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Optimization of opencast mines using minimum cut algorithm – a case study from iron mine

The demand and supply gap are on a rising trend in this developing world for all the minerals/ores. There is an acute need for suitable technological advancements in the field of mine planning with an aim for zero mining waste. The advanced technology will not only help in the optimum extraction of ores but will also maximize the profit ensuring safety and productivity. In this paper, an open pit optimization algorithm is proposed using a minimum cut algorithm and heuristic algorithm. The parametric minimum cut algorithm is used to generate pit shells, same as other mining software, and the resource constraints are imposed on the generated pit shells results using the heuristic algorithm to optimize the production plan. A case study is presented in an iron ore deposit from India, and the results were compared to the traditional method.

Keywords: *Modeling of deposit, open pit optimization, opencast mines, surface mining, surpac, numerical modeling.*

1.0. Introduction

The fast-paced development of society demands increased supply of raw materials for its sustenance which has pressurized the mining industry. The raw materials being non-renewable, are finite in nature. Optimum exploitation of these minerals is thus, needed for sustainable development. Depending on the nature of occurrence of these raw materials, a suitable method of mining is decided for its exploitation. The method of mining which offers a fast return on investment (ROI), better economic viability and safety is always preferred. Depending on the depth of the ore deposits, there can be two broad methods of mining the orebody, i.e., from surface mining or from underground mining. The surface mining operations can be classified as an open pit, opencast, strip, alluvial and in-situ mining (Hartman and Mutmansky, 2002). Opencast mining is an improvement to the already existing concept of open pit mining, catering to optimum land utilization for piling overburden for future reclamation purposes. It is the method of choice for extracting shallow depth deposits if other factors like depth of ore deposit, land acquisition, environmental clearance, ROI, etc. commends opencast mining techno-economically feasible. On the other hand, the underground method of mining is done for extracting deep-seated deposits which are not economic to be extracted from the surface. Underground mines have a comparatively long gestation period (Envis, 2016), as initially an access road is made to reach the ore deposit and subsequently development headings are made below ground to expose the ore before production commences. This causes delay in ROI. With the availability of high capacity heavy earth moving machines (HEMMs) in opencast mining, the rate of production is fast, while ensuring the safety of men and machinery. High capacity machineryfacilitates faster removal of overburden thus, facilitating early ROI. Hence, an opencast method of mining is the preferred choice if socio-economic parameters are in favour of such exploitation.

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The ore deposits need to be optimally exploited as it is non-renewable in nature. A great concern also exists in terms of optimal land use since land acquisition is a serious concern while planning surface mines. Hence, mine planners have to keep a vigil on optimum use of the available land while optimizing the ore production. The profitability of any mining operation depends on how meticulously its planning has been done (Songolo, 2010).

Defining the ore boundaries, mining configurations, pit limits, sequences/pushbacks, optimizing the production and net present value (NPV) of an ore deposit manually based on the available geotechnical information is a herculean task. With manual calculations, the extent of mines being planned was confined to a smaller scale with a limited number of blocks. Optimizing large scale operations having millions of blocks is not possible manually (Edmonds and Karp, 1972). Advancements in computer technologies and availability of bespoke mine-planning and designing software have made it possible to optimally plan large mines. With the use of mine planning software earlier economically unfeasible low-grade deposits can now be mined profitably (Dowd and Onur, 1992). The software can solve complex mine problems, which have lessened the burden of mine planners from doing manual calculations which were tedious, time-consuming and prone to errors (Dorigo and Stutzle, 2004).

The extraction of ore forming pit is a sequential process. It gets completed in a number of phases with different pit layouts in each phase. These time dependent sequence of pits are called as push-back designs. It describes how a pit will expand optimally in due course of time depending on varying economic parameters. The mining operation in each push-back is so conducted as to maintain the overall slope angle and pit geometry. These push-backs form important input for short term production planning which is nested to get long-term planning (Hochbaum and Chen, 2000; Johnson, 1968; Wilke and Reimer, 1977). Final mining sequence is decided such that the maximum economic return is obtained subjected to all operational constraints (Sevim and Lei, 1998). With the sole objective of developing push-back designs to optimize the NPV, net profit and extraction from the pit, a sequence is established which leads to maximum extraction (Jordi and Currin, 1979). Several pushback algorithms have been developed since 1960's. These algorithms provide a computing search technique to find solutions to optimization problems. The essence of pushback design lies in production scheduling and sequencing, and thus determines the mine life and therefore, the subsequent cash flows including capital requirements, operational costs and revenues (Songolo, 2010).

Open pit optimization means, determination of optimal pit limit for an ore deposit under a set of mining and economic constraints giving optimized NPV (Schofield and Denby, 1993; Cardu et al., 2006). The pit limits are set as the first step in long and short-range mine planning ensuring that ultimate pit limit represents the final boundary of deposit to be extracted within the pit. The ultimate pit limits thus define the amount of mineable ore, metal content and associated amount of overburden to be removed during the life of operation (Kennedy, 1990). Optimization depends on parameters like metal price, the cost of mining and the cost of processing. The irony is, most of the factors governing the open pit design i.e., the geometry of the orebody, grade distribution of ore within the orebody, maximum allowable slope angles, metal cost, etc. are beyond the control of mine planners.The economics of operation depends on stripping ratio selected, production rate, equipment selection, etc. which rely on hands of mine planners and engineers (Hartman, 1992). The optimized pit layout should reflect the overall profitability of mine investment.

The ultimate pit gives a list of blocks which is to be extracted giving maximum NPV while obeying the slope constraints (Kennedy, 1990). Within the ultimate pit, pushbacks are designed to divide the deposit into nested pits starting with lowest stripping ratio and maximum ore value to largest pit with relatively higher stripping ratio and lower ore value. These pushbacks also provide adesign for haul roads alignment during different phases of production on yearly basis to schedule yearly production from different benches (Dagdelen, 2001). This roughly corresponds to the optimal evolution of the mine over time. The production schedule is developed keeping in mind the annual production targets of both overburden and ore.

Optimization algorithms like, Ford-Fulkerson algorithm (Ford and Fulkerson, 1956; Ford and Fulkerson, 1957), Lerchs-Grossmann algorithm (Lerchs and Grossmann, 1965), minimum-cut/maximum-flow algorithm (Dinic, 1970; Picard, 1976; Goldberg and Tarjan, 1988; Padberg and Rinaldi, 1990; Hao and Orlin, 1992; Hochbaum, 2001; Hochbaum, 2008), meta-heuristic algorithm (Whittle, 1990; Sattarvand and Delius, 2008; Sattarvand and Delius, 2013), fundamental tree algorithm (Ramazan et al., 2005), etc. serves as an handy tool for mine planners in developing optimized mine plans for opencast mines. This ensures maximum profitability from production based on the BEVs of blocks present in ultimate pit limit (UPL) design. These algorithms are simple to formulate, requires lesser computational time and can incorporate complex mining constraints like working slope angle to provide better accuracy and reliability while being user-friendly (Dowd and Onur, 1992). Overall life of the mine is given as the probable time required to mine all blocks present in UPL, in such a sequence as to maximize the profit. Ultimate pit limit algorithm (Dagdelen and Johnson, 1986) based on Lagrangian parametrization help in generation of block models having different BEVs to develop time-dependent push back designs. Push backs with minimum stripping ratio is then developed (Ramazan and Dagdelen, 1998). The push-back so obtained is used to plan short-term planning and then developing daily, weekly, monthly, quarterly, half-yearly and yearly production plans (Hochbaum and Chen, 2000; Johnson, 1968; Wilke and Reimer, 1977). The block model method of open pit optimization has been presented in this paper.

In this paper, a hybrid minimum cut algorithm with the heuristic algorithm as proposed was used for pushback design and production planning of an open pit iron mine from India. The study aims to generate pushbacks for meeting long-term production target. This will provide a competitive edge in global mining scenario as meticulous planning of ore reserve for optimized production is the need of the hour.

2.0 Methodology

In nature ore occurs in conjunction with waste materials (overburden) as shown in Fig.1. The ore presented in the Fig. 1 is in lenticular shape surrounded by waste materials. These waste materials need to be removed sequentially from the surface to reach to the ore. This operation if done from surface is termed as opencast mining. As mining progresses, the land is excavated in a proper sequence to form pits or push-backs. The size of push-backs increases gradually to give ultimate pit design before mining ceases. The final shape of the pit is to be decided during planning stage keeping various operational and economic constraints into consideration (Johnson, 1968; Jordi and Currin, 1979;

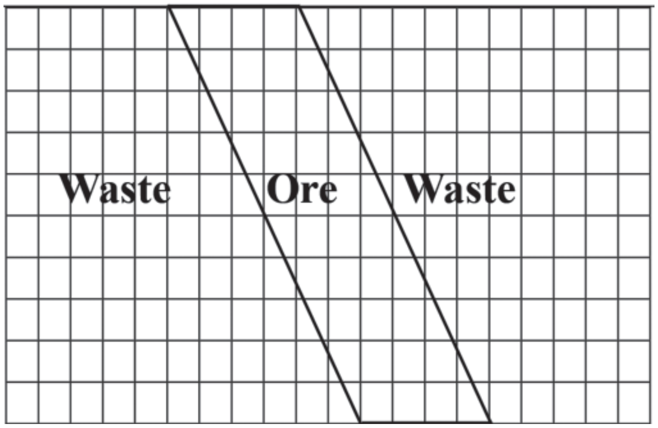

Fig.1 A block diagram showing ore and waste as it occurs in nature (Sainsbury, 1970; Lerchs-Grossmann, 1965; Hustrulid and Kutcha, 1995)

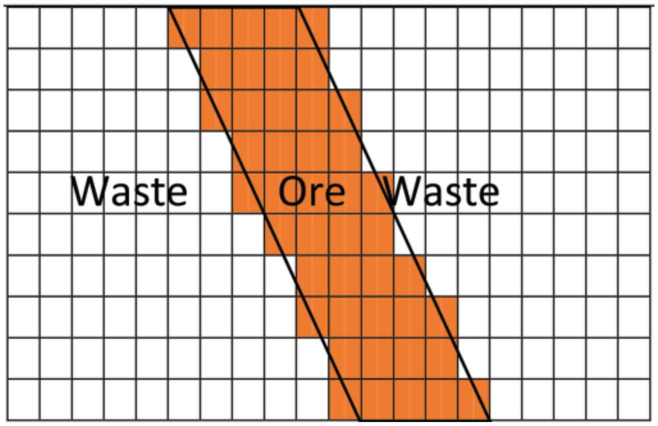

Fig.2 Ore and waste blocks have been assigned adifferent block economic value as shown in different colors.

Mathieson, 1982; Dagdelen and Johnson, 1986; Zhang et al., 1986; Whittle, 1990; Dowd and Onur, 1992; Hustrulid and Kutcha, 1995; Ramazan and Dagdelen, 1998; Sevim and Lei, 1998; Ramazan et al., 2005). In order to optimize the economics of production, the whole reserve is divided into 3-dimensional blocks of equal sizes. The assay value and grade (G) of the ore is ascertained for each blocks present in the deposit. Net revenue is calculated using eqn. (1), as given by Frimpong et al., 1998, having parameters like the planned rate of production {in tonnes (T)}, average recovery (REC), market price of the processed ore and the cost of mining and processing.

Net revenue = T×G×REC×(market price – MC –PC) ... (1)

where, T is the tonnage production of ore, G is the average grade of processed ore, REC is the recovery (in percentage), *market price* is the price of finished ore, MC is the mining cost of the ore (including overhead charges like royalty, compensation, etc.) and PC is the processing cost of the ore.

A cut-off grade is determined such that the *net revenue,* is a positive value. Once the cut-off grade is determined, all blocks having average ore grade below the cut-off grade is considered as waste as shown in Fig.2. Determination of cut-off grade of a deposit is of prime importance as all planning calculations are based on cut-off grade values. Block economic values (BEVs), are then calculated for each of the ore blocks using eqn. (2) as,

$$BEV_i = \begin{cases} Net\ revenue_i - MC_i - PC_i, \ if\ Net\ revenue_i > PC_i \\ -MC_i, otherwise \end{cases} \quad ...(2)$$

Where, BEV_i is the block economic value of i^{th} block, *net* $revenue_i$ is the net revenue generated from i^{th} block using equation (1), where, T_i is the tonnage production from i^{th} block, G_i is the average grade of the i^{th} block, REC_i is the recovery from the i^{th} block, MC_i is the mining cost of the i^{th} block, and PC_i is the processing cost of the i^{th} block.

If the total cost of production, handling, and processing exceeds overall selling price, mining such deposits would be non-economical and hence BEVs of such block is negative else positive values are assigned to the blocks. BEVs of discretized block is determined and is represented in Fig.3.

There are a variety of algorithms available for open pit optimization based on linear programming and graph theory (Hao and Orlin, 1992; Hochbaum, 2001; Picard, 1976). In this paper, graph theory based minimum-cut or maximum-flow algorithm is used to optimize the pit shape. In optimizing

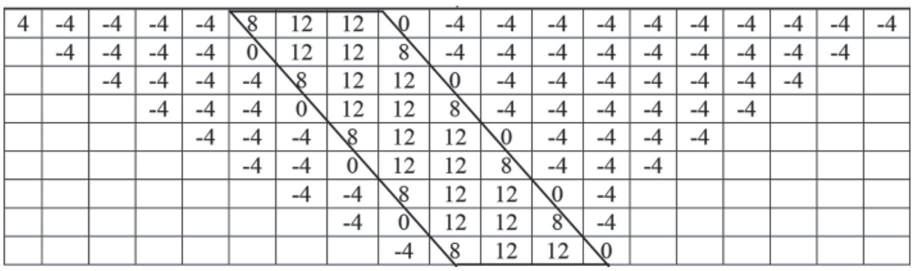

Fig.3 Final block economic value of each block (Lerchs-Grossmann, 1965)

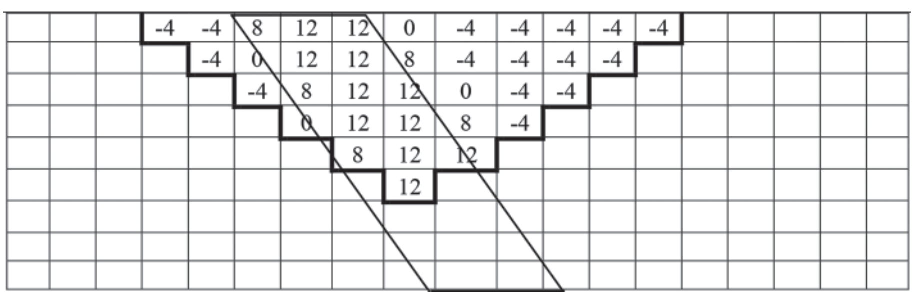

Fig.4 Optimum pit limits superimposed on the block model (Lerchs-Grossmann, 1965; Hustrulid and Kutcha, 1995)

opencast mining operation with the minimum cut algorithm, each 3D block is represented as a node, the slope requirements, and other operational constraints are represented by precedence relationship given by a set of arcs A in the graph G. In such cases, the pit design problem can be represented using a directed graph, $G = (V, A)$, where V gives the set of nodes and A the set of arcs (Hao and Orlin, 1992; Hochbaum, 2001; Hochbaum, 2008; Padberg and Rinaldi, 1990; Dinic, 1970; Goldberg and Tarjan, 1988; Picard, 1976).

In order to optimize the production and profit, a set of nodes are so chosen in the graph which provides maximum profit such that all the successor nodes are also included in the set. A set of such blocks based on their BEVs and obeying operational constraints are shown in Fig.4, which gives the maximum number of blocks which can be mined profitably. Such optimized set is the maximum closure of the graph (Ford and Fulkerson, 1956; Ford and Fulkerson, 1957; Dinic, 1970; Goldberg and Tarjan, 1988; Picard, 1976) and is called as the ultimate pit limit design.

2.1 Ultimate pit limits using minimum cut algorithm

Maximum closure problems can be reduced to minimum cut problems by applying efficient maximum flow algorithms to calculate the values (Picard, 1976). As stated above, the positive-valued blocks represent ore blocks, whereas negative-valued blocks represent waste blocks. The ultimate pit limit problem can thus be formulated as given in eqns. (3 and 4):

Maximize $P = \Sigma W_j * x_j$ ... (3)

Subject to: $x_j - x_i > 0$; $\forall (i, j) \in A$. and $x_j \in [0, j]$ ... (4)

Where, x_j is the binary variable with value 1, if it is present within the ultimate pit and 0, if it is present outside the ultimate pit. w_j is the economic value of the j^{th} block, and x_i is the block that need to be mined to get access to the block x_j. This optimization formulation (equations 3 and 4) can be solved using the graph cut method.

The orebody model can be represented as a directed graph. Each mining block is considered as a node of the directed graph. There are two special nodes: a source (s) and a sink (t). The source node is connected to all nodes designated as ore blocks in the model. The capacities of those arcs are the blocks' economic values of the respective block. On the other hand, all nodes designated as waste blocks in the model are connected to the sink node. The capacities of those arcs are the absolute value of the waste blocks' economic values.

To mine a given block $x(i, j)$ one needs to access that particular block. Unless, the overlying blocks are extracted, it is impossible to access that particular block and mine it.This may be achieved by maintaining slope constraints. Slope constraints are obeyed by identifying the overlying blocks that need to be extracted before extracting the target block. The safe working conditions with stable slope angle is incorporated for design of optimal pit (Dagdelen and Johnson, 1986; Dowd and Onur, 1992; Hustrulid and Kutcha, 1995; Johnson, 1968; Jordi and Currin, 1979; Mathieson, 1982; Ramazan and Dagdelen, 1998; Ramazan et al., 2005; Sevim and Lei, 1998; Whittle, 1990; Zhang et al., 1986). Fig.5 presents the number of blocks which need to be mined before the ore can be mined for 45^o slope angle in 3 dimensions.

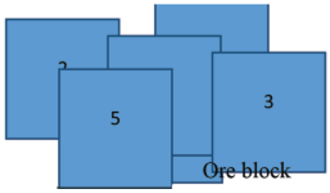

Fig.5a 3-D representation of 1-5 pattern (Laurent et al., 1977)

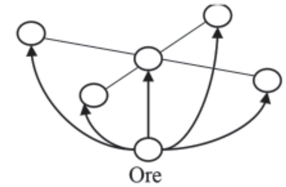

Fig.5b Directed graph representation of 1-5 pattern (Laurent et al., 1977)

For orthogonal set of blocks, two geometries of approximating an open-pit is considered.These are, (a) the 1-5 pattern, where 5 blocks are removed to gain access to the ore block (a level below), and (b) 1-9 pattern, where 9 blocks are removed to gain access to the ore block (present a level below) as per the Lerchs-Grossmann (1965), 3D algorithm. The 1-5 pattern has been used in this paper as shown in Fig. 5a. In order to extract the ore block (one layer below) in Fig. 5a, five (5), waste blocks (numbered 1, 2, 3, 4 and 5) on upper layer needs to be removed to maintain slope angle of 450 in 3 dimensions. For representing the situation in 3D algorithm, directed graph with slope constraints are created as shown in Fig.5b. The arcs from the ore block to all the overlying blocks (5 in number) are created. The capacities of the slope constraint arcs are assigned an infinite value. The infinite value of slope constraint arcs ensures that these arcs will never be the minimum cut. Thus, the minimum cut will provide a valid pit because the slope constraint will not be violated.

2.2 Pushback design

The pushback design proposed in this paper is a two stage process. In the first stage, the parametric minimum-cut algorithm has been used, and in the second stage, repair heuristic algorithm has been applied to generate a feasible solution for pushback design. The pushbacks or sequences are designed keeping in mind the ultimate pit design, which is obtained from analysis of BEVs of each block. Operating design on developing pushback includes information on bench width, road width, slope angle, overall operating slope, bench heights, etc. (Shishvan and Sattarvand, 2015). The pushbacks are highly motivated by maximizing the NPV and to provide stable cash flow.

2.2.1 Parametric minimum-cut algorithm

The minimum-cut network flow algorithm, same as Lerchs-Grossmann algorithm (Lerchs-Grossmann, 1965), generates a single pit which is the optimal ultimate pit for the surface mine.

To generate pushbacks, parameterization of the minimum cut algorithm can be implemented. The parameterization algorithm of the Lerchs-Grossmann algorithm is well documented in various literature (e.g. Seymour, 1995) and is used in commercial implementations (Whittle, 1998). By scaling the economic values for all blocks using a Lagrangian multiplier parameter λ, a series of "nested" pits were generated. The value of λ is monotonically non-decreasing and used to directly multiply the block economic value. The increasing λ values will generate pit from small to large pit size until the ultimate pit limit is reached. In this paper, λ was chosen to be multiplied with the capacity of the arcs from source to the ore blocks nodes. The arcs from waste blocks nodes to sink are kept as-it-is since the objective is to scale the economic value of the ore blocks.

It is clear that the parameter λ, a multiplier of the capacity of the arcs in the network algorithm, plays a key role in producing nested pits or pushbacks. However, selecting a series of λ values for nested pits generation is a tedious undertaking and at the same time, it will not respect the production constraints. The arbitrary choice of λ may produce pushbacks with large gaps, which is undesirable from mining standpoint. In this paper, an iterative algorithm has been applied for selection of the suitable value of λ. By selecting the parameter value, different size pits or pushbacks can be generated depending on the resource constraints. The algorithm starts with a small Lagrangian parameter (λ) value to calculate the minimum cut of the directed graph. The increasing Lagrangian parameter produces larger and larger size pits or pushbacks. The λ value was incremented with $\Delta\lambda$ until the production target constraint is violated. The choice of initial λ and increment value $\Delta\lambda$ have a great effect in this algorithm.

2.2.2 Repair heuristic algorithm

The good choice of the Lagrangian relaxation produces a decent upper bound for the pushback design, however, it will not guarantee exact feasible solution with production constraints. The heuristic algorithm has been applied to obtain the feasible solution for the pushback design problem which constrained the production target. In this paper, the production target constraint has only been considered. However, any constraint, as well as multiple numbers of constraints, can be incorporated in this algorithm.

To obtain the feasible solution, some nodes need to be eliminated to obtain a new pushback that satisfies the production constraints. Nodes are selected for elimination in such a manner that the value of the minimum cut decreases as little as possible and at the same time the amount of violation of production constraint is reduced as much as possible. Apart from that, the eliminated node from the current pushback should be selected in such a manner that none of its predecessors in the directed graph belong to the current pushback. After selecting the set of candidates for the elimination by respecting the predecessor constraints, the best node has to be selected from the candidate set.

The heuristic algorithm iteration was done in a loop until the feasible solution of the present pushback is reached. At each stage in the loop, the heuristic algorithm sorted the elements of the candidate set according to the selection criterion and eliminated the best candidate. Then, violation of the production constraint is re-calculated. If the violation of the production constraint is less than or equal to zero, the algorithm stops otherwise run in the loop until it reaches the feasible solution.

3.0 Optimization algorithms

The Lerchs-Grossman algorithm used in this paper assumes that the BEVs of each block is known (using eqns. 1 and 2), which is calculated as a result of the concentration of ores and impurities in each block. The algorithm decides the number of blocks present in the ultimate pit and the sequence in which they will be extracted (Lerchs-Grossmann, 1965). The algorithm further optimizes the overall profit from the pit by maximizing the cost difference between the value of ore extracted, extraction cost of ore, as well as extraction cost of waste required to extract those ore blocks (Hustrulid and Kutcha, 1995). In this, the slope constraints are applied such that the wall slope should not increase beyond the maximum slope angle varying with the depth of the pit. This algorithm works by manipulating the BEVs and arcs. In optimization packages, the slope requirements are translated into a large number of block relationship in the form of arcs (Soigolo, 2010). During the optimization process, the algorithm marks the block which is to be mined and these marks can be considered or left depending on optimization. The block remains marked if it currently belongs to the linked group of a block having a total positive value. Optimization deals with the problems of minimizing or maximizing a function with different variables having equality or inequality constraint conditions. Many design problems are very complex and difficult to solve using conventional optimization techniques.

3.1 Production planning

The mine planning is based on divide and conquers rule. In this, the entire reserve/deposit is discretized into blocks of equal size. In order to optimize the production, the blocks are sequenced in different time dependent pushbacks or sequences. Once the optimized pit layout is available, these smaller size pits are comparatively easier to manage. The production starts from the area which gives fast and maximum ROI, i.e., area with the minimum stripping ratio. Successive sequences are made progressively depending on ROI contributed by them ultimately reaching the ultimate pit shape (Mathieson, 1982). The extraction continues from a sequence having highest average profit ratio (APR) to lowest profit ratio and the relation given in eqn. (5).

Average profit ratio = Revenue/all costs incurred ... (5)

Operating layout of the mine is the key element in production planning. The operating layout is developed keeping in mind slope angle of the pit and various operational constraints of mine design. The push backs or sequences are so organized as to meet the long-term production plan (Hochbaum and Chen, 2000; Johnson, 1968; Wilke and Reimer, 1977). It provides an estimate of the rate of advancements of mining operations. The overall objective is to meet the long-term production target of the entire mine, which is segregated into several medium term plans and further divided into short term plans. The long-term planning aims at ensuring a steady state of production, maximizing the NPV and total profit from production process while satisfying operational constraints of working slope angle, processing constraints, grade blending and ore production (Frimpong et al., 1998). This acts as a guide for the medium-term and short-term planning. These medium and short term plans are an indicator of overall achievement of target and can be accordingly modified to meet the overall target based on the situation volatility.

4.0 Case-study of iron ore mine

The study was carried out on a hill top narrow strip deposit of iron ore. Iron ore are formed by the secondary process of leaching and enrichment of iron-bearing rocks under certain structural and meteorological controls (Wilke and Reimer, 1977). The ore produced comprises varying physical, textural and chemical compositions. The ore so formed gets deposited in varying spread and thickness over several prominent hills generally following strikes of country rocks. The orebody considered is bounded by banded hematite jasper (BHJ) on one side and iron floats and talus on the other giving it a lenticular shape. Ore is generally harder at top and softer at depths. The irregularly laterized harderore forms the crest of the orebody as shown in Fig.6, which have been used in present case-study. The Fig.6 also shows various surface features, mine leasehold boundary surrounding the ore deposits. There are three sections in which the entire deposit have been divided in order to optimize production from each area. The area C (shown in circle) have been considered for the modelling and analysis purposes in this paper.

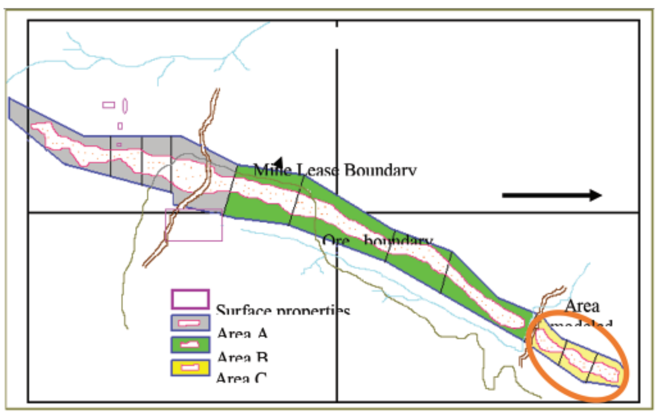

Fig.6 Surface plan showing the lenticular ore deposit, surface properties, ore boundary and mine lease boundary along with the area modeled using surpac.

A geological database is created from the available 222 boreholes information in the beginning to determine the extent of the ore deposit and other geostatistical parameters in the concerned area. A geological database based on the borehole information of the concerned area has been modelled to show the extent of deposit. The Fig.7 shows the presence of various borehole in a concerned area with respect to the collar value (i.e., surface coordinates) and survey file information. The borehole in the entire area is sectioned at regular intervals (here 100m) and are digitized to form ore strings. The ore strings are gradually concatenated to cover the entire deposit. The ore strings so formed, are oriented in a clockwise direction and subsequently triangulated to form a solid model of the deposit. The object after triangulation is validated for the presence of edges, triangles, etc. Once validation is done, the objects are set to solid. The solid model thus obtained is shown in Fig.8. The deposit is modelled depending on different assay values i.e., iron content present in the borehole section.

The volume of the reserve is estimated from the solid model so formed. The reserve in the deposit is calculated using ordinary kriging method (Goovearts 1997). Directional variograms are drawn to determine the direction of anisotropy of the deposit (Remy, 2004). The variogram in the current

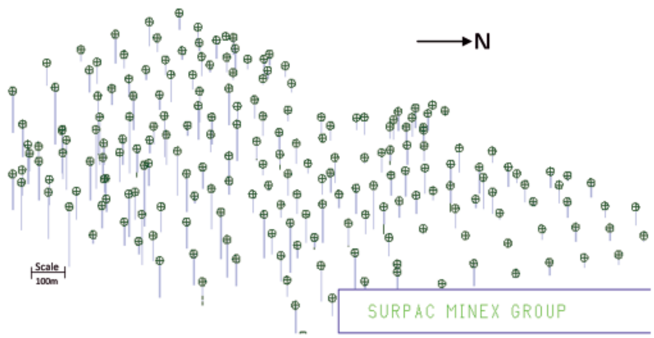

Fig.7 Geological database of borehole information

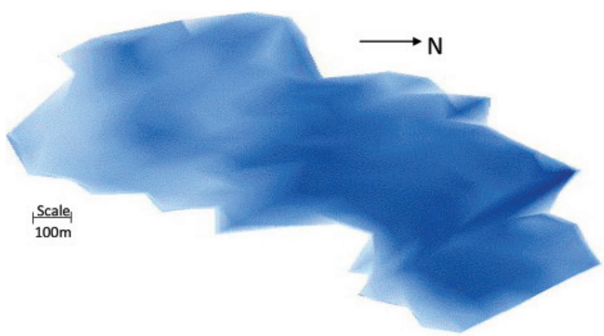

Fig.8 A Solid model of the deposit

study has been drawn at 0º, 45º, 90º, 135º, and –90º (vertically below). These variogramshelp in determining major, semi-major and minor axes for carrying out ordinary kriging in order to determine the reserve (Gemcom, 2010). The data obtained by compositing borehole information at 5m intervals, different variograms for 0º, 45º, 90º, 135º, and –90º (vertically below) were obtained as shown in Figs.9(a-e). This kriging file is generated with bearing 0, dip 0, plunge 0, semi-major axis 0, ratio major/semi-major 2.23, and major/minor 7.27, search radius 450, range 376 in *x*-direction and search radius 75, and range 51 in vertical direction respectively.

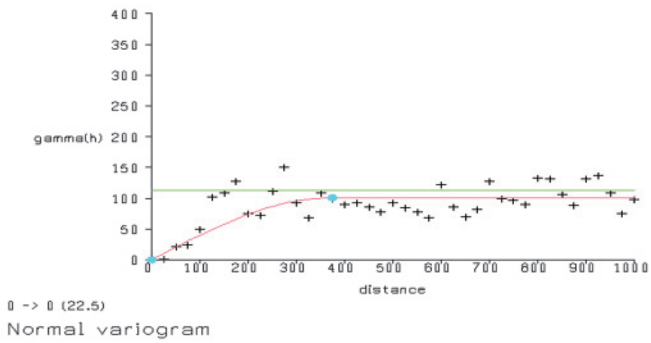

Fig.9a: Normal variogram at 0º dip and 0º azimuth with 22.5º spread

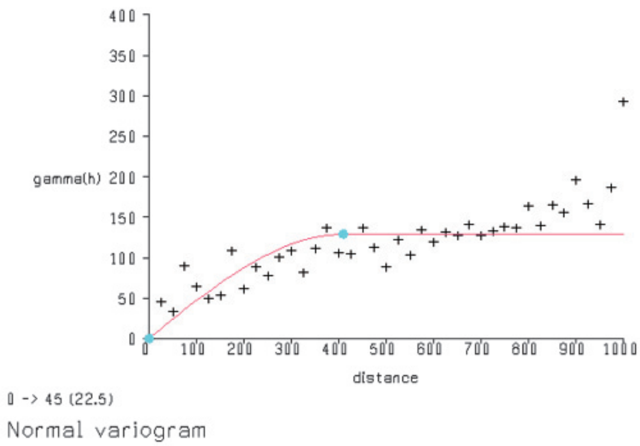

Fig.9b Normal variogram at 0º dip and 45º azimuth with 22.5º spread

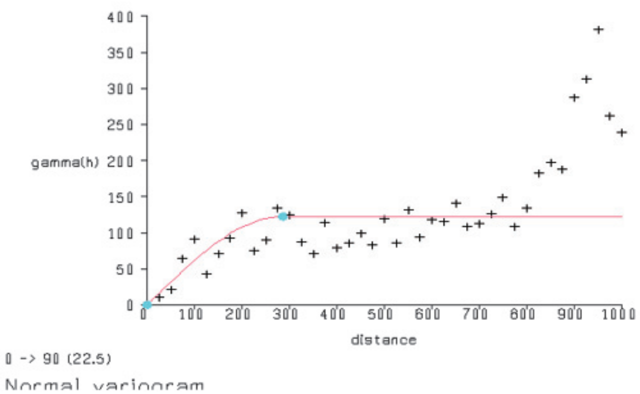

Fig.9c Normal variogram at 0º dip and 90º azimuth with 22.5º spread

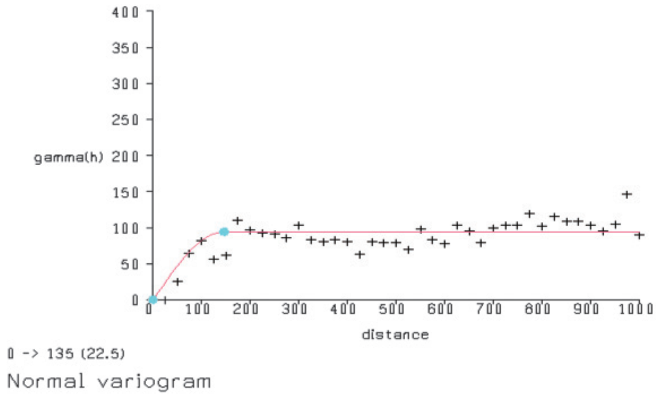

Fig.9d Normal variogram at 0º dip and 135º azimuth with 22.5º spread

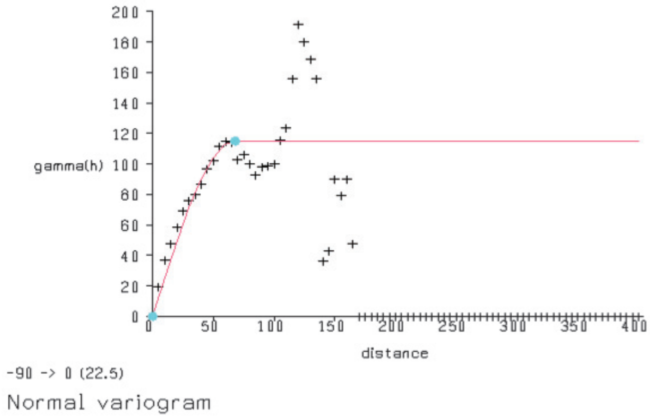

Fig.9e Normal variogram at –90º dip and 0º azimuth with 22.5º spread

The solid model is fitted into block model of regular size to generate constraint block model. The solid model so generated is incorporated in the block model of the regular shape of 50m × 50m × 10m size to form constraint block model (Fig.10). In the constraint block model, extra blocks falling outside the ore deposit are removed for better estimation of deposit using ordinary kriging.The data so generated upon ordinary kriging of the constraint block model resulted in 25900 blocks with ablock size of 50m × 50m × 10m size to be present within the deposits.

The block economic values of each block (BEV_i) are then calculated using ordinary kriging method, taking all pertinent

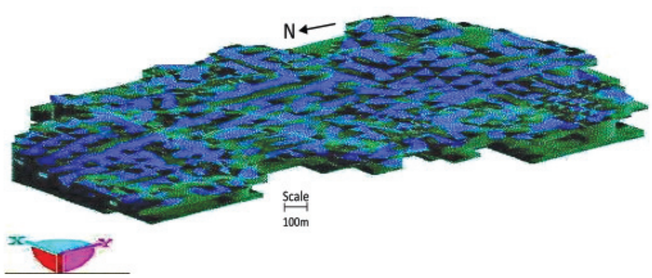

Fig.10 Estimated block model developed from ordinary kriging showing the variation in the deposit

Table 1: Economic parameters

Iron price (US$/MT)	160.67
Selling cost (US$/tonne)	3.36
Mining cost ($/tonne)	0.6
Processing cost ($/tonne)	6
Processing recovery	0.9

parameters into consideration as mentioned in equation (2). The market economic parameters considered for BEV determination are given in Table 1. After calculating BEV_i, net revenue is calculated using eqn. (1). The data so obtained is then used as input parameter for optimization algorithm (here, Lerchs-Grossmann algorithm). The optimization algorithm for design of ultimate pit limit is then formulated using constraint conditions as depicted in eqns. (3-4), as well as other economic and slope constraints. These optimization algorithms so formed are allowed to iterate in software like Matlab (Mathworks, 2011) to sequence blocks present in ultimate pit design. Further geostatistical analysis of result has been carried out using SGeMS software (Remy, 2004).

4.1 Ultimate Pit Generation

In order to generate the ultimate pit, the directed graphs are constructed using the block economic value of orebody models. The block economic value is calculated in this paper as an undiscounted value. The discounting of the block economic value during ultimate pit limit generation can also be implemented in an indirect way and is beyond the scope of the present study. The simulation is performed within the mineralized zone; in order to generate a smooth topography, some waste blocks are introduced in the non-mineralized zone to form a regular 3D orebody model. A directed graph is constructed, where ore blocks are connected with the source node and waste blocks are connected to the sink node, as described in Section 2.1. To maintain slope constraints, an infinite capacity arc is formed for underlying blocks to overlying blocks. The slope angle of the study mine is 45º, thus infinite capacity arcs are directed from an underlying block to nine overlying neighbour blocks. A high positive number is chosen to maintain the infinite arc capacities (here, 9999). After generating the graph, the push re-label maximum flow algorithm is used to generate the ultimate pit. The Fig.10 shows two sections of the ultimate pit generated using described method. The minimum cut algorithm returned 23563 blocks which were present in the ultimate pit layout. The stripping ratio (SR) was calculated considering the cut-off value of ???, and the value is ??.

Can you add some discussion about the ultimate pit results.

4.2 Pushback design

To generate a series of nested pits, parameterization of the minimum cut algorithm was performed. The pushbacks were generated by scaling the economic value of the ore blocks using the λ parameter, and applying heuristic algorithm as described in Section 2. In this study, the number of pushbacks was selected based on the mining equipment capacity. The mine is operated with shovel and dumper combination, and the total amount of materials the shovel dumper combination can handle is ?? MT. It was observed from the results that proposed study generates 6 pushbacks after satisfying the mining constraints. The figure presents two sections of pushback sequences for the mine under consideration.

The stripping ratios of six pushbacks are calculated and presented in Fig.11. It is observed from the Table 2, that the stripping ratio is low in the earlier pushbacks, which ensures that the generated pushbacks need fewer amounts of waste extraction in the earlier periods of mine production. It is also observed from the Fig.12 that after the fourth pushback, there is a paradigm shift in the revenue. This gives rise to suspicions that the mine may not be profitable to extract after the fourth pushback since the stripping ratio is almost doubled thereafter. This may be caused by the fact that the model presented in this paper is based on an undiscounted block economic value, thus the time value of mine is not considered.

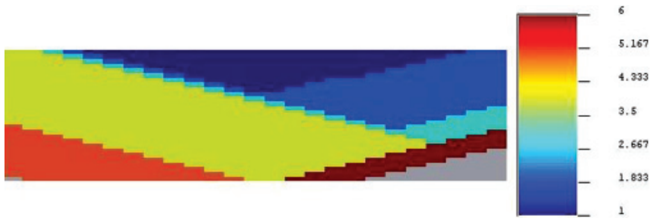

Fig.11 Vertical section of the pit layout

Table 2: Revenue from different pushbacks

Year	Total ore	Waste	Ore - Waste	DCF (Million $)	Cumulative DCF (Million $)
1	161424335	0	161424335	146.7493955	146.7493955
2	163769168	0	163769168	135.3464198	282.0958153
3	128729753	12441	128717312	96.70722164	378.8030369
4	349304690	89661	349215029	238.5185636	617.3216005
5	224309127	58344	224250783	139.2420929	756.5636934
6	32792581	234663	32557918	18.37809593	774.9417894

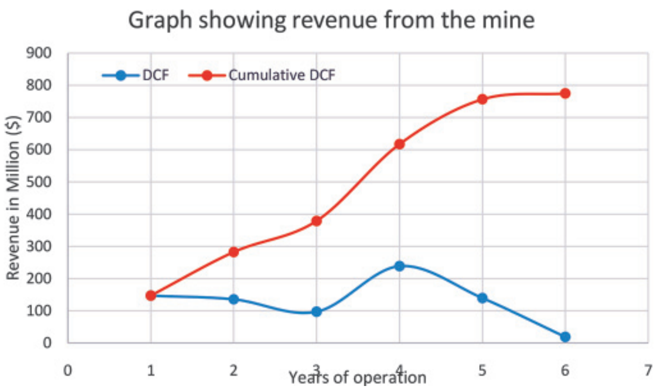

Fig.12 The discounted cash flow obtained for 6 years

4.3 Production Scheduling

To calculate the discounted cash flows and total NPV for the case study, a year-wise mine production scheduling needs to be assessed. The technical parameters presented in Table 1 were used for the purpose of production scheduling.

Production scheduling was then done to determine yearly production target and time-dependent push backs or sequences (Hochbaum and Chen, 2000; Johnson, 1968; Wilke and Reimer, 1977). The values so obtained was plotted using SGeMS and time-dependent pushbacks were obtained as shown in Fig. 11 (Agrawal, 2012). The deep blue colour shows the pit shape after the first year, while cyan colour shows the shape during the second year and so on and so forth. The gray colour shown at the bottom right-hand side shows the waste blocks which are outside the ultimate pit limit design and hence will not be mined.

5.0 Conclusion

Owing to the flexibility and compatibility offered by Surpac in using the data obtained from Surpac in different software, an in-depth analysis of BEV and other operational constraints in opencast mining can be easily done. The optimized blocks present in the pit can be easily modelled and used as a rough and ready yardstick in planning the long, medium as well as short term pushbacks. This study finds relevance to the top management people in keeping track of the overall objective of steady production and cash flow in a hassle free manner while optimizing the extraction from the area.

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