b}^{r} C_k y_k \tag{8.22}$$

Subject to:

$$y_k = \frac{1}{2}\sum_{j=1}^{p} w_{kj} \qquad \forall\, k \tag{8.23}$$

$$z_{kj} - z_{(k-1)j} \leq w_{kj} \qquad \forall\, j,k \tag{8.24}$$

$$z_{(k-1)j} - z_{kj} \leq w_{kj} \qquad \forall\, j,k \tag{8.25}$$

$$\sum_{j=1}^{p} z_{kj} = P \qquad \forall\, k \tag{8.26}$$

$$\sum_{j=1}^{p} x_{kij} = 1 \qquad \forall\, i,k \tag{8.27}$$

$$x_{kij} - z_{kj} \leq w_{kj} \qquad \forall\, i,j,k \tag{8.28}$$

$$x_{kij} = \begin{cases} 1 & If\ face\ i\ is\ assigned\ to\ point\ j\ in\ period\ k \\ 0 & Otherwise \end{cases} \tag{8.29}$$

$$z_{kj} = \begin{cases} 1 & If\ crusher\ is\ located\ on\ point\ j\ in\ period\ k \\ 0 & Otherwise \end{cases} \tag{8.30}$$

$$y_k = \begin{cases} 1 & If\ crusher\ is\ relocated\ in\ period\ k \\ 0 & Otherwise \end{cases} \tag{8.31}$$

Where $i, j,$ and k are indices over the number of mining faces to be mined in a certain period, candidate in-pit crusher locations, and extraction periods, respectively. And $r, p,$ and m_k are the total number of periods, the total number of candidate locations for in-pit crusher, and the total number of mining faces to be mined in period k, respectively. F_{kij} is the total cost of transporting material from the mining face i to candidate in-pit crusher location j in period k. Capital and operating cost of in-pit crusher to move material from candidate location j to the processing plant is considered at each period by adding an extra transportation cost to the equation as $m_k + 1$. They also added the relocation cost of C_k that consists of all the costs associated with the relocation of the in-pit crusher in period k. x_{kij}, z_{kj}, and y_k are decision variables and w_{kj} is a logical variable.

The optimization model presented above equation (8.22) minimizes total material transportation costs, including truck transport and IPCC transport. The equations (8.23) to (8.25) incorporate costs of IPCC relocation to the decision-making model. Equation (8.26) confirms that P number of crushers are open in period k of the mine life. The model uses equation (8.27) to make sure that in period k, active mining face i has assigned to a destination. Equation (8.28) constraints the model to assign the active mining faces to the crusher locations that are open in period k. There are three other constraints in the model, equations (8.29) to (8.31) that are used for binary variables.

The best locations to install and re-install the in-pit crusher over the mine's life are determined by minimizing the total transportation cost using the decision-making model presented in equation (8.22) to equation (8.31).

Summary

Approximately 90% of the raw material are mined using surface mining methods. Among all the surface mining methods, open-pit mining has the most contribution to this material movement. Thus, in this chapter, we outlined how different analytics methods can help surface mine and, more specifically, open-pit mine managers in their decision-making with and without incorporation of uncertainties. Four primary analytics approach that can be extensively used in surface mining activities are descriptive analytics, analytics hierarchy process, optimization modeling, and predictive analytics. Descriptive analytics such as exploratory data analysis methods are useful for operational data preprocessing and analysis for trucks and shovels or other types of material handling systems. AHP is often used as a procedure with which the right methods are selected. The best practice in making optimal decisions in long-/short-term planning and equipment dispatching and IPCC allocations is to use optimization models. And finally, predictive models and, more specifically, discrete event simulations can be used to evaluate technology implementations and changes to the mining operation.

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