LONGTERM SCHEDULE OPTIMIZATION OF AN UNDERGROUND MINE UNDER GEOTECHNICAL AND VENTILATION CONSTRAINTS USING SOT

by

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Abstract

Long-term mine scheduling is complex as well time and labour intensive. Yet in the mainstream of the mining industry, there is no computing program for schedule optimization and, in consequence, schedules are still created manually. The objective of this study was to compare a base case schedule generated with the Enhanced Production Scheduler (EPS®) and an optimized schedule generated with the Schedule Optimization Tool (SOT). The intent of having an optimized schedule is to improve the project value for underground mines. This study shows that SOT generates mine schedules that improve the Net Present Value (NPV) associated with orebody extraction. It does so by means of systematically and automatically exploring the options to vary the sequence and timing of mine activities, subject to constraints.

First, a conventional scheduling method (EPS®) was adopted to identify a schedule of mining activities that satisfied basic sets of constraints, including physical adjacencies of mining activities and operational resource capacity. Additional constraint scenarios explored were geotechnical and ventilation, which negatively effect development rates. Next, the automated SOT procedure was applied to determine whether the schedules could be improved upon. It was demonstrated that SOT permitted the rapid re-assessment of project value when new constraint scenarios were applied. This study showed that the automated schedule optimization added value to the project every time it was applied. In addition, the re-optimizing and re-evaluating was quickly achieved. Therefore, the tool used in this research produced more optimized schedules than those produced using conventional scheduling methods.

Keywords: Mine Schedule, Schedule Optimization, Schedule Optimization Tool (SOT), Genetic Algorithm, Geotechnical Sequencing, Ventilation constraint.

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1 Introduction

Underground mine scheduling is a procedure used to make a plan outlining which mine activities should be executed over the life of a mine. Mining activities must be scheduled in order to organize and complete a mine project in a timely, efficient and profitable manner. An effective mine schedule sets realistic mine development rates, assigns appropriate operational resources and maintains ore grade and production levels. An effective mine schedule should also ensure that the execution of mining activities takes into account operational resource (equipment fleets, crew) requirements and utilization, cost and revenue. During schedule optimization, operating costs are not necessarily reduced and revenues are not necessarily improved, but the positive impact of both on the project value, realized through a discounting process, is increased.

Schedule improvement is generally required for an economically viable mining project. In particular, it improves the project value through: (i) accessing higher revenue stopes sooner and (ii) increasing utilization of operational resources. Schedule improvement is an iterative process that relies on multiple variables such as mineral price, exchange rate and constraints, and so mine schedule improvement for a complete mining project can be a complex undertaking, due to the challenges associated with adhering to various constraints imposed by physical adjacencies and operational resources. A constraint can limit options for schedule improvement, which can negatively affect the profitability of the project. Many examples of this exist, for instance, the annual hoist capacity could constrain a mine's optimum ore production; annual jumbo drilling capacity could constrain mine development and successor activities; incomplete development of ventilation networks could delay activities such as stoping.

The scheduling process should incorporate the practical aspects of mining including geotechnical, ventilation and operational resources constraints, in addition to the financial inputs such as capital investment, operating costs and discounting rate. The mine design, mine plan and mine schedule projections are often created based on one set of assumptions. As soon as the underlying assumptions are altered, the corresponding mine schedule may no longer be pertinent and must be revised under the latest assumptions.

A conventional method of mine schedule improvement involves multiple iterations and manual linking of the mining activities to reflect logical precedence, typically done within a commercial software package such as Mine2-4D® (2014) and Enhanced Production Scheduler (EPS®) (2014). Conventional methods of schedule improvement, based on the experience of mine planners, are relatively intuitive and provide flexibility however, they are labour intensive and arduous to implement. Due to the time required to set up and modify each link between mining activities and the reliance on experienced engineers to select the proper combination of mining activities to achieve the objectives, several iterations may be necessary before finalizing the schedule.

Alternatively, automated schedule optimization methods, which are able to consider complex scheduling problems, rapidly provide new information to the mining engineers that can be used to evaluate which schedule is most appropriate to adopt. In addition, once the set of rules and parameters are defined within such automated procedures, they can easily be transferred from one project or user group to another.

Automated schedule optimization is only used for long term planning for which multiple alternate scenarios must be considered and analyzed in a relatively short period of time. Different approaches are available to optimize amine schedule, as described in Chapter 2. Each approach has advantages and disadvantages in terms of their design and functionality. The one being considered here is called the Schedule Optimization Tool (SOT)(Maybee, 2010).

1.1 Schedule Optimization Tool

SOT is designed to optimize a long-term underground mine schedule. It uses a set of linked activities and optimizes their sequence and timing to make the project more profitable(Maybee, 2010). To explore feasible solutions, SOT uses an evolutionary algorithm that is seeded with heuristics and policies that have been known to improve schedule value. Subsequently, SOT generates priority lists of activities to be evaluated based on achieving the maximum NPV. SOT achieves this by reaching ‘*the best stopes*’ and ‘sliding’. The ‘sliding’ is to SOT what to JIT to EPS®, that ensure *‘just-in-time’* (JIT) development and ore production at earlier phase of mine. *‘The best stopes’* not only contain high mineral grade but also may be accessed early in the mine life to expedite higher revenues sooner. The mechanism of pulling ore production activities earlier and pushing back development activities that are not needed in the immediate future is termed ‘sliding’. ‘*Sliding’* is SOT’s JIT action; further details are given in section 2.1.

SOT sets the Net Present Value (NPV) as an objective measure of schedule effectiveness and thus evaluates different mining scenarios based on the NPV. Each scenario can be represented by a set of properties such as capital investment, operating cost, operational resource capacities and mineral values. Over and above this basic financial valuation, SOT’s optimization algorithm improves utilization of equipment fleet capacity and adheres to imposed equipment thresholds throughout the mine life.

Due to its automated functionality, SOT is able to create thousands of feasible schedules in relatively short time periods, which allows for a thorough investigation of the project being assessed including any risks associated with a particular scenario.

1.1.1 Definitions of various terminology used in this study

'Operational resources' are essentially the equipment fleet used for the ore access tunnel development (which includes levels, crosscuts), ventilation raise development, ore handling, ore hoisting, and the creation of other mine tunnels such as escape ways and travel ways. Clearly, a given fleet has a threshold level of tunnel development that it can achieve in a given time, but the actual productivity of the fleet depends on the mining method system. The amount of operational resources required, as well as its availability, limits the number of activities committed to a period.

In this study, an 'activity' is notionally a small section of excavation that is designed, planned, carried through and has associated properties of duration, advance rate, cost, mass, length and required resource level. Generally, the type of activities fall into classes of mine development activities and stoping activities.

'Predecessor' and 'successor' links can be defined as a logical relationship between two activities that dictates the order in which they must be undertaken.

An 'unoptimized' schedule is typically a manually created schedule made with EPS®. It may have also been subjected to a process called 'levelization', which delays or interrupts activities until sufficient operational resources are available. An outcome of improved sequencing with SOT is an optimized, although perhaps not optimum schedule.

1.2 Objective

Despite its apparent advantages, SOT has not yet been widely adopted by mining companies. The objective of this case study was to determine if employing SOT could improve the NPV associated with the underground mine schedule of a real orebody of interest. Such determinations were accomplished by comparing the NPV of unoptimized and optimized schedules.

The case study also aimed to demonstrate that the automated schedule optimization software could permit the rapid re-assessment of orebody value in the face of new constraint scenarios. At the suggestion of the mine planning team, the constraint scenarios explored were: (i) geotechnical, i.e., the application of additional precedence relations between mining activities to bring about stoping sequence patterns that were thought to mitigate the effects of mining in highly stressed environments (as is often the practice in the mining of deep orebodies to mitigate the risk of rock bursts) and (ii) ventilation, i.e., changing the flow rate of ventilating air supplied to the mine sections, which would affect the development rates achievable by the assigned development fleet. The scenarios considered are depicted in Figure 1-1.

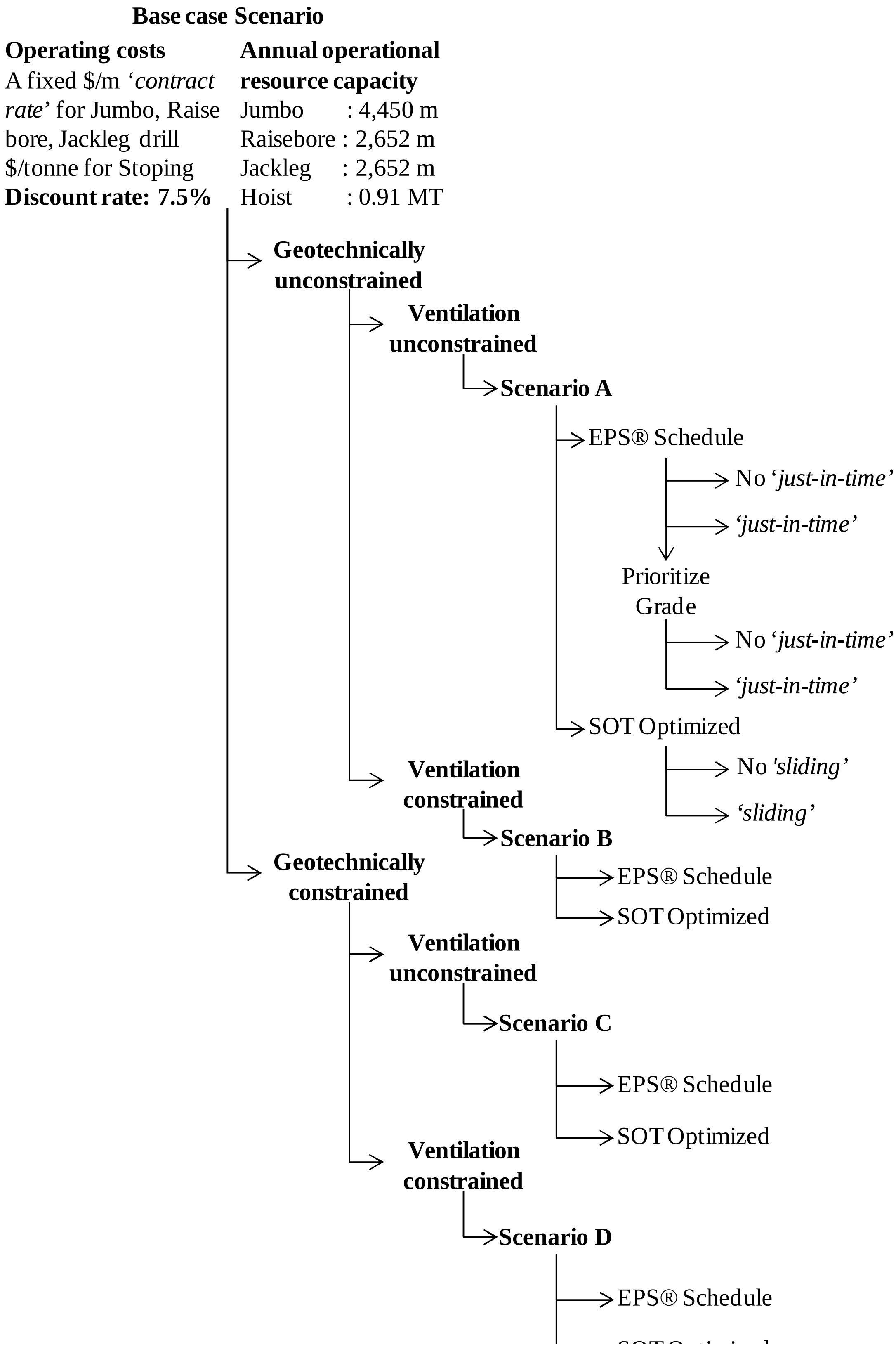


Figure 1-1 Structure of the investigation with different scenarios

1.3 Methodology

The study commenced by organizing the digital data of the mine, which were available in the form of a block model of the orebody, a mine layout design and stope layout design. A set of computer-aided mine design layouts pre-established by the mine planning teams were used in this study. At this point, predecessor and successor links for the mine activities had not been established by the mine planning team, so Mine2-4D® software was used to create precedence links between 2,055 development and stope activities. Following the linking process, a feasible base case schedule was generated using EPS®. The basic set of constraints considered during this step were: (i) physical adjacencies and (ii) operational resources.

The base case EPS® schedule was a levelized schedule. At this stage, the value of the base case schedule was determined. SOT was then applied to the base case schedule to identify whether its value could be improved by changing the timings of activities. This scenario did not apply additional constraints that the mine planning scheme could apply, such as mine equipment relocation penalties and greater operating costs with depth.

This study was extended by adding ventilation and geotechnical constraints to the base case mine schedule to evaluate the effect of these constraints on the project value, as illustrated in Figure 1-1. The geotechnical constraint amounted to adding precedence relations between the mining activities to achieve a stoping sequence that had a ‘chevron’ pattern (Morrison, 1995), considered primary and secondary stopes and left sill pillars(Henning and Mitri, 2007; Villaescusa, 2003). The ventilation constraint considered changing the volume flow rate of ventilating air that could be supplied to the mine section. The ventilation constraint was applied on ore production and headings (i.e. including development activities), corresponding to the amount of ventilating flow. The air quantity was calculated based on mass and duration, as stated by Howes (2013).

1.4 Thesis outline

The thesis is organized as follows:

Chapter 2 contains a review of schedule optimization approaches, generally and specifically for an underground mine schedule optimization process. This chapter includes a description of underground mine design, mine planning and mine scheduling.

Chapter 3 defines the formulation, methodology and procedure of the SOT optimized mining schedule.

Chapter 4 outlines the details of the problem considered. The mine operations are described and the key constraints (geotechnical and ventilation constraints) influencing the mine schedule are defined. It also discusses how the base case schedule was created. This chapter describes project details considered for this study, which included mine design, mining operation financial inputs and constraints.

Chapter 5 describes the results of Scenario A, a scenario without either ventilation or geotechnical constraints. Scenario A was considered to evaluate the upside potential of the project.

Chapter 6 contains the core optimized schedule indicators for the mine prospect such as ore production, jumbo drill development, raise bore development, cash flow and NPV. These indicators were compared for scenarios B, C and D. Graphs of unoptimized and optimized schedules are presented to reflect schedule optimization impact using evolutionary algorithms.

Chapter 7 shows the results of extended assessments performed by changing operating cost for all four scenarios and the ventilation capacity for scenario B. The chapter also describes extended assessments for variable operating cost and airflow quantity and the impact of doing so.

Chapter 8 summarizes the major findings and discusses opportunities for future work.

2 Underground mine scheduling and optimization

Underground mine projects are large and challenged by many constraints such as geotechnical and operational resource capacity. In addition, reducing operating cost, improving operation resource utilization, and cash flow are among the most important problems in underground mine scheduling. In order to create an optimized mine schedule, many methods and solutions have been used to solve these problems, namely mathematical models and algorithms in particular.

2.1.1 Mine design, mine planning and mine scheduling

In the context of this study, mine design is a statement, graphical or otherwise, of the location and dimensions of excavations that are proposed to be made through the execution of mining activities. The mine design statement may include specification of the equipment that is to be used and could include a statement of rockmass stabilization methods. However, it does not define a timetable to coordinate the activities or excavation sequences. In fact, a mine plan constitutes a mine design with the addition of coordinated time dimensions.

Mining plans typically include all major technical functions performed in mining operations for the recovery of the *in-situ* ore reserve. The mining plan guides the efficient and economic production of ore. Scheduling is a core constituent of mine planning as it adds a coordinated time dimension to all mine activities. It ultimately specifies the sequence, start time and duration of activities, and thus leads to the allocation of operational resources to each activity.

Conventional practices for mine scheduling are dependent upon existing scheduling techniques, data integrity, knowledge, perception and experience. It is possible for the entire timetable of activities to be completed manually. However, the complexity of the process means that conventional scheduling practice, at the time of writing, involves the use of computer-aided design programs such as Mine2-4D®, Vulcan MineModeller® and GEOVIA Surpac® with activity schedulers, such as EPS® and Deswik.Scheduler®. Once the design is finalized, the sequence of mine activities is created by manually linking activities while adhering to rules of physical adjacencies and following planning guidelines specified by mine engineers and management teams. These guidelines are generally based on mining practices, and may be influenced by precedent practices.

Considering the use of Mine2-4D® and EPS® as an example, a mine planner would first define precedence links between the activities. With hundreds of stoping activities and thousands of development activities, this process can be lengthy. It must be done interactively by a skilled mine planner, and is still be subject to human error. This first step of the design process takes place in the Mine2-4D environment. Figure 2-1 shows a Mine2-4D® representation of links or dependencies. Each mine activity is then associated with additional properties such as advancement rate, development category, mine area and levels.

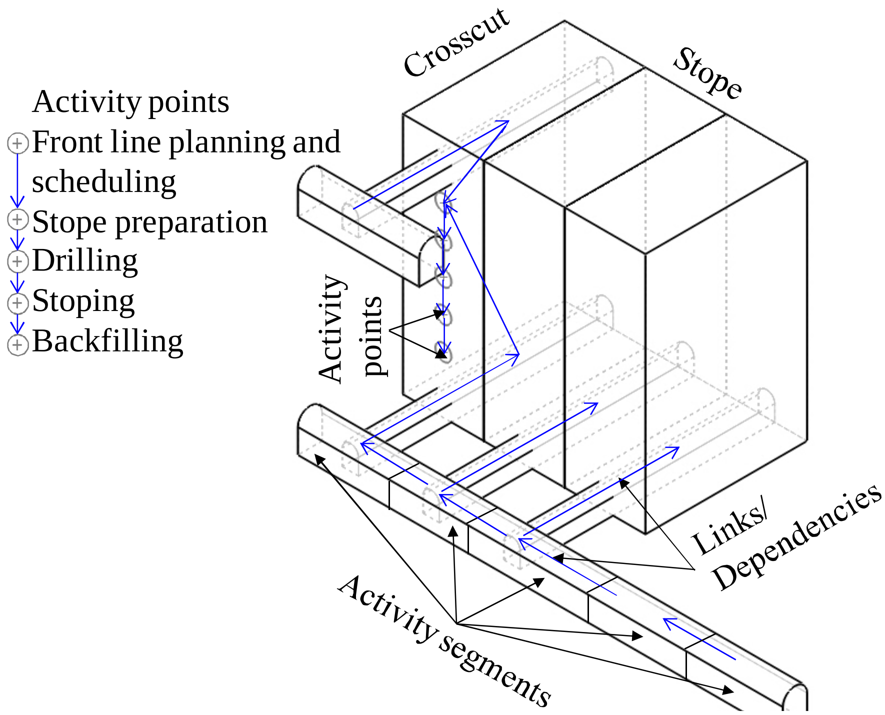


Figure 2-1Mine2-4D® representation of links or dependencies between activities

Subsequently, the linked activities are passed to EPS® where operational resources are assigned to each activity. As the operational resources may only be used with specified rates of use, the combination of the precedence relation and the operational resource utilization rates together define an initial, feasible, solution for the mine schedule, that is, one for which the resulting timetable of activities satisfies constraint such as activity precedence and the threshold of resource availability .

EPS® automatically applies an algorithm to assign the operational resources to activities. It has the option to assign one class of operational resources to activities, so that this operational resource is consumed at the threshold rate throughout the mining plan. Such a process is called ‘levelling’. Figure 2-2 and Figure 2-3 show the effect of ‘levelling’ for an unoptimized schedule in EPS®.

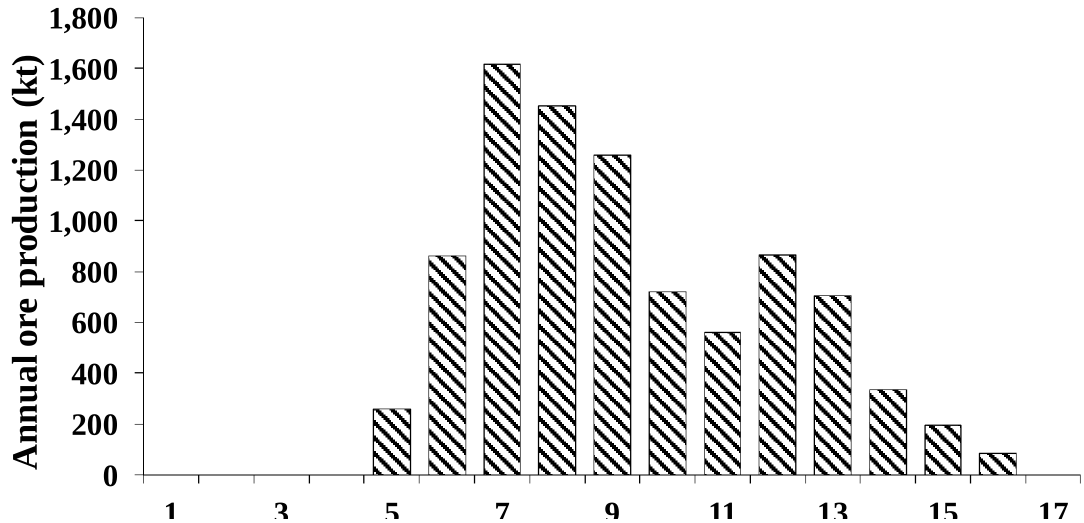


Figure 2-2 EPS® schedule: Annual ore production profile for the unoptimized and not levelled mining plan

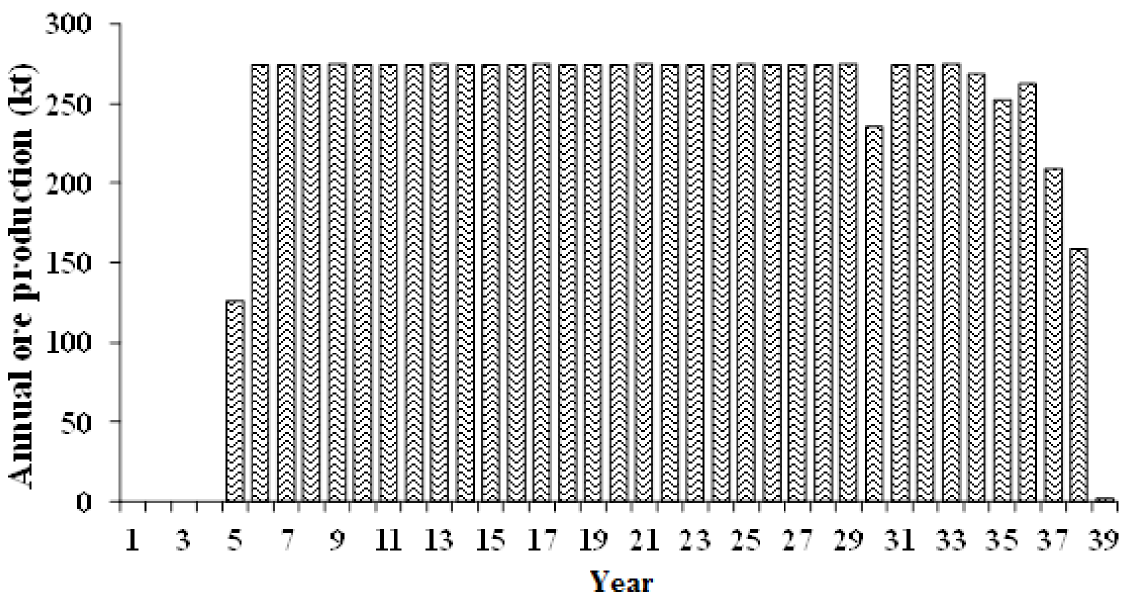


Figure 2-3EPS® schedule: Annual ore production profile for the unoptimized and levelled mining plan

Once a feasible schedule is established (whether levelled or not), the coordinating time dimension is added to the mine design to create a mine plan. A projection of the timing of revenues and operating (and other) costs can be established in a cash flow model. The concept of '*the time value of money*' can be applied to the cash flow model to determine the value of the mine plans in the form of the Net Present Value (NPV). The NPV is computed as the sum of the discounted cash flows. Typically, the discounted cash flows are formed from the NPV associated with the initial, feasible mining plan and can be increased by inspecting the plan and offering timetabling improvements.

This indicates that the initially feasible mine plan developed using conventional techniques is not the optimum solution, and suggests that additional techniques are required to identify a better schedule for the exploitation of a prospect.

2.1.2 Mine scheduling using *just-in-time*

'*Just-in-time*' (JIT) is defined as a dynamic translation that executes an activity at 'run-time' rather than prior to execution. 'Run-time' can be defined as a specified behavior of an activity that is eventually invoked, causing that action to be directed by a schedule (Aycock, 2003). For example, if activities were not subjected to JIT procedure then some activities would be scheduled for earlier than actually needed.

The JIT functionality in mine scheduling is explained through application to a demo dataset, illustrated in Figure 2-4, Figure 2-5 and Figure 2-6. Eight development activities and three stopes with identical properties such as length, duration and mass, were considered. For the schedule, fixed annual operational resource capacities were assigned for development and stoping. The operational resource capacities were assigned in a manner that not more than two development activities and one stoping activity could be executed in a year.

Mine development under two jumbo categories is shown by A and B. For jumbo category A development activities were linked with dependency. For jumbo category B, no predecessor was specified, while for stoping, development was considered as a predecessor. The resulting schedules are described as follows:

(a) In the EPS® default schedule, all activities were constrained *as soon as possible*, shown in Figure 2-4. All the activities in this schedule were levelized through operational resource capacities. The impact was perceptible through development activities that were finished earlier than required.

(b) In the EPS® schedule with application of JIT, development activities were to be *as late as possible* and ore production activity *as soon as possible*. Figure 2-5 shows that the development activities were delayed in this schedule; however, the successor stoping activities were also postponed. In EPS®, levelling the operational resources is an integral process of JIT that introduces delay to activities, if sufficient capacity is not available. However, EPS® does not guarantee an optimum operational resource scheduling (*EPS V2*, 2012).

(c) SOT has a similar feature to the JIT in EPS®, called ‘sliding’. In addition to JIT rearrangement, SOT also analyzes the schedule to remove further slack so that stoping activities are undertaken sooner, as illustrated for comparison in Figure 2-6.

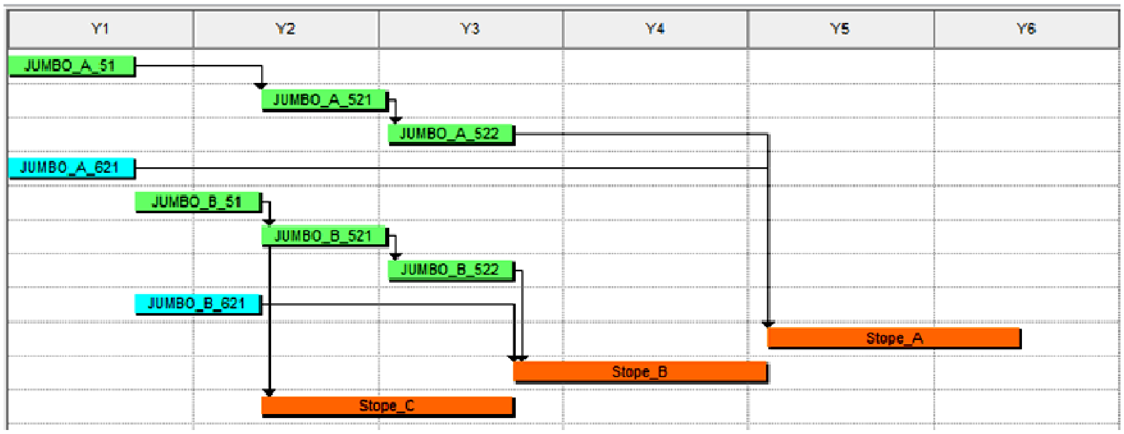


Figure 2-4 EPS® default schedule without 'just-in-time' development

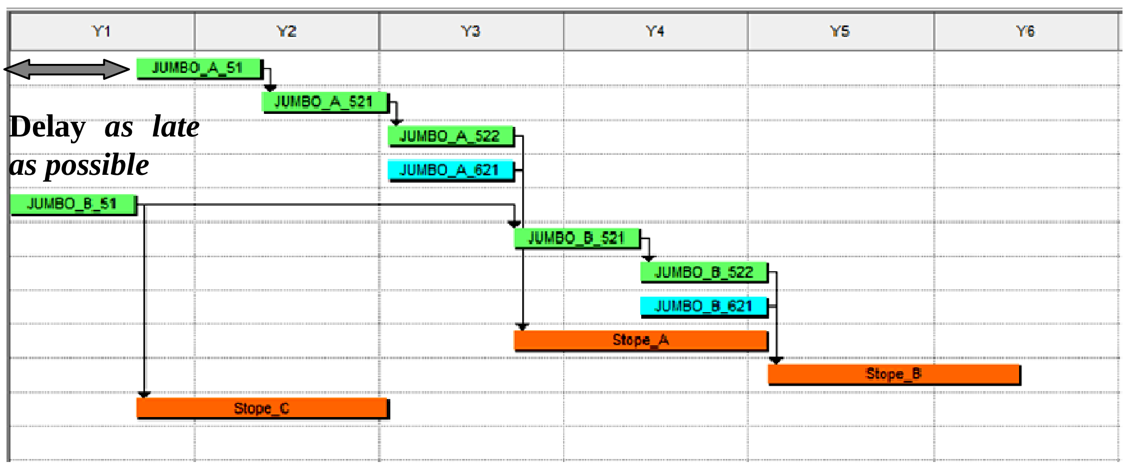


Figure 2-5EPS® default schedule with 'just-in-time' development

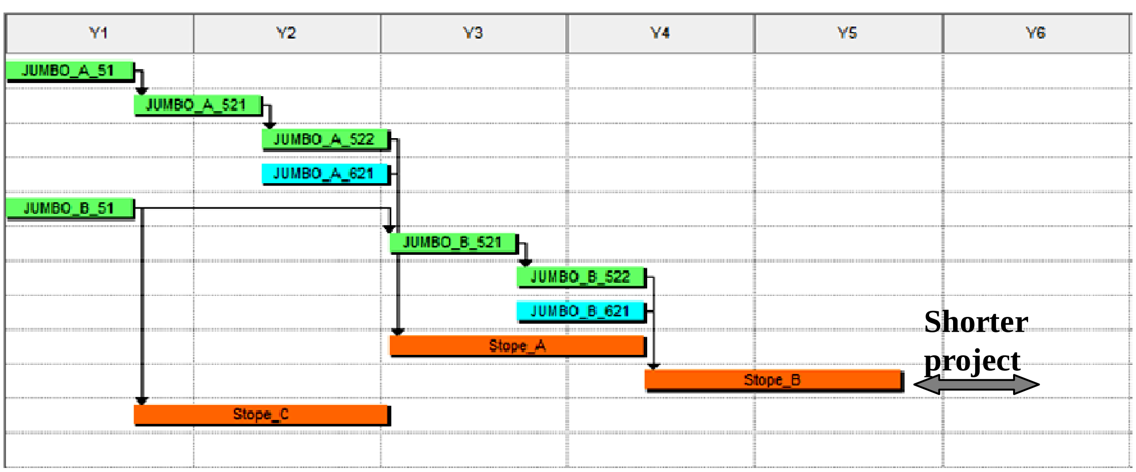
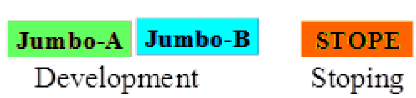


Figure 2-6SOT schedule with 'sliding'



2.2 Approaches for schedule optimization

Underground mine schedule optimization encounters similar challenges to those in other disciplines, such as the ‘Vehicle Routing Problem’ (VRP) in the field of transportation, distribution and logistics. VRP is defined as “*the determination of the optimal set of routes to be performed by a fleet of vehicles to serve a given set of customers*” (Toth and Vigo, 2001). In the manufacturing industry, an equivalent problem is the ‘Job-shop Scheduling Problem’ (JSP), where a set of machines is allocated to a set of jobs and each job is assigned with precedence operations constraints. For each operation, one machine is required and machines are continuously available without delay. The sequence of the operations on the machines, given a performance indicator, is optimized (Pezzella *et al*., 2008; Yamada and Nakano, 1997).

The process of deciding the chorological order of mine activities and committing operation resources is as critical as prioritizing the job relation and optimizing the resource constraints in the manufacturing industry (Sakalauskas and Felinskas, 2006). The decision variables represent the time at which various mine activities are timetabled to take place. Typical objective functions seek to maximize NPV or minimize costs.

Classical optimization techniques are suitable to find solutions of unconstrained, continuous or differentiable functions. These techniques are analytical methods and use differential calculus to get optimum solutions. For that reason, conventional optimization techniques have limited scope in practical applications. In succession, when the objective function is linear and the dataset is specified by linear equalities and inequalities; numerical optimization techniques are useful (such as linear programming). However, classical optimization linear programming is not an appropriate alternative to solve a problem with nonlinear inputs or objective function(Kok and Lane, 2012).

The Mixed Integer Programming (MIP) approach is a relatively flexible technique for optimization problems. MIP has the ability to integrate logical expressions and nonlinear expressions. Several commercial and open source software systems for MIP are readily available. Due to flexibility, MIPs show efficient solver performance (Smith and Taskin, 2008) but solving a large scale problem remains a concern (Floudas and Lin, 2005).

The Genetic Algorithm (GA) approach is a general-purpose population-based stochastic search technique that mimics the principles of natural selection and genetics proposed by Darwin. Holland (1975) and Goldberg (1985) first investigated GAs as intelligent search procedures that are based upon the mechanisms of natural genetics. This approach was first used to solve optimization problems by De Jong (1975). For a large set of data and variables, GA is a quicker method of optimizing than the MIP approach(Foster *et al.*, 2014).

Many studies have been done on the complexities, classifications and techniques required for schedule optimization. Figure 2-7organizes various algorithms that have been developed to solve different kinds of optimization problems (Sivanandam and Deepa, 2008). However, due to the inherent complexity of scheduling optimization, most exact solver approaches are limited to very simple classes of problems and approximation heuristics for optimizing them.

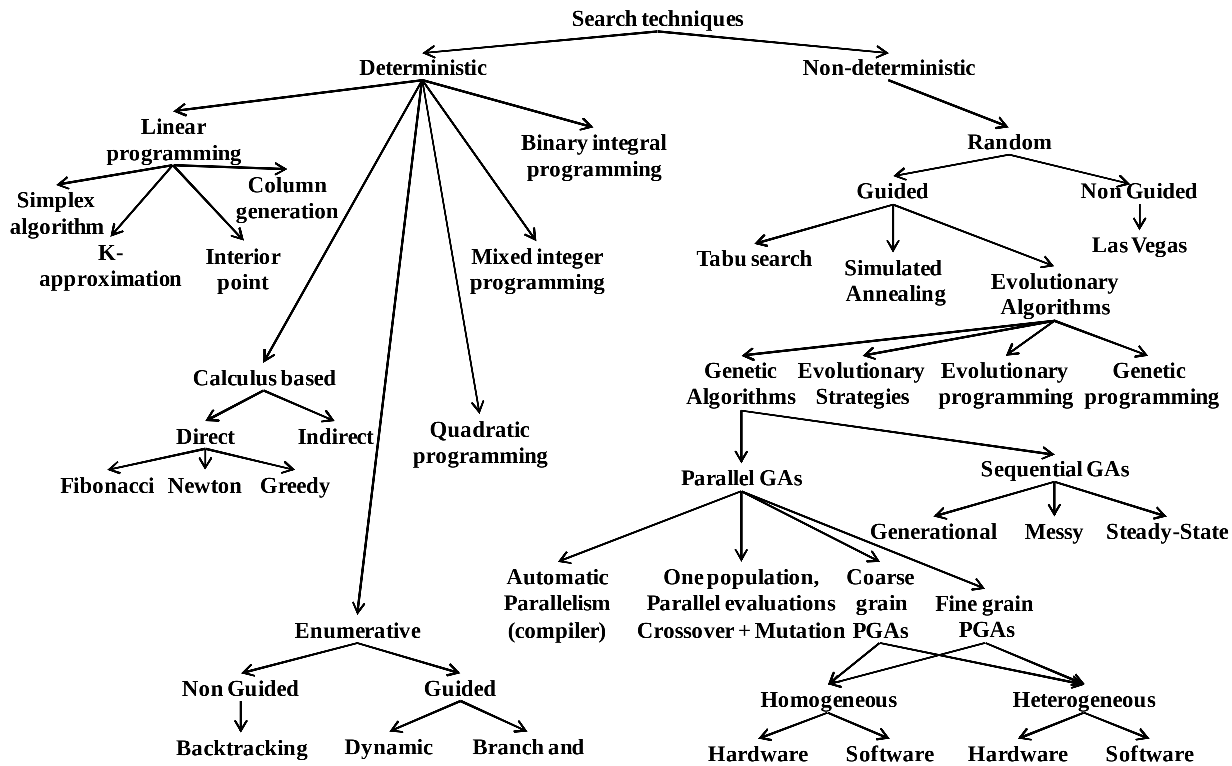


Figure 2-7Search techniques on different solution methods for standardized sets of problems based on Sivanandam and Deepa (2008)

2.3 Solutions and methods for schedule optimization

Evolutionary algorithms are the collective name for a range of problem-solving techniques. While several evolutionary algorithms have been developed in the area of artificial intelligence, these techniques are being increasingly applied for schedule optimization in mining and other industries. This section reviews techniques adopted for mine schedule optimization (summarized in Table 2-2).

Blattman (2003) developed an unnamed program using the shareware scripting language Tool Command Language in the MineSched™ (2010) software to solve non-linear objective functions based on the ‘hill climbing’ method. On the basis of theoretical calculation processing time by Blattman (2003) for15 stopes, there could be $1.3X10^{12}$ solutions requiring 41 years to evaluate all these solutions. Thus, it is impractical to optimize a large set of mine activities through 'hill climbing'. To overcome such limitations, Blattman(2003)enhanced the 'hill climbing' method by incorporating a set of user selectable choices to provide "destination-driven" sequences with high NPV. For example, the program chooses one stope, lists all the precedence activities associated with it and then selects the next stope. This method was facilitated with a heuristic to guide the program to prioritize stopes based on mass and revenue. For a schedule containing 7 stopes, Blattman (2003) evaluated 7!(5,040) solutions. This exercise gave an optimized solution by iteration of partial sequences in three steps. However, this method needs to be improved for a larger dataset and multiple variables, since it failed when Blattman attempted to use more than eleven stopes.

Brazil *et al.*(2002) developed an algorithm to solve a mining design network problem to minimize development and hoisting costs, both of which are significant in underground mining. Brazil *et al.*(2002) aligned the algorithm with the three-dimensional Steiner Network Problem (SNP).The SNP can be defined as a problem that involves determining a way to efficiently allocate resources by being required to find the shortest interconnection for a given set of objects (Hazewinkel, 2001).The algorithm methodology was to minimize network length in Euclidean 3D space. The algorithm was based on mathematical modeling of the weighted networks, for a mine network that contains 11 ramp-links and 3 shaft-links. The algorithm objective was to optimize the development cost, without considering the gradient constraint. The limitation of the Brazil *et al.*(2002) algorithm is that it can only take into account the development cost for the optimization, not other financial data such as capital investment or revenue, although it is conceivable that these limitations are minor and relatively easily overcome.

Underground mine scheduling and optimization

To enhance the strategic planning process in an underground gold mine, Ballington*et al.*(2004) developed a prototype tool called Economic Optimization Model (EOM) in Microsoft Excel®. Ballington *et al.*(2004) define optimization as *"the allocation or configuration of resources, within the control of management, which will maximize (or minimize) a specifically desired objective*". Here, the desired objective is not only a high profit but also feasibility of the mine project as well as evaluation of influence of one variable (geological, geotechnical and financial, mineral price, exchange rate) on another. Optimization needs to consider the interrelation between the various input variables that influence the outcomes and that are not possible to evaluate through programming. Ballington *et al.*(2004) found that EOM exhibited an ability to run multiple scenarios for the strategic planning and project valuation. However, the EOM solver was unable to solve a large problem size. Ballington *et al.*(2004) defined complexity by number of dependencies through mathematical relationship within a model.

Denby and Schofield (1995) mentioned that conventional optimizers (steepest descent (SD) and successive quadratic programming (SQP)) do not consider uncertainties such as mineral grade, price and operating cost. Together, all considered factors could add to the combined effect of uncertainties into the mine schedule. Denby and Schofield (1995)used a prototype application based on a GA to produce an optimized schedule. They incorporated a 'Penalty Term' in the objective function to discard any breaches of defined constraints. The prototype application was not reported to have been developed further to use the penalty function (PF) with overlaid constraints and risk assessment, based on grade uncertainties, into the scheduling methodology. Since PF cannot take into account any sequence, most of the conditions have been met except a little over-constraint.

The significance of activity duration, order, aggregate regular expression (maximum, minimum), and leg (time for successor activity) constraints and their sequential patterns defined as monotonicity, anti-monotonicity and succinctness were investigated by Pei *et al.*(2002). This study demonstrated the importance of constraints for effective and efficient mining applications, as constraint-based algorithms effectively reduce a large search space to a small one in sequential pattern mining.

Smith(2007) used an approach for project evaluation through cash flow optimization based on mathematical programming, termed the Life of Business Optimization System (LOBOS). LOBOS uses a graphical user interface (GUI) for data management and all other components of the system that allows graphical definition of a planned scenario. The distinguishing abilities of LOBOS over other methods are (i) a provable optimum solution and (ii) to instantly recognize an infeasible scenario using the means to trace the source of infeasibility though a GUI. LOBOS uses a mathematical programming and a LP-based model to find a mathematically provable optimum solution. For all feasible solutions, LOBOS displays and generate Excel® reports. LOBOS's GUI includes utilities for database management in order to evaluate results from various scenarios and makes decision-making easier. However, an excessive number of variables is a key concern since it increases completion time.

For schedule optimization, MIP is a good tool to model and solve optimization problems.MIP uses a set of constraints, decision variables, parameters and an objective function. Compared to linear programming, MIP problems are more difficult to solve since they involve the optimization of a linear objective function, subject to linear equality and inequality constraints. Despite that, some or all of the variables are required to be integers. MIP gives optimized solutions; however, scalability and solution times are a concern. Heinz and Beck (2012) empirically demonstrated the solving time for MIP. They used an Intel Xeon E5420 2.50 GHz computer (in 64-bit mode) with 6MB cache, running Linux, and 6GB of main memory. Heinz and Beck (2012) considered two set scheduling problems (UNARY and MULTI). Whereas they defined a set of jobs, *J*, and a set of resources, *K* with a capacity, each job *j* assigned to a resource, *k*. Each job was assigned a release date, a deadline, a resource-specific processing time, an assigned cost and a resource requirement. The associated constraint defined, for each time point, that the sum of the resource requirements of the executing jobs must not exceed the resource capacity. Table 2-1shows the results for the MULTI test set. In the table, ‘opt’ is the number of instances solved to prove optimality and ‘feas’ is the number of instances that are solved to get a feasible solution.

Zhanyou *et al.*(2009) developed a short-term planning software tool that used a mixed integer liner programming (MILP) to solve open-pit and underground mine planning problems. The tool is useful to accomplish infeasibility analysis to find the violating constraints such as operational resources and precedence. Zhanyou *et al.*(2009) used liner programming to define the constraints thus it limited the use of the tool to a comprehensive set of data.

Table 2-1 Running time of a MULTI test set problem using MIP (Heinz and Beck, 2012).

		MIP			
$\lvert\mathcal{K}\rvert$	$\lvert\mathcal{J}\rvert$	opt	feas	nodes	time
2	10	5	5	38	1
	12	5	5	147	1
	14	5	5	202	**1**
	16	5	5	2339	**11**
	18	4	5	25 k	162
	20	3	5	71 k	401
	22	2	5	151 k	1442
	24	2	5	305 k	2197
	26	3	5	578 k	**2977**
	28	2	5	333 k	2503
	30	1	5	669 k	5429
	32	0	5	816 k	–
	34	1	5	322 k	3448
	36	1	5	446 k	6052
	38	0	5	460 k	–
3	10	5	5	7	**0**
	12	5	5	100	**1**
	14	5	5	220	**1**
	16	5	5	3622	14
	18	5	5	164 k	429
	20	4	5	409 k	1124
	22	2	5	818 k	6014
	24	2	5	439 k	3253
	26	0	5	452 k	–
	28	2	5	200 k	1829
	30	0	5	376 k	–
	32	0	5	471 k	–
4	10	5	5	13	**0**
	12	5	5	18	**1**
	14	5	5	210	**1**
	16	5	5	363	2
	18	5	5	18 k	38
	20	5	5	108 k	309
	22	4	5	64 k	324
	24	0	5	535 k	–
	26	0	5	485 k	–
	28	1	5	370 k	5034
	30	0	5	364 k	–
	32	0	5	323 k	–
		109	195	34 k	442

Nehring *et al.*(2010) used Mixed Integer Programming (MIP) and proposed a Classical MIP model to solve production schedule optimization problems with Frontline's Xpress Solver®("XPRESS Solver Engine," 2014). Nehring *et al.*(2010) recognized that the computation time was not practical to determine an optimum solution through MIP for a long-term production schedule, which is coupled with subscript notation, sets, parameters cost and variables. Subscript notation was defined as schedule period, unique identity of internal stope development activity, stope production drilling activity, stope extraction activity, stope backfilling activity, metal type and backfill type. Sets were classified based on stope and development activities. Through classical MIP, a schedule that contains 50 stopes and 9,749 variables took 64.2 hours to optimize. This shows that solution times for the mathematical models are increased when the numbers of variables associated with the model are increased.

Using a base of classical MIP, Nehring *et al.*(2010) used a new model computation to reduce solution time. Without any time delay for successor stope, the new model is based on the standard sequence and commencement of predecessor activities of stopes. For the schedule optimization, Nehring *et al.*(2010) considered operational resources and geotechnical constraints in the stope excavation cycle and primary-secondary stope excavation sequences. The new model reduced optimization time for the same 50 stopes schedule to 2.3 hours. Additionally, for this model, the number of variables was reduced by 1,627 by using a single variable (stope development activity) phase compared to four separate phase variables (stope development, drilling, extraction and backfilling activity) in the classical MIP.

Bley and Terblanche (2011) computed a schedule optimization problem with MIP. The scheduling problem was defined within an operational resource (production capacity) framework. Since it was difficult to distinguish between different types of mining activities when defining the decision variables, they referred to this programming issue as a Resource-based Mine Scheduling Optimization Problem (RMSOP).The limitation of RMSOP was that it stopped functioning properly when solving problems size of 50 blocks. Based on a low resolution time discretization (monthly time period), Bley and Terblanche (2011) introduced a Low Resolution with Micro Selectivity (LRMS) model for high resolution time discretized problem formulation.

Underground mine scheduling and optimization

Martinez and Newman (2011) optimized the short-term and long-term mine schedule of LKAB's Kiruna mine through MIP using an optimization-based decomposition heuristic. The heuristic was formulated to achieve optimized solutions more quickly than by solving the entire set of problems. The heuristic first solves subproblems of a data set and using information from the subproblem solutions solves a constrained problem. Subdividing the problem leads to obtaining better solutions, more quickly than attempting to solve an entire problem directly. However, the resulting solution to the entire problem is suboptimal although better than the feasible solution of the schedule. Martinez and Newman (2011)used operational resources, physical adjacencies and production capacities as constraints. The objective of the optimization was to minimize deviation of the ore production rate in comparison to targets by placing more emphasis on a short scheduling period. P is the penalty associated with deviations in time period t, $\underline{z}_{kt}$ deviation below the target demand for ore grade k in time period t (ktons), $\bar{z}_{kt}$ deviation above the target demand for ore grade k in time period t (ktons)

$$(P): \quad \min \quad \sum_{k,t} p_t(\underline{z}_{kt} + \overline{z}_{kt})$$

Smit and Lane(2010) used a non-graphical rule based scheduling solution known as the Anglo Platinum Mine Optimization Tool (APMOT) for mine design and schedule optimization. Their case study included options to reduce and postpone the capital investment; however, they did not describe the concept of the programming algorithm.

Kawahata *et al.*(2013) report on a study of schedule optimization of Newmont's Twin Creeks Mine through MILP. The study considered a problem size with 10 benches and 30 variables for each set of benches for a period of three years. They show that the technique returns the mathematically proven optimum solution. However, a well-established fact for MIP is that the solution time becomes an issue when the model size increases, especially with a large number of physical adjacencies.

Using a MIP model, Wang and Wu (2003) have created the concept of multi-period, multi-product and multi-resource production scheduling (M^3PS) problems for underground mining. The approach is to maintain production, while considering variables and operational resource constraints. Their study concluded that mathematical programming techniques are only practical with a small-scale (problem size is 9) M^3PS problem, although a hybrid GA could overcome the limitations.

Particle swarm optimization (PSO), is a population-based stochastic optimization technique developed by Eberhart and Kennedy (1995). Many similarities exist between PSO and other evolutionary computation techniques such GAs. The system is initialized with a population of random solutions and searches for optima by updating generations. However, evolution operators such as crossover and mutation do not exist in PSO. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles(Kennedy, 2010). Therefore, PSO is mainly used to solve unconstrained, single-objective optimization problems. However, PSO algorithms have been developed to solve constrained problems, multi-objective optimization problems, problems with dynamically changing landscapes, and to find multiple solutions (Engelbrecht, 2006).

Evolutionary algorithms are less complex and easier for computer programming (Blum *et al.*, 2012). The concept of uniform crossover was given by Ackley (1987), and further investigated by Burjorjee (2013). He used uniform crossover performance optimization in GA and explained the strength of heuristic, dependence on the cost and acceptance of the cost function. His hypothesis of '*staggered conditional effects'* is the key to understanding the uniform crossover performance capacity for the optimization. Staggered conditional effect is a fitness distribution, where hyperclimbing heuristic is recursively repeated.

Wong *et al.*(2010) compared MIP and GA for construction site facility layout planning and concluded that GAs are suitable and more efficient for combinatorial problems with a large search space. However, the solution might be suboptimal. Results obtained from a MIP approach were slightly better and are truly optimal.

The general use of computing methodology in mining applications was discussed by Jang and Topal (2014). They describe the capability of computing to address imprecision and uncertainty through expert system, fuzzy algorithm, artificial neural network, neuro fuzzy system and GA. Considering the orebody structure and mine design-specific location of a ventilation raise, Bai *et al.*(2014) developed a heuristic for stope optimization using GA that also optimized stope sequence through single and multiple raise options.

Hartmann (1998) proposed the classical Resource-Constrained Project Scheduling Problem (RCPSP), a GA-based solver. He used permutation-based genetic encoding that uses three different crossover operators (one-point, two-point and uniform crossover) and considered precedence relations that contain problem-specific knowledge. He compared RCPSP with two different types of GA based on priority to value and rules, and concluded that the outcomes by RCPSP were faster and 100% optimal.

Yun and Liu(2002) developed a new approach to determine the opening layout in underground sublevel caving mining. Based on genetic programming, they investigated the optimized reproduction rate, crossover rate and mutation rate. In the study, in the absence of defined precedence, crossover was constrained through attributes. The attributes are defined as a property to categorize any activity, for example, a horizontal or inclined development category. Dao and Marian (2011)used GA with novel encoding, crossover and mutation strategies to optimize the precedence-constrained production sequencing and scheduling.

Varendorff (2003) summarized and explained intelligent technologies in mine schedule optimization such as Expert system, Fuzzy logic, Neural networks, Liner programming and GA. This review showed that selecting and adopting these evolutionary technologies requires an understanding of required solutions and available infrastructure. Such intelligent technologies might be useful for strategic planning, project engineering operations scheduling and operations management.

To optimize underground mine production planning, Yun *et al.*(2003) combined GA, genetic programming (GP), evolutionary strategy, evolutionary programming and developed new Evolutionary Algorithm (EA). '*Genetic programming is a branch of genetic algorithms. The main difference between genetic programming and genetic algorithms is the representation of the solution, namely, genetic programming creates computer programs in the Lisp or scheme computer languages as the solution while genetic algorithms create a string of numbers that represent the solution*'(Pop and Matei, 2012). GP usually gives many '*if/else*' statements to explain the solution. The Evolutionary Algorithm works on the mechanism of self-adaptive searching (generate random individuals to form the initial generation) to find the solution close to optimal solution. It operates in two steps: it identifies the profitable blocks and then it maximizes the production target.

Fava *et al.*(2005) conceptualized a parallel GA to optimize long-term and multi-objective constrained underground mine schedules. Fava *et al.*(2005) added the concept of a 'village' to allow crossover in a confined environment. Their technique obviates to breach any defined constraints. As a result, it accelerated the capacity of solver to solve for larger problem sizes.

Saavedra Rosas (2009) used a modified version of a GA to solve stochastic optimization problems. This was known as the Genetic Optimizer for Stochastic Problems (GOSP). For the study, Saavedra used GOSP to determine the number of scenarios required, based on the distribution characteristics of geological uncertainties, thus avoiding the risk of poor quality of results by underestimating and overestimating while computation was inexpensive. The GOSP approach is to generate scenarios sequentially until no perceptible change in the current solution of the problem is achieved. This study also showed that the GOSP's 'elitism' technique increased the learning speed of the GA. GOSP reuses the in-progress optimal population to reduce the number of iterations. To incorporate new scenarios into the optimization process, learning capabilities of GA are advantageous to reduce the computational time. Figure 2-8 shows the classical and proposed methodology of GA learning.

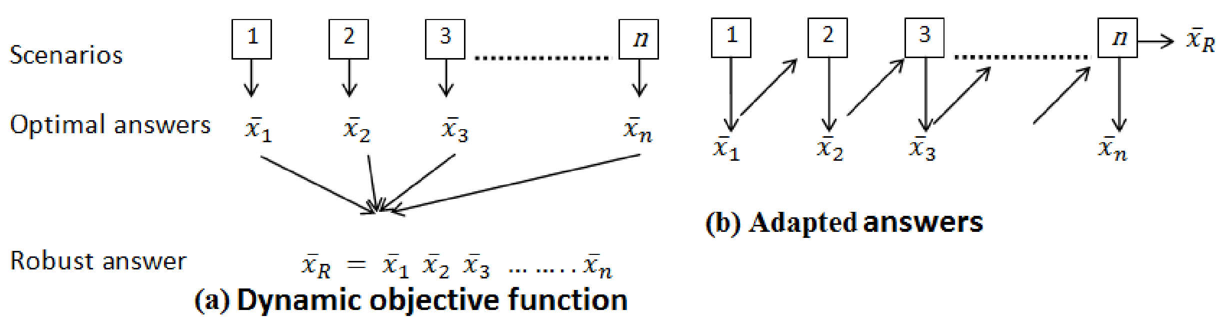


Figure 2-8 (a) classical methodology (b) proposed methodology (Saavedra Rosas, 2009)

The standard GA uses ordinary evaluation function; it runs on a set of activities and obtains a standard sequence. The adopted evaluation function of GA is run for the robust sequence.

Without specifying the number of unanticipated scenarios, GA select good enough solutions not for a specific environment but for a whole set of scenarios that allow GOSP to integrate uncertainty into the decision making process by evaluating numerous optimized solutions.

Using SOT, optimized mine schedules were found within different scenarios of resource availability. The scenarios were designed based on the consideration of additional potential economic mineral reserves at different phases of mine life, varying mineral price, operating cost and operational resources. An unlevelized schedule of 7,485 production and development activities under operational resource and precedence constraints were investigated with three scenarios. The scenarios were based on variable operational resource capacity (jumbo drill), operating cost and mineral price as well as guided by the NPVs obtained through the scenario, therefore showing how schedule optimization can guide decision-making in mine planning (Fava *et al.*, 2012).

A case study was reviewed by Fava *et al.*(2013) based on various targets for gold production and an optimal production rate was selected for a consistent production profile. This study also showed an impact on the solution process of the particular heuristic selected to guide optimization. Fava *et al.*(2013) suggest conducting 'trial' runs to prioritize the most suitable heuristic for the particular application. This study also showed how so-called '*just-in-time*' (JIT) development improves the project NPV.

GAs differ from conventional optimization techniques in the following manner: (i) GAs search function operates on whole populations of solutions whereas conventional optimization techniques generally search for a single solution. Depending on heuristically set parameters, a GA can circumvent local optima and enhance the probability of finding global optimum solutions; (ii) Conventional optimization techniques use identical parameters while GAs function through coded versions of the problem parameters. For example, a GA works with a coding of the solution set, not with the solution set itself; (iii) For evaluation, conventional optimization techniques use derivatives of a function of a real variable whereas GAs use fitness functions. GAs can be applied to any kind of continuous or discrete optimization problem. However, in order to execute, a GA has to have an effective decoding function; (iv) Conventional methods for continuous optimization deploy deterministic mathematic operators, whereas GAs use probabilistic logic.

Correspondingly, some limitations are associated with GAs:(i) they have setbacks to recognize fitness function; (ii) premature convergence can occur; (iii) difficulty in defining the description and classification to represent the problem; (iv) inconsistent to decide parameters such as population size, mutation rate, crossover rate, selection methods and its strength; (v) they do not use gradients to improve the solution or to incorporate problem-specific information; (vi) they are not good at identifying local optima and are not effective to terminate unimproved solutions. (vii) they need to be coupled with a local search technique (heuristics) to find solution quickly; (viii) it is complex to search out the precise global optimum using Gas (Sivanandam and Deepa, 2008; Zaknich, 2006).

Mine schedule optimization problems are too computationally intensive to find an exact solution but sometimes a near-optimal solution is sufficient. In such situations, evolutionary techniques can be effective. Due to their non-deterministic nature, evolutionary algorithms are never guaranteed to find an optimal solution, however they will often find a good solution if one exists. The automated optimization software SOT, based on evolutionary algorithms, was used in this study to achieve an optimized solution.

Table 2-2 Summarized properties of key optimization approaches discussed in section 2.3

Properties	GAs (RCPSP, SOT,LRMS)	MIP	Hill climbing	LOBOS
Parallelism	Efficient	-	-	-
Solution space	Wide	Restricted	Restricted	-
The Fitness Landscape	Complex	NA	-	-
Discover global optimum	Efficient	Efficient	Efficient	-
Multi objective function for problem	Exist	-	Exist	-
Evaluations	Uses function.	-	-	-
Handles noisy functions	Efficient		NA	-
Search spaces	Handles large, poorly unstated search spaces easily	Limited	Limited	-
Multi-modal problems	Efficient	Efficient	Not efficient	Not efficient
Robustness	Very robust	Very robust	-	-
Response surface	Not require knowledge	Require knowledge	Require knowledge	-
Discontinuities present on the response surface	Little effect on overall optimization	Yes	No	-
Effect of local optima	Resistant to trapped in local optima	Guarantees Global Optima	-	-
Large-scale optimization problems	Perform very well	-	-	-
Variety of optimization problems	Can be employed	Can be employed	Can be employed	-

2.4 Approaches to sensitivity and scenario analysis of mine schedule optimization

Torries (1998) determined the combined effect of scenario analysis on the outcome of a schedule while allowing multiple variables to fluctuate simultaneously in a project. Torries (1998) and Gamble (2007) investigated scenario analysis by determining the best and worst case scenarios that establish the upper and lower bound range of a potential project value. The possible range of the project's outcome obtained with scenario analysis identifies the potential magnitude of project uncertainty. As a part of sensitivity analysis, Torries (1998) and Gamble (2007)also examined the potential project value under defined '*what if*' scenarios. The analysis provided details regarding the impact of variables that require subjective judgment on the probability of outcomes. '*What if*' scenarios were used to determine variables that substantially influence the project value and would eliminate all other variables examined from inclusion in probability analysis. In addition, Mun (2006) has mentioned that including correlation between project variables can assist in defining the scenario analysis. It can also help to determine the critical variables of a project and the interrelationships between variables that the sensitivity analysis was unable to identify.

For underground mine valuation to accommodate the existence of financial and technical scheduling risk, Maybee (2010) developed a Risk-based Evolution Methodology (RbEM). RbEM allowed an earlier decision-making opportunity through identifying and evaluating an optimum strategy for mining schedule. Maybee (2010) used various mining strategy such as highest mineral grade, mineral weight, lowest development cost, uncertainties of mineral grade, discounting factor, mineral price, selection of operational resources capacity and showed the consequence of technical scheduling aspects on financial uncertainty using Modern Portfolio Theory (MPT). MEP helps to maximize the project value; the objective is to select a scenario to diversify risks without reducing project value.

2.5 Optimization challenges in underground mine scheduling

Hall (2007) stated that mine schedules are unlikely to ever be the most optimal, since they depend on various factors that are still not routinely incorporated into mine schedule optimization such as operating strategy, cut-off grade and grade characteristics. Hall (2007) used linear programming for a strategy optimization study to maximize the project value. Sensitivity analysis on a single operating scenario was found to be uncomplicated; however, analysis certainty was limited. To enhance scenario analysis practice, Hall (2007) used the 'Hill of Value' (HoV) method, which incorporated strategic decision variables and generated a realistic model that might alter the mine operating strategies (for example, modify the ore production rate and cut of grade). The efficiency of the HoV is affected by an increasing number of variables.

Newman *et al.*(2010) conducted a review of operations research in mine planning. However, for underground mines, the review was limited to the optimization of block sequencing and operational resources. In underground mines, the ventilation airflow requirement is based on the amount of diesel particulate matter, heat, mineral dust, gaseous products of blasting and other mining processes to ensure statutory compliance. Stinnette (2013) compared various underground mining methods to determine their airflow requirements and concluded that mine ventilation airflow quantity does not exclusively depend upon the proportion of diesel engine capacity.

Musingwini *et al.*(2003) defined JIT development through a parallel program for re-assessing mine development rates and concluded that JIT development can increase the NPV of Shabanie mine, a sub-level caving underground mine in Zimbabwe. Musingwini performed correlation and regression analysis between buffer time and buffer mineral reserves, and ore reserves and development. He proposed that reducing the mine development rate from 330m per month to 160m per month could save 50% on the supporting cost annually.

3 Formulation of the mine schedule optimization problem

The Schedule Optimization Tool (SOT) utilized and explained in this work is a technique that automatically improves feasible mine schedules that are subject to constraints, and is driven by an objective function that constitutes the NPV(Maybee *et al.*, 2010b). However, the decision making process is limited by the number of alternate feasible schedules that can be evaluated in a given phase of planning. It is highly unlikely every possible feasible schedule can be evaluated by assessing their associated economic value and the sensibility of their associated resource allocations.

SOT optimizes schedules for an underground mining project. In particular, it improves the sequence of activities in a manner that maximizes the NPV of the project. In the input dataset, there are 'i' activities to be scheduled. Each activity is assigned deterministic parameters such as mass, length and duration. In the optimization process, each activity completes uninterruptedly, once it executes. For each activity, a deterministic amount of operational resources must be assigned to support its execution (Eivazy, 2013).

The mine scheduling problem of SOT could be expressed as follow:

Maximize: NPV
Subject to:
Resource constraints
Precedence constraints
'Must start on' constraints
Detailed subsets constraints

3.1.1 Objective function based on (Eivazy, 2013)

$$Maximise\ NPV = \sum_{i=1}^{I}\sum_{t=1}^{T} \mathrm{DF}_t * fa_t^i * (\mathrm{MR}_i * O_i^t * RF_i^t - PC_i^t - fc^\tau * FC^t)$$

3.1.2 Notation

The following specific is used to define the model in general terms.

i	activity identification number (i= {1, 2, 3...|I|}).I is the set of activities to be scheduled.
j	j is an activity that can processed after activity i $(i, j \in N)$
e	set of possible operational resources
E	number of operational resources types
t	schedule time period
l	length of scheduling period
n	number of scheduling periods $= 1 + \frac{lifeofproject}{l}$
N_z	number of detailed subsets except blank subset
l_j	length of scheduling period of detailed subset j
NZ_j	number of detailed subsets except blank subset $= 1 + \frac{lifeofproject}{l_j}$
fa_i^t	fraction of activity i proceed in period t.
fc^τ	a variable to check the fixed capital investment in period τ
τ	periods when fixed capital invested

3.1.2.1 Data

The following input data are required for the model

Table 3-1 Scheduling problem constant and definition

Constant	Definition
RF_i^t	Recovery factor in percentage for activity i in period t
PC_i^t	Cost of processing activity i in period t
MR_i	Revenue factor for per tonne of ore $/t for activity i
r	Effective interest rate
DF_t	Present value discount factor for period $t = (1+r)^{-t}$
MS_i	Start time of must start on activity i
E_i^e	Amount of operational resource e needed by activity i
MX_e	Maximum number of threshold capacity of equipment e
EC_e^t	Available capacity of operational resource e in period t
d_i	Duration of activity i
S_i	Start time of activity i $(\forall i=1….I)$
O_i^t	Ore tonnage mined from activities i in period t
ES_i	Early start of activity i
ES_j	Early start of activity j
LT_{ij}	Lag/lead time between activities i and j time when operation j is processed directly after operation i $(i, j \in N)$
PO_{ij}	Partly overlap, activity j could start when its predecessor activity I completed by PO_{ij} %
FC^t	Fixed capital invested in period t
MAZ_j^t	Maximum number of active activities for detailed subset j in period t

3.1.3 Decision variables (Eivazy, 2013)

Binary

$$X_i^t = \begin{cases} 1, if fa_i^t > 0 \\ 0, otherwise \end{cases} (\forall i = 1 \dots I, \forall t = 1 \dots n)$$

Real

fa_i^t = fraction of activity *i* proceed in period *t*. fa_i^t is a variable depends on start time of activity *i*

$$0 \leq fa_i^t = \frac{[minimum(t * l, ES_i + d_i) - maximum(ES_i, (t-1) * l)]}{d_i} \leq 1 \ (\forall i = 1 \dots I, \forall t = 1 \dots n)$$

Binary

fc^τ is a variable to check the fixed capital investment in period τ

$$fc^\tau = \begin{cases} 1, lifeofproject \geq \tau \\ 0, lifeofproject < \tau \end{cases} (\forall i = 1 \dots I, \forall \tau \in \{periodswhenfixedcapitalinvested\})$$

Binary

$$XZ_{i,j}^t = \begin{cases} 1, activitiyiindetailedsubsetjisactive \\ 0, otherwise \end{cases} (\forall i \in j, \forall j = 1 \dots N_z, \forall t = 1 \dots NZ_j)$$

3.1.3.1 Fixed capital investment

Fixed capital is the investment made at multiple phases of a project. The variable fc^τ is used to calculate fixed capital on period τ.

Formulation of the mine schedule optimization problem

$$\text{Fixed capital} = \sum_{i=1}^{I} \quad \sum_{t=1}^{T} fc^{\tau} * FC^{t}$$

3.1.3.2 Revenue

For the study, revenue was a precalculated value in $/tonne and only calculated for the ore tonnage. A fixed recover factor, also used for ore tonnage

$$\text{Revenue} = \sum_{i=1}^{I} \sum_{t=1}^{T} \mathrm{DF}_{t} * fa_{t}^{i} * (\mathrm{MR}_{i} * O_{i}^{t} * RF_{i}^{t})$$

3.1.3.3 Operating cost

The operating cost was defined for each activity and discounted for period *t*.

$$\text{Operating cost} = \sum_{i=1}^{I} \sum_{t=1}^{T} \mathrm{DF}_{t} * fa_{t}^{i} * PC_{i}^{t}$$

3.1.4 Constraints

3.1.4.1 Operational resource constraints

Each activity was assigned with an operational resource and levellized with maximum capacity within scheduling time period.

$$\sum_{i=1}^{I} X_{i}^{t} * E_{i}^{e} \leq EC_{e}^{t} \ \ (\forall e = 1 \ldots E, \forall t = 1 \ldots n)$$

3.1.4.2 Precedence constraints

Mandatory dependencies for each activity are inherent in a schedule, e.g. stoping is dependent on crosscut development. Discretionary dependencies are those defined on best practice. Once the dependencies are established, they can be mapped into precedence links by identifying activities, which (i) can only be completed after another activity; (ii) can be done at the same time; or (iii) don't depend on other tasks at all.

One set of precedence constraints of three could define the predecessor or successor links between two activities. If activity j is a successor to activity i, then

Finish-to-Start (FS)

$ES_i + d_i + LT_{ij} \leq ES_j i \; (\forall i = 1 \ldots . I, \forall j \in \{FS\ successorofactivityi\})$

Start-to-Start (SS)

$ES_i + LT_{ij} \leq ES_j i \; (\forall i = 1 \ldots . I, \forall j \in \{SS\ successorofactivityi\})$

Partly overlap (PO)

$ES_i + d_i \times PO_{ij} \leq ES_j i \; (\forall i = 1 \ldots . I, \forall j \in \{PO\ successorofactivityi\})$

3.1.4.3 Grouping of precedence constraints using or/and

Grouping of precedence constraints between two or more activities could be defined through or/and function. As shown in Figure 3-1activities i, j and k are the precedents for activity z.

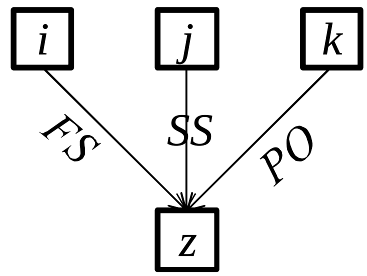


Figure 3-1 Precedence constraints between group of activities defined by *or/and* function

Herewith an example of possible combination of precedence rules. However, at a time either 'or' or 'and' logical operator can apply.

$ES_i + d_i + LT_{iz} \leq ES_z$ or/and

$ES_j + LT_{iz} \leq ES_z$ or/and

$ES_k + d_k \times PO_{kz} \leq ES_z$

Must start on constraints

Some activities have a fixed time to start and have highest priority over remaining activities in a schedule. Therefore, such activities require resource and equipment fleet allocation on a priority base. These constraints are indicated as follows, where ES_i is fixed for all 'must start on' activities *i*.

$$ES_i = MS_i \ (\forall i \in \{must\ start\ on\ activities\})$$

3.1.4.4 Detailed subsets constraints

For each scheduling problem, the number of subsets could be defined and the total number of activities *I* could be partitional into these subsets. Each activity could be part of more than one subset or be not part of any subset. Each detailed subset is defined to include activities with common attributes. The detailed subset constraints imply that only a few activities of a detailed subset could be active in one period. For each detailed subset, a specific period length is defined, which may be different from the scheduling period length (Eivazy, 2013).

$$\sum_{i} XZ_{i,j}^{t} \leq MAZ_{j}^{t} \ (\forall j = 1 \dots N_{z}, \forall t = 1 \dots nz_{j}, \forall i \in detailedsubsetj)$$

3.2 SOT heuristic solution to mine schedule

"*An ideal tradeoff to many engineers between the optimization and the computer-assisted scheduler is to add some "intelligence" to the computer-assisted program. That is, some algorithm can be provided that places priorities on which production volumes (blocks, in many models) could be mined first. That algorithm is known as a heuristic"*(Gershon, 1985).Heuristics provide a good initial point to start optimization but there is never a guarantee that an optimized solution is obtained. Such approaches could only be assisted to work interactively.SOT uses an evolutionary algorithm, custom heuristics and a fixed proportion in relation to a whole guidance to start the process to determine an optimum mining schedule with the operational resources subject to applied constraints (Fava *et al.*, 2013). Heuristics are experience-based techniques (computation principles) to guide the starting point of learning to find a solution. The 'heuristic' schedules are used to initialize and 'seed' initial solution populations used in the GA solver of SOT. Seeding with heuristics is not guaranteed to be optimal, but inequality is good enough for a given set of goals. Where an exhaustive or prolonged search is impractical, heuristic seed solutions are used to accelerate the process of finding a satisfactory solution population(Pearl, 1984). The heuristic and guidance amounts can render computationally intractable problems tractable so that solutions are obtained in a reasonable time (≈ hours). The heuristics could be different for each case scenario. SOT currently defines 15 heuristics as illustrated in Table 3-2. Each of these is defined in the following section.

Table 3-2 Predefined heuristics in SOT based on Fava *et al.*, (2011)

Heuristics	Priority factor		Computation equation
1	Highest mineral grade	=	mineral grade by activity
2	Highest mineral grade mine area	=	[1]area mineral grade ×[2]grade shift factor + mineral grade
3	Highest mineral weight	=	mineral weight by activity (where mineral weight is tonnage × mineral grade)
4	Highest mineral weight mine area	=	[3]area mineral weight ×[4]mineral weight shift factor + mineral weight
5	Indexed highest mineral grade mine area	=	([1]area mineral grade / [5]maximum mineral grade) × mineral grade
6	Indexed highest mineral weight mine area	=	([3]area mineral weight / [6]total mineral weight) ×mineral weight
7	Indexed least access by mineral weight mine area	=	(([3]area mineral weight / [7]area non objective access length) / ([6]total mineral weight / [8]total non objective access length)) × mineral weight
8	Indexed lowest cost mineral weight mine area	=	-1 × (([9]area cost / [3]area mineral weight) / (total cost / [6]total mineral weight)) × (cost / mineral weight)
9	Least access by mineral weight mine area	=	([3]area mineral weight / [7]area non objective access length) ×[4]mineral weight shift factor + mineral weight
10	Lowest cost mineral weight	=	-1 × (cost/mineral weight)
11	Lowest cost mineral weight mine area	=	-1 × [([9]area cost / [3]area mineral weight) ×[10]cost by weight shift factor + (cost/mineral weight)]
12	No guidance	=	all objective activity selections are random
13	Rank	=	-rank
14	Rank then stope grade	=	-rank ×[2]grade shift factor + mineral grade
15	Rank then stope mineral weight	=	-rank × mineral weight

- [a]Maximum mineral weight is the maximum weight of the driving mineral among all objective activities in the mine.
- [b]Maximum cost per weight unit is the maximum cost per weight unit of the driving mineral among all objective activities in the mine.
- [1]Area mineral grade is the area mineral weight divided by the total weight of the objective activities in the mine area.
- [2]Grade shift factor can be computed as $10^{\wedge \mathrm{ceil}(\log 10(\text{Maximum mineral grade}))}$
- [3]Area mineral weight is the total mineral weight for the objective activities in the mine area.
- [4]Mineral weight shift factor can be computed as $10^{\wedge \mathrm{ceil}(\log 10(\text{aMaximum mineral weight}))}$
- [5]Maximum mineral grade is the maximum grade among all objective activities in the mine.
- [6]Total mineral weight is the sum of mineral weights for the objective activities in the complete mine.
- [7]Area non-objective access length is the sum of activity lengths for all activities that are not objective activities in the given mine area.
- [8]Total non-objective access length is the sum of activity lengths for all activities that are not objective activities in the complete mine.
- [9]Area cost is the sum of all costs for the given mine area.
- [10]Cost by weight shift factor can be computed as $10^{\wedge\ \mathrm{ceil}\ (\log 10\ (\text{bMaximum cost per weight unit}))}$.

3.3 SOT optimization process

SOT is based on an evolutionary algorithm that optimizes the mine schedule. The fundamental course of action of schedule optimization through SOT based on (Maybee *et al.*, 2010a)is shown in Figure 3-2.

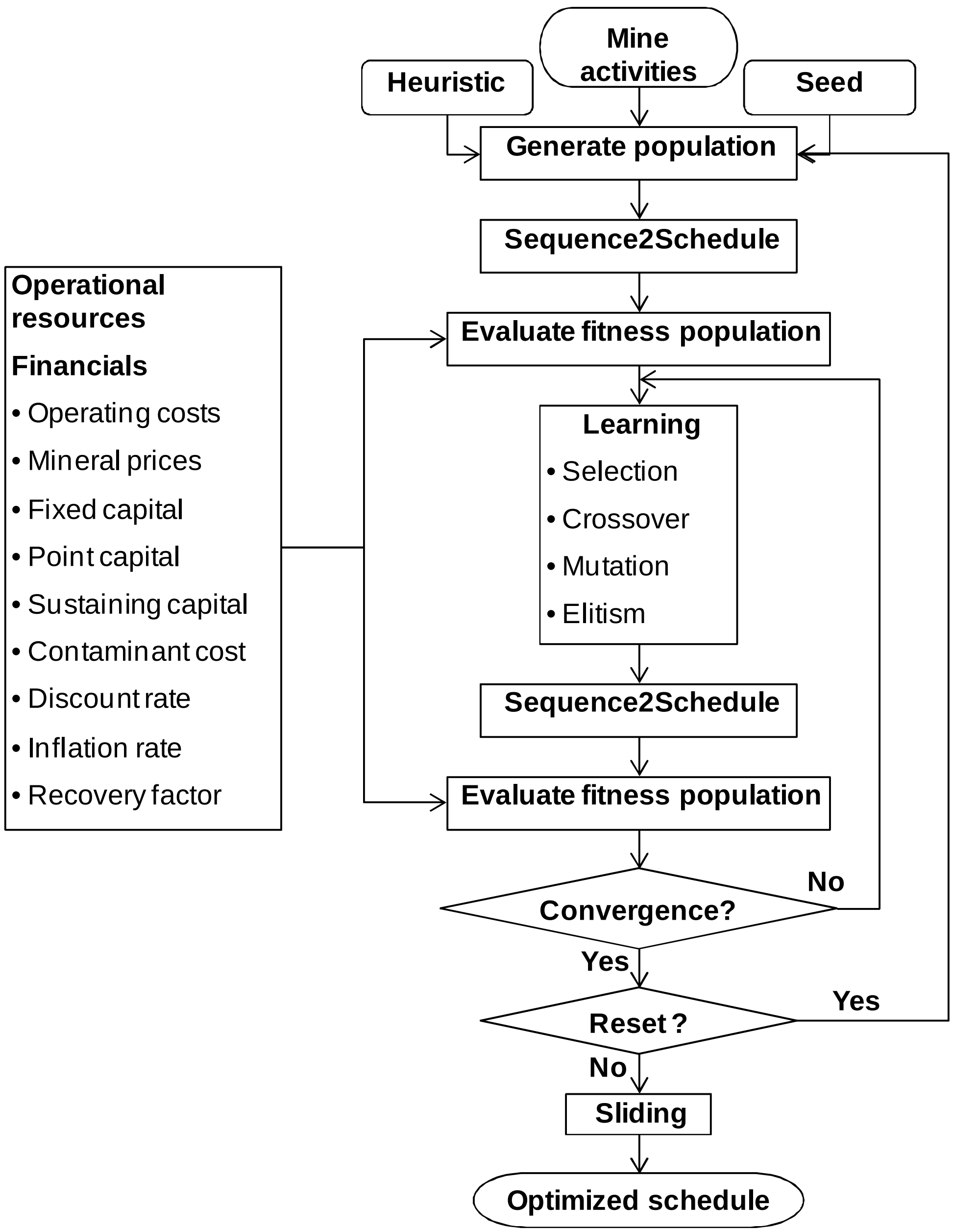


Figure 3-2 Flow diagram of the SOT optimization process modified from Maybee *et al* 2010a

Formulation of the mine schedule optimization problem

SOT operates on the activity sequence, but evaluates the sequence in its schedule form. The process of optimization involves activities undergoing sequence alteration driven by a requirement for better economic performance. In this manner underground mine schedules are obtained that, subject to applied constraints, improve the NPV of a prospective orebody by means of systematically and automatically exploring the options to vary the timing of development and stoping activities.

The NPV is the sum of all discounted future cash flows over a period; consequently, discounting renders revenue and cost that occur in different time periods; comparable by expressing their values in present terms. The discount rate uses for the Discounted Cash Flow (DCF) valuation to determine the expected a project worth in present day dollars. The present value, equivalent cost and revenue are shown in the following formulas.

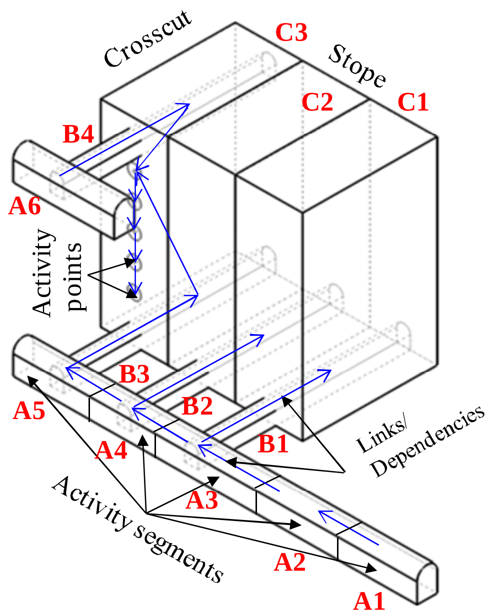
$$\text{Present value} = \text{Future value} \times (1+\text{discount rate})^{-n}$$

n= time period

$$\text{Equivalent cost} = \text{Actual cost} \times \underbrace{(1+\text{ discount rate})^{-n}}_{\textbf{This factor gets smaller with bigger 'n'}}$$

$$\text{Equivalent revenue} = \text{Actual revenue} \times \underbrace{(1+\text{ discount rate})^{-n}}_{\textbf{This factor gets smaller with bigger 'n'}}$$

For a feasible mine sequence, project value may increase by delaying activities that render to add cost and prepone activities that generate revenue. To illustrate the process, a possible mining sequence is shown in Figure 3-3. A total of thirteen development and stoping activities are shown in this figure. Each mining activity has a defined dependency, physical dimensions, and mining rates.



A possible sequence
A1→ A2 → A3 → A4 → A5 → B1 → C1 → B2 → C2 → B3 → A6 → B4 → C3

Figure 3-3 Physical adjacencies between mine activities for a feasible mining sequence

The procedure starts with an initial list of mining activities. SOT then generates an initial population of possible solutions from a given set of data (mine activities). The initial population is usually done on a random basis, however, it is possible to 'seed' (a mine activities sequence) the initial population with realistic but suboptimal solutions. In SOT, the initial population could be comprised by a predefined computation rule defined as a 'heuristic' (Fava *et al.*, 2013), which provides an immediate starting point for optimization.'*Sequence2schedule*' is the process of transferring a sequence (possible changed order of activities) to a schedule form. For each solution, the 'fitness' calculates the NPV of the schedule.

Further, new generations of solutions are generated using a reproduction operator comprising of selection and crossover. During this stage, the chances of reproduction are based on the fitness values of the previous generation. Hence, multiple copies of the superior solutions may occur in the new generation and underperforming solutions tend not to be selected. Following the selection phase, pairs of the selected solutions are combined by the 'crossover' operator. Crossover involves producing new solutions by combining the genetic solution from two selected solutions. A given fix percent of the individual of the new population will be selected randomly and mated in pairs. A crossover point will be chosen for each pair. The information after the crossover point will be exchanged between the two individuals of each pair. In order to reduce the chances of false optima being located, another operator called ‘mutation’ randomly alters solutions. ‘Mutation’ is used to make small and random changes to solutions. Specifically, mutation applies random changes to a single individual in the current generation to create next.

As a means of improving the performance of GA, ‘elitism’ is employed as a form of ‘local optimization’. Elitism involves producing a number of priority solutions that will be carried over to subsequent solution population without modification, from one iteration to the next.

Fitness is again calculated for the new set of solutions for those solutions not already tested. The series of operations such as reproduction, crossover, mutation, elitism and fitness calculation are usually termed one ‘generation’. The GA procedure executed over a number of generations, generally improves the average and maximum fitness of a generation, and thus evolves an ‘optimum’ solution gradually. A GA is usually said to converge when there is no significant improvement in the values of fitness of the population from one generation to the next. The stagnancy criterion in this study was dollar value. A limit of $1,000 value was placed on the GA run. Additional criteria may be introduced, as soon as the algorithm finds a suitably low fitness individual, lower than a specified fitness threshold it will converge. The procedure terminates when some predefined situation occurs. This is typically when no further improvements in fitness have occurred over a set number of generations (Michalewicz, 1996).

‘Resets’ is a norm and expressed by a number that direct the learning process. The number of specified resets is the total number of times a new initial solution will be created.

4 Outline description of the prospect

4.1 Project information

A planned section of an underground mine was selected for the case study. The orebody was planned to be extracted using the sublevel stoping mining method. The section shares infrastructure with an existing mining operation including production shaft, ventilation raises, buildings, etc. Ore production was planned by adopting conventional methods of drilling, blasting and mucking. For the ore handling, the use of diesel equipment was planned. The orebody extends from Level A0to Level V (from approximately 600m to 1,600m depth); its thickness varies between 5m and 76mand its strike length is approximately 550m. The orebody disposition is a steeply plunging (ranging from 50° to 80° to the east)elongated pipe with longer dip lengths than strike length.

4.2 Mine scheme and design

For this case study, only the section between Level A (610 m) and Level M (1,190 m) of the prospect was considered. The selected section is depicted in Figure 4-1. It was subdivided into two sections named Zone A (between Level A0 and Level F) and Zone B (between Level F and Level M). Two drifts at Level A0 (610 m) and Level F (870 m) were planned to access the orebody from the exiting shaft, as per the defined mine design. Level F (870 m) was planned to connect the mine with the main shaft and Level A0 (610 m) was planned to access the existing developed level where ventilation raises will be started. In addition, Level M (1,190 m) was designed to connect the mine with future mine projects.

An exploration drift at Level F (870 m) was designed for further exploration of the orebody. Eleven levels were designed between Level A0 and Level K with a consistent level spacing of 45.7 m. For the prospect, a ventilation network is planned with two fresh and two return air raises, each set with diameter of 3.7 m and 7.3 m. To connect all the levels, two internal ramps advancing either upwards or downwards, were planned. Zone A (from Level A0 to Level F) and Zone B (from Level F to Level M) have two accesses from the main shaft. From the mine design, 158 stopes between Level A and Level K were considered. All the stopes have a height of 45.7 m and a width of 15.2 m, while the length of each stope varies with the orebody thickness from 6 m to 72 m. Table 4-1 shows the number of stopes on each level.

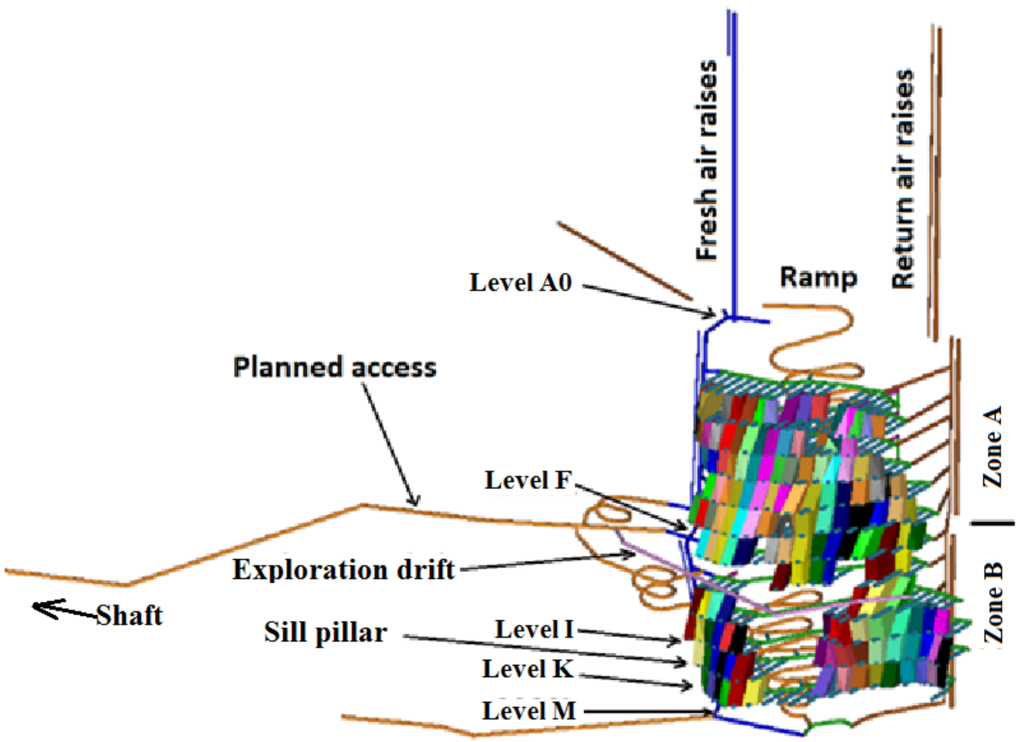


Figure 4-1 3D view of mine layout showing mine accesses, stopes, ventilation raises, sill pillar and defined Zone A and Zone B.

Table 4-1 Mine levels and number of stopes on each level

Level	No. of Stopes
A	15
B	18
C	15
D	17
E	17
F	15
G	6
H	8
I	15
J	16
K	16

4.2.1 Excluded development sections in the financial evaluation

For an equitable financial comparison between the unoptimized and optimized schedules, a section of development activities was excluded from the project cost estimation. Specifically, these were an exploration drift, six cross-cuts not associated with stopes, ramps below Level K and segments of ventilation raises at Level M, all shown in Figure 4-2. The excluded portion of the development was not precedent to any activities that generated the revenue. The evolutionary algorithm causes these development activities to be scheduled at the end of mine life. Thus, the excluded development activities were scheduled as soon as possible. The excluded development is the amount of nonessential development required to maintain mineral reserves at a stationary level relative to the rate of extraction of the mining operation.

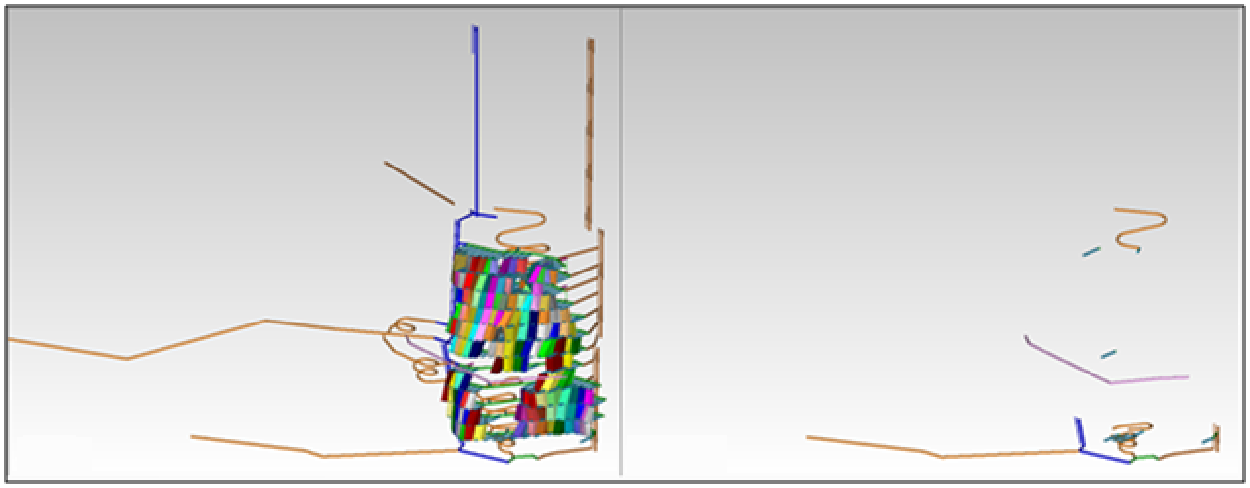


Figure 4-2 Mine development sections that were excluded from cost estimation

4.3 Mining operation

The orebody is planned to be accessed centrally from a drift on the Level F in the footwall of the orebody. Level accesses to the mineralized zone will be developed from the ramps. Cross-cut intersections are established in mineralized zones within the stoping block.

4.3.1 Physical adjacencies

The block model, mine development design and stope design were provided by the mine in digital form. Systematic mine activities were linked using precedence links representing physical adjacencies. This was done with Mine2-4D® (2014). The number of development activities and stoping activities considered in this study were 1,265 and 790, respectively. Initially, through the Mine2-4D® software, a total of 2,055 development and stope activities were linked in mine development and stope design files. These links were sequenced to comply with physical adjacencies, and then information that identified the spatial location of mine activities was stored as coordinates. Additionally, 194 milestone activities were added to guide a conditional development sequence. A milestone is a significant event in the schedule, but it also confines successor activity. After linking the mine activities and defining milestones, a base case schedule was generated using EPS®.

For all scenarios, the physical adjacencies were considered as the principal constraint. A set of physical adjacencies applied to: mine development and ventilation raise development, front line planning and scheduling (FPLS), stope preparation, drilling, stoping and back filling. The FLPS concept was introduced to INCO by MacMillan and Ross(2004). FPLS is a production scheduling system that attempts to manage interruptions to operations through planning routine events, while engaging all members of the workforce in both the planning and execution of the production schedule. Activities and sequences of activities were precedence-linked between mine development and stopes to prevent a stope from being mined before completing the ventilation circuit, drift cross-cuts and FPLS activities. The conceptual relations between different types of underground excavation are represented in Figure 4-3.

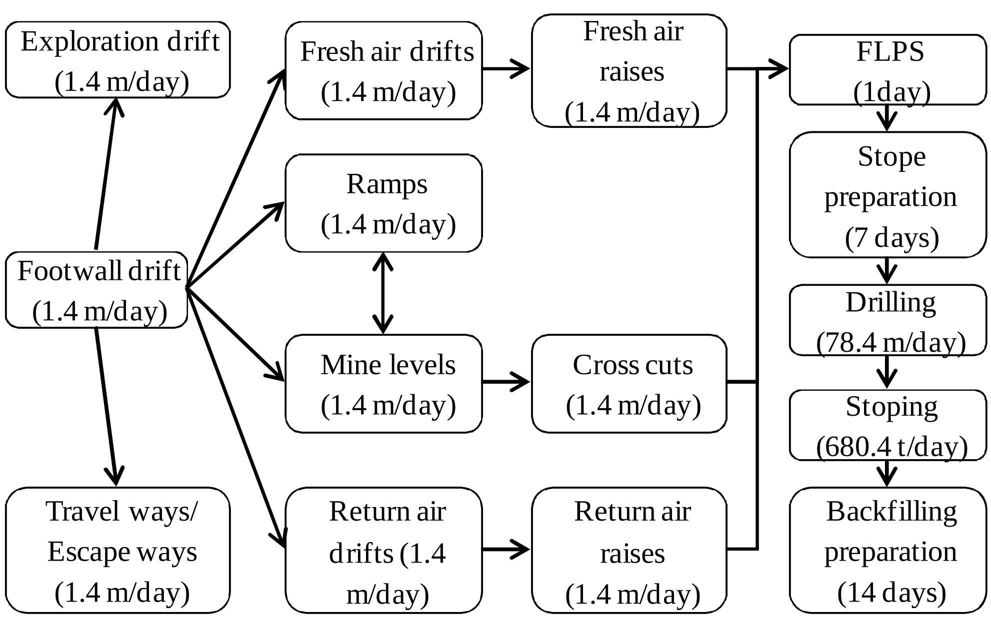


Figure 4-3 Schematic layout of the physical adjacencies defined between various mine activities

4.3.2 Mine activities considered for scheduling

An underground mine schedule consists of numerous activities, tasks and actions. Since the selected mine project was a small section of a multi-orebody offset, limited mine development activities were considered. Subsequently, several mine development activities were excluded such as shaft sinking and development of Level A0. The backfilling activity was also excluded from the schedule. The activities of mine development and stoping in the model are a simplification of reality to evaluate a long-term mine schedule. Adding detailed backfilling process and mine operations constraints may affect the schedule by delaying mine operation and lead to a longer mine life.

4.3.3 Ventilation system

For the mine, the system ventilation network was designed to provide parallel paths for the primary fresh air intakes through operating areas to return airways connected to the return air raises. The initial stage of the ventilation network is completed with one fresh air raise; however, later in the production schedule, a second ventilation raises is completed. Initially, ventilation raises were planned to be developed from the drifts at Level F and Level A0. The drift accesses created a link to connect the vertical connections of the ventilation raises. To accelerate ventilation raise development, the ventilation network was divided into three segments at three different levels: Level A0, Level F and Level I. Each stope is permitted to start mining only after a supporting ventilation network is in place.

4.3.4 Operational resources constraints

The operational resources were rationalized into four groups based on different categories of ore production and mine development, i.e. jumbo drilling, jackleg drilling, raise boring and ore hoisting. The footwall drift, exploration drift, access ramps, mine levels, crosscuts and ventilation drifts were assigned to development using jumbo drill resources. The development of travel and escape ways were assigned to jackleg drill development resources. The development of fresh air and return air ventilation raises were assigned to raise bore development resources. Stoping activities were assigned to an ore hoist resource. To generate levelized schedules as in Fava *et al.*(2012), operational resource threshold capacities were applied on annual mine development and ore production resources. The annual capacity of each operational resource was defined as 4,450 m for jumbo drilling, 2,652 m for each jackleg drilling and raise bore development and 0.91 MT for ore hoisting, as shown in Figure 4-4. The details of mine activities with assigned development rate, fixed duration and lag are given in Table 4-2. The term lag is a modification of a logical relationship that deliberately generates a delay in the next activity.

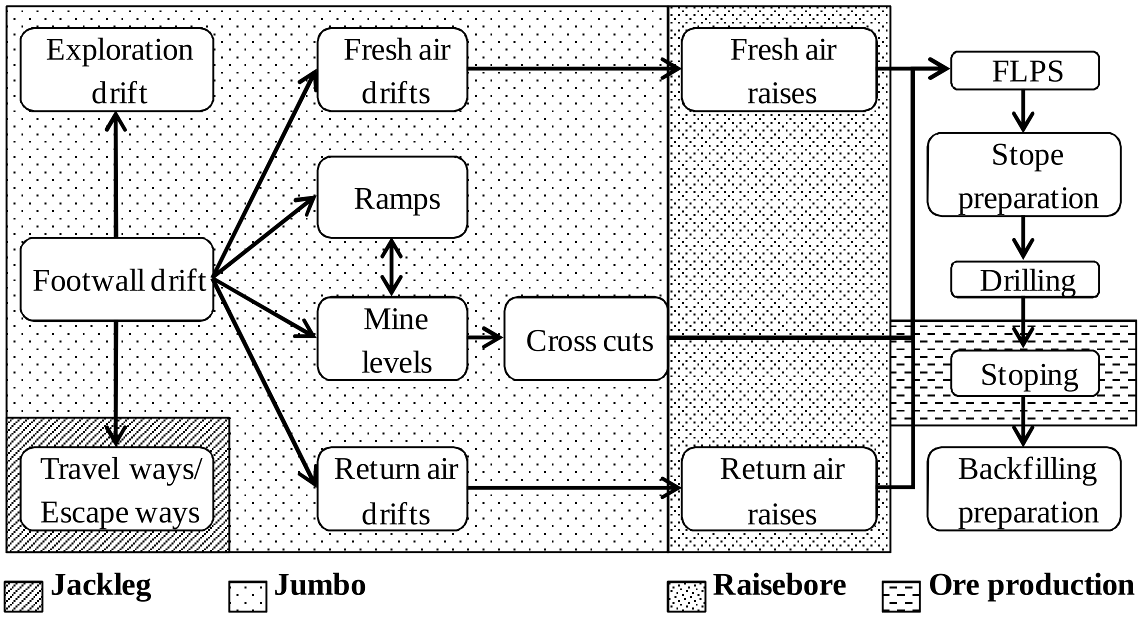


Figure 4-4 Operational resources categories and annual capacity

Table 4-2 Mine activities with assigned advancement rate, fixed duration and lag (time for successor activity)

Activities	Advancement Rate (m/day)	Duration (days)	Time for successor activity(days)
Footwall Drift	1.4	-	-
Exploration Drift	1.4	-	-
Travel ways/Escape-ways	1.4	-	-
Ramps	1.4	-	-
Mine levels	1.4	-	-
Fresh air drifts	1.4	-	-
Return air drifts	1.4	-	-
Fresh air raises	1.4	-	-
Return air raises	1.4	-	-
FLPS	-	1	-
Stope preparation	-	7	-
Drilling	78.4	-	7
Stoping	680.4 tonne/day	-	-
Backfilling preparation	-	14	-

4.4 Revenue and operating cost

For all scenarios, as mentioned in Figure 1-1, a uniform discount rate of 7.5% was used.

4.4.1 Revenue

Precalculated revenue factors per tonne of ore were used to reflect all valuable mineral content, grade and mineral price. The revenue factor is based on values from the block model, which consists of blocks that have revenue ($/tonne) attached to them. The revenue factor is calculated based on a computation of mineral price and forecasting strategy for the predominant mineral and other associated valuable minerals and cost for penalty minerals. Revenue factors were calculated solely for ore within designed stopes; revenue from ore arising from development activities were excluded from revenue calculations.

The mine has 158 stopes, varying by tonnage and ore grade. Figure 4-5 shows stope size based on tonnage. Figure 4-6show the revenue factor of each stope. Based on the revenue factor and tonnage, an undiscounted revenue can be calculated, as illustrated in Figure 4-7.

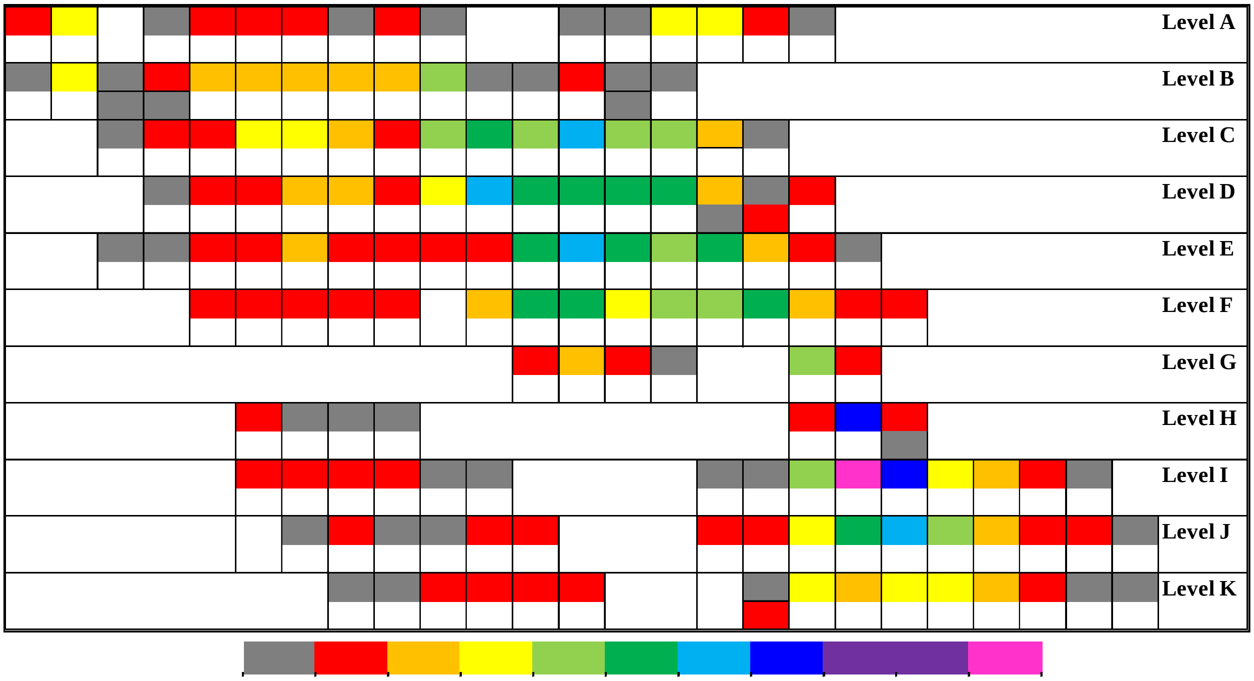


Figure 4-5 Stope size based on tonnage. Colour attributes are based on percentile score.

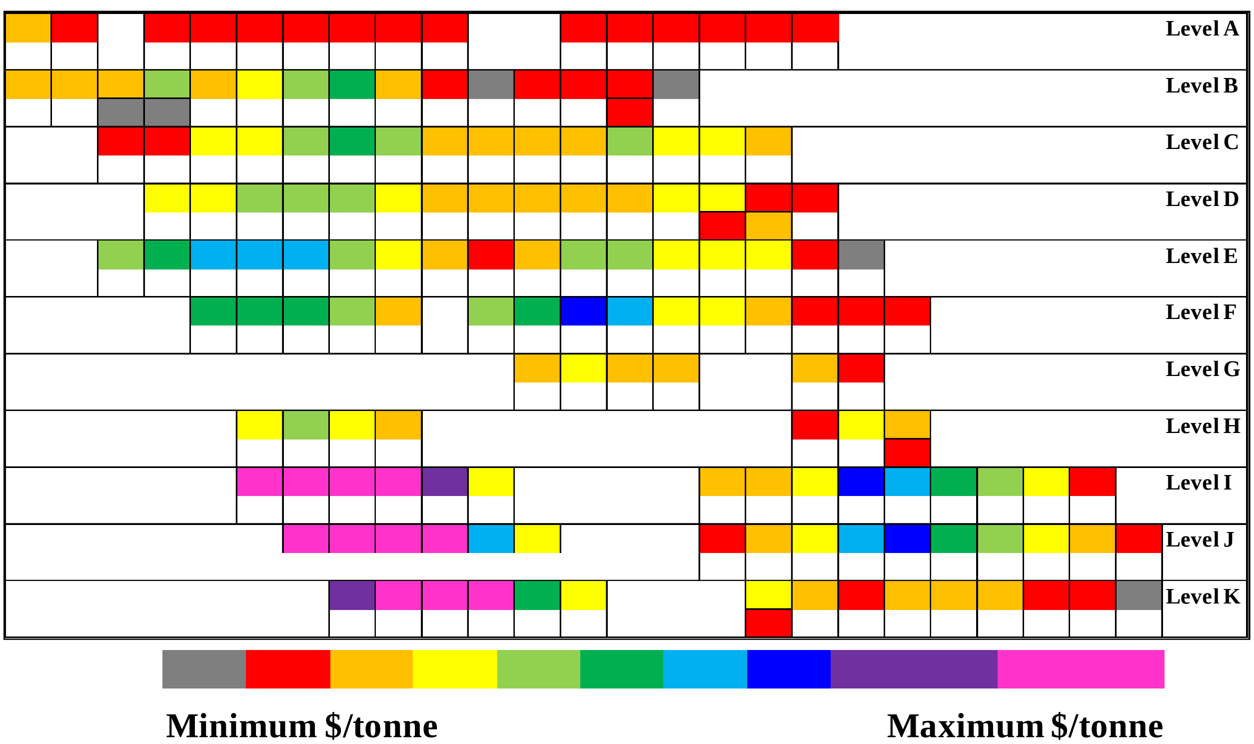


Figure 4-6 Precalculated revenue factor of mine stopes

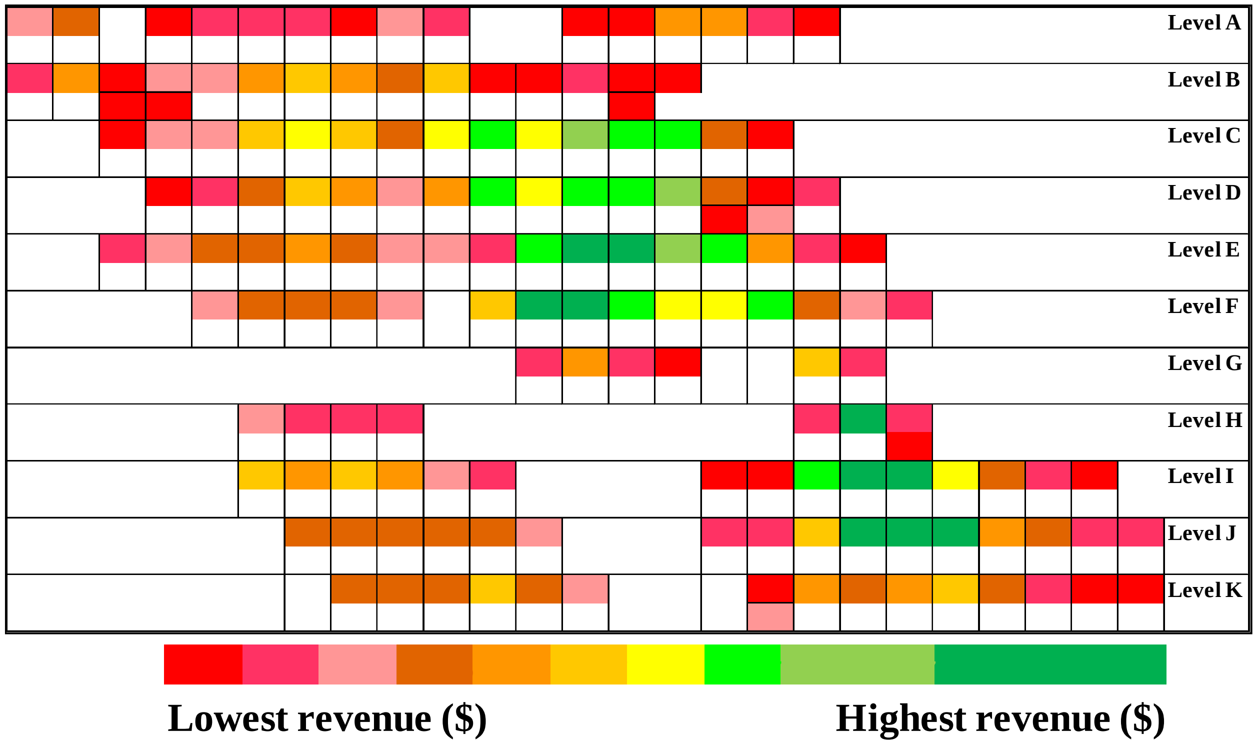


Figure 4-7 Undiscounted revenue from stopes based on revenue factor and tonnage

4.4.2 Operating costs

'Contract rates' for operational resource utilization were adopted instead of a more detailed breakdown that include fixed and variable operating costs, time dependent costs, fixed capital investment and sustaining capital expenditures. The set of values for the costs of utilizing a given operational resource, applied for different categories of development, was applied over the mine life. 'Contract rates' are deemed the amounts that would be paid to a contractor using their own equipment to complete the various development and production tasks. Consequently, amounts attributable to capital expenditure for equipment procurement and commissioning should be deemed to be embedded within the rates.

4.5 Geotechnical constraints

For the prospect, the sublevel stoping method was adopted. An undercut and overcut were designed at a vertical interval of 45m. Crosscuts were planned to be excavated at a spacing of 15m, which depends on the stope width. For the mine prospect, primary-secondary stoping is used. In this method, primary stopes are mined first and then filled. Secondary stopes are then mined. In the prospect mine, the stopes are sequenced to maintain a pyramid or chevron shape. This is accomplished by mining vertically with a lead stope, then outward along the slope of the pyramid /chevron away from its base. A long sectional view of the ‘chevron’ stoping pattern is schematically shown in Figure 4-8, where numbers show the sequence of stoping.

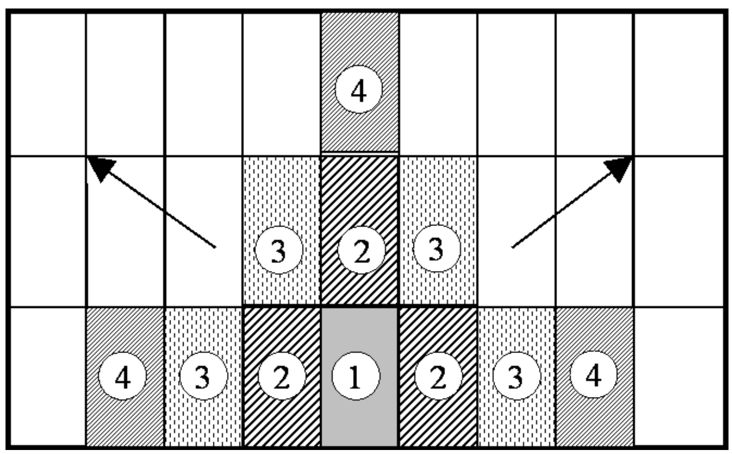


Figure 4-8 ‘Chevron’ pattern for stope sequencing in sublevel stoping method (Morrison, 1995)

The prospect was planned to be mined from two horizons (Zone A and Zone B) (Figure 4-1), both of which were planned to be extracted using a pyramid primary-secondary mining sequence. This sequence was constructed in Zone A. Zone B’s extraction commenced using the pyramid approach at Level I; however, an addition symmetrical pyramid sequence was planned for the sill pillar at Level K.

Outline description of the prospect

The methodology for incorporating the geotechnical constraint was tactical and strategic in design. The tactical design approach was to pursue the ‘chevron’ pattern and primary-secondary stope sequence(Henning and Mitri, 2007; Morrison, 1995; Villaescusa, 2003). The strategic design approach was to use tactical design separately for Zone A, Zone B and the sill pillar. The practice included creating additional mine activity links using Mine2-4D® and EPS® software. Figure 4-9 shows a schematic diagram of precedence links that were added manually. The geotechnical constraint significantly narrows the span for the schedule optimization and utilization of the full capacity of the operational resources.

Morrison (1995) studied the geotechnical limitations of conventional primary-secondary stope sequencing and proposed a pillar-less centre-out mining sequence. Villaescusa (2003) reviewed the general practice used for stope excavation order in sublevel mining methods for various types of ore bodies. Villaescusa (2003)concluded that continued stope advancing is difficult to implement in actual mining practice, since it is obligated to complete an entire stoping cycle, which includes drilling, blasting, mucking and filling, before extracting the adjacent stopes. In addition, he noted various possible issues that could appear during the operations such as unexpected stress concentrations and inefficient rockmass reinforcement.

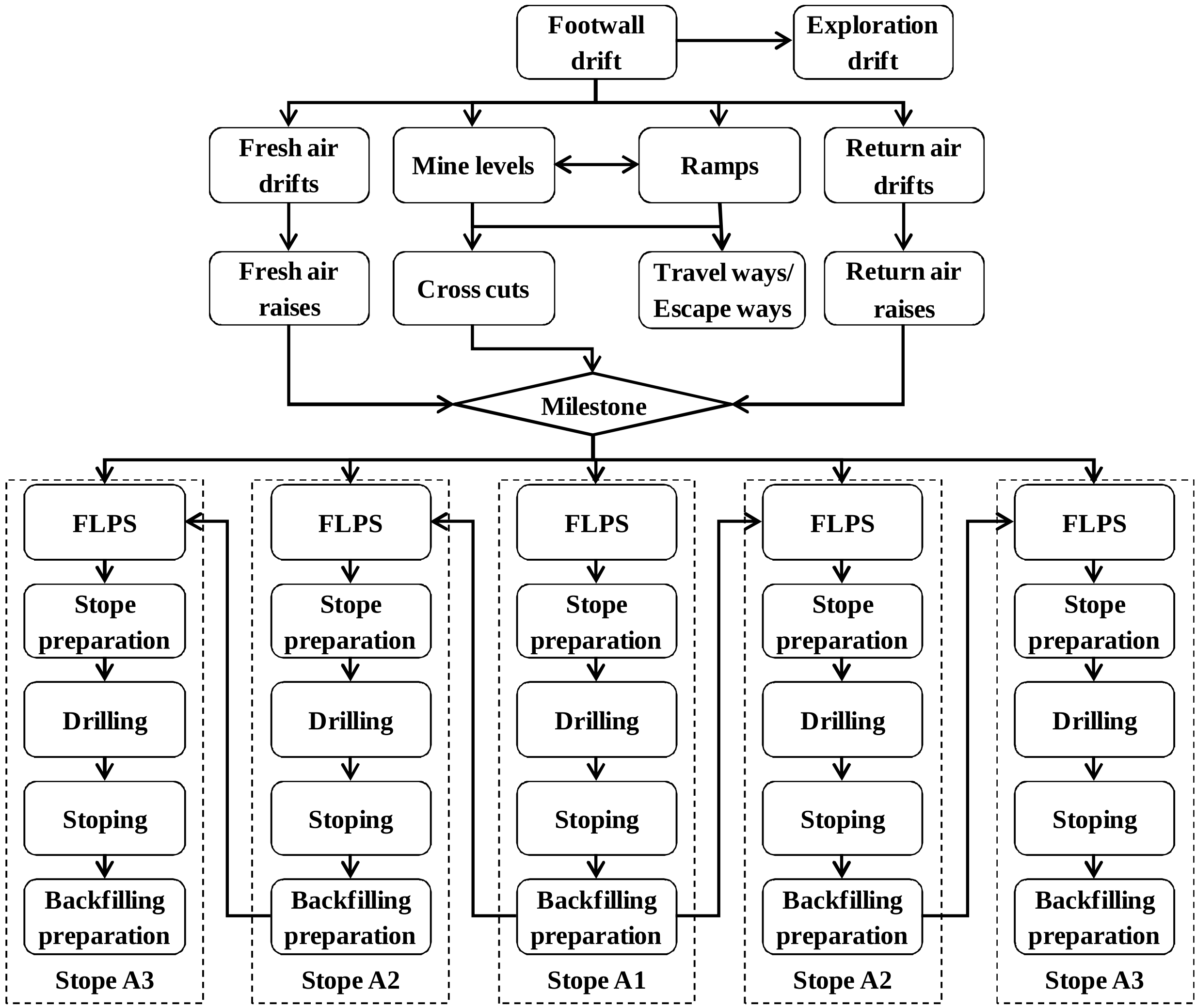


Figure 4-9A schematic diagram for linked mining activities for geotechnically constrained scenario, incorporated in addition to the physical adjacencies

4.6 Ventilation constraints

The function of the mine ventilation system is to provide an adequate quantity of fresh air at the working area and to exhaust air from the mine. Accurate estimation of the required air quantity at each of the workings is critical. The air quantity requirement is generally based on mine equipment, working area and mining method (Brake and Nixon, 2008). Ventilation network modeling was not undertaken, as the aim was just to validate the ventilation requirements. Evaluations of the ventilation constrained scenarios were centered on the provision of a fixed amount of airflow assigned for the mine section. Since the prospect was part of a multi-mine project, the ventilation airflow available had already been established using the daily ore tonne production rate (a standard mine practice) (Wallace, 2001). The physical condition of whether or not a mine would be able to provide that amount of air is another question of interest outside the scope of this work. However, based on a set of ore weight and constraints, ventilation could be adjusted accordingly or the adjustable constraints could be changed to achieve the required ore production. The aim of adding a ventilation constraint was to outline the importance of conducting long-term ventilation impact on the prospect NPV and to introduce a methodology for reconciling ventilation and production planning. The practice of adding a ventilation airflow constraint was to establish a maximum ore production rate given the available ventilation capacity. The method used by Brake and Nixon (2008) was adopted in this study.

Brake and Nixon (2008) mentioned ventilation as a hidden constraint that impacts production targets and productivity specifically for deep underground mines when ventilation networks become longer and more convoluted. Brake and Nixon also introduced various methods to estimate primary airflow such as benchmarking through adjacent and similar mine operations. Ventsim® modeling physically distributes airflows to individual activities based on location, time period and estimating the total diesel engine equipment capacity. D'Angelo and Gardner (2008)stated, "*As with geotechnical stress, ventilation is a significant driver when optimizing the mine design and schedule, even more so as the depth of mining increases*."

Wallace (2001) collected ventilation survey data and correlated these against mining methods, production rates and airflow requirements based on ore production. Wallace noted difficulties interpreting precise airflow requirements due to specific mine characteristics. For example, ventilation circuit length, complexity, air shock losses, air leakage, dispersion of the working faces and additional heat loads due to virgin rock temperatures can be different in each mining method.

Adding ventilation constraints contributed to improving the ventilation system and the practical applicability of such an approach. The approach ranges from adjusting ventilation capacity to determining the limits of existing ventilation system capacity to maximize ore production. The optimization of the airflow volumes could allow the mine to increase threshold ore production. Table 4-3 shows the airflow calculation method adopted for this study.

Table 4-3 The airflow calculation method adopted for this study

Parameters	Value
Ventilation capacity	408 m^3/s
Annual ventilation capacity	12,867 Million m^3
Annual air mass capacity	15.5 MT
Annual ore production capacity	0.91 MT

Figure 4-10 shows the relationship between mine ventilation and ore production through a ratio between air and ore mass (where air density was considered 1.2 kg/m^3). However, that ratio varied from one mining method to another, as well as by ore production rate, since ventilation is not only required for stoping but also for development activities and for the duration of the associated mining activities. For example, a stope of 75,000 tonnes needed 337 million m^3 or 405,915 tonnes of air, as shown in Table 4-4.

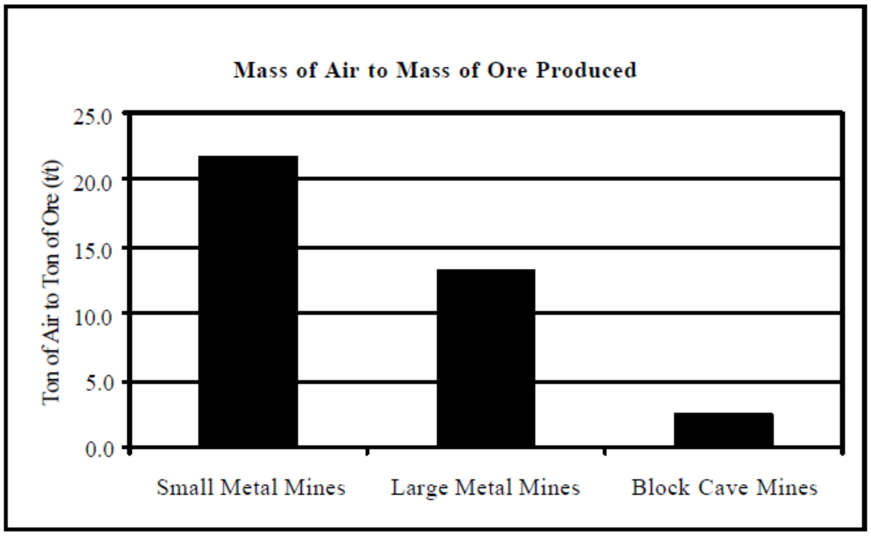


Figure 4-10 A generalized air mass (in ton) and ore ton ratio observed from computation of air flow at different mines(Wallace, 2001)

Table 4-4 Ore tonne and airflow requirement

Activity Type	Mined Tonne	Duration (days)	Air million m^3
STOPE 1	75,000	100	337
STOPE 2	45,000	60	121

Table 4-5 shows details of constants used for airflow quantity computation for each activity in the schedule, followed by equations.

Table 4-5 Constant and description used for airflow quantity computation

Constant	Description
i	activity identification number i=1, 2, 3...I, I is the total number of activities
d_i	duration of activity i
O_{it}	tonnage mined from activities i in period t
AFi	Factor to use air quantity for each mined tonnage (0.52×10^{-3} m^3/s)
t	schedule time period
l	length of scheduling period
n	number of scheduling period $= 1 + \frac{life\ of\ project}{l}$
$AQit$	Air quantity required for activity i during the period t
X_i^t	Variable
VC_t	available capacity of ventilation in period t

Outline description of the prospect

Variable as defined in section 3.1.3

fa_i^t = fraction of activity *i* proceed in period *t*. fa_i^t is a variable depends on start time of activity *i*

$$0 \leq fa_i^t = \frac{[minimum(t * l, ES_i + d_i) - maximum(ES_i\ , (t-1) * l)]}{d_i} \leq 1\ (\forall i = 1 \dots N, \forall t = 1 \dots n)$$

$$X_i^t = \begin{cases} 1, if fa_i^t > 0 \\ 0, otherwise \end{cases} (\forall i = 1 \dots I, \forall t = 1 \dots n)$$

$$AQ_i^t = d_i \times O_i^t \times AF_i\ (\forall i = 1 \dots I, \forall t = 1 \dots n)$$

Ventilation constraints

$$\sum_{i=1}^{I} X_i^t \times AQ_i^t \leq VC^t\ (\forall i = 1 \dots I, \forall t = 1 \dots n)$$

5 Upside potential of mining without geotechnical and ventilation constraints

5.1 Scenario A: EPS® default schedule (base case schedule)

Using EPS®, a base case schedule was created. The EPS® default or base case schedule is an *unoptimized* schedule. The precedence links for the base case schedule followed the physical adjacencies and milestones but were geotechnically unconstrained. The mine schedules were levelized with and without operational resource capacity, to take into account the EPS® *just-in-time* function.

5.1.1 Constraints

The base case schedule possesses two principal types of constraints: (i) operational resource constraints, which limit the number of activities over a period based on equipment capacity, and (ii) adjacency constraints, which dictates the order in which activities must be completed.

5.1.2 Base case schedule results

From the EPS® base case schedule, ore production, mine development and project NPV were investigated.

5.1.2.1 Annual ore production

For the unoptimized schedule, the ore production started in the fourth year and reached maximum capacity in the sixth year. The annual ore production profile was stable between year six and thirteen. At the end of mine life, the ore production was close to the maximum capacity, as illustrated in Figure 5-1.

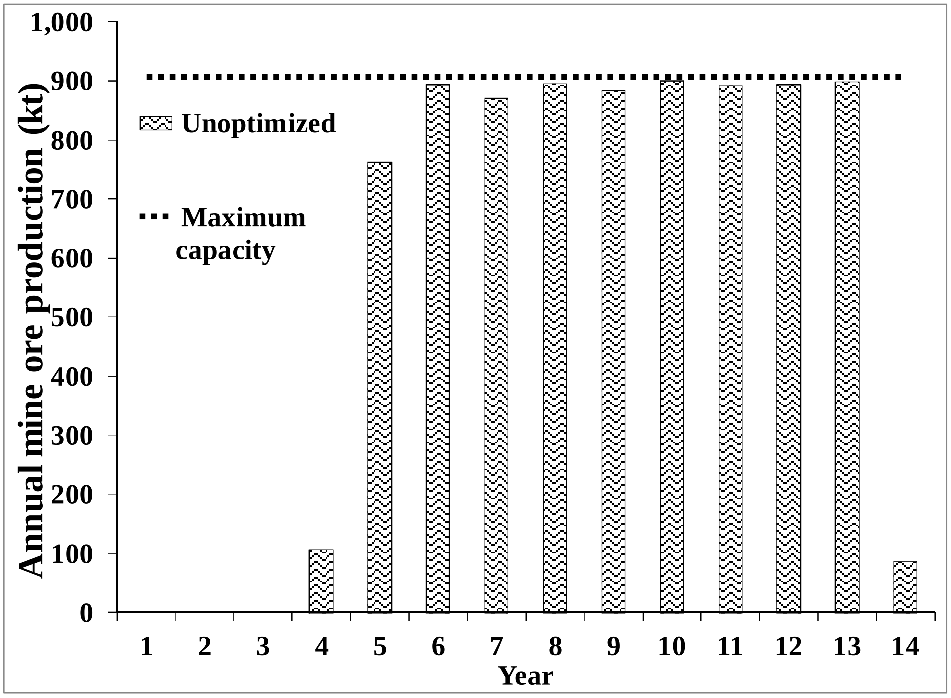


Figure 5-1Scenario A: Annual ore production profile of the unoptimized schedule.

5.1.2.2 Annual mine development

The annual mine development profile consolidated from the jumbo drill resources category is shown in Figure 5-2.In year four and eight annual mine development was constrained by the threshold capacity, and aside from this, it was underutilized over the mine life and varied from year to year. The total operational resource capacity for jumbo development was 2.25 times higher than the total length of mine development over the life of the prospect. This indicates that jumbo development resource was underutilized in this unoptimized, yet feasible mine schedule. It is important to realize that although the resources were underutilized, the underutilization did not have a cost. Thus, it is possible that the surplus resource could be utilized in other parts of the mine, outside the prospect.

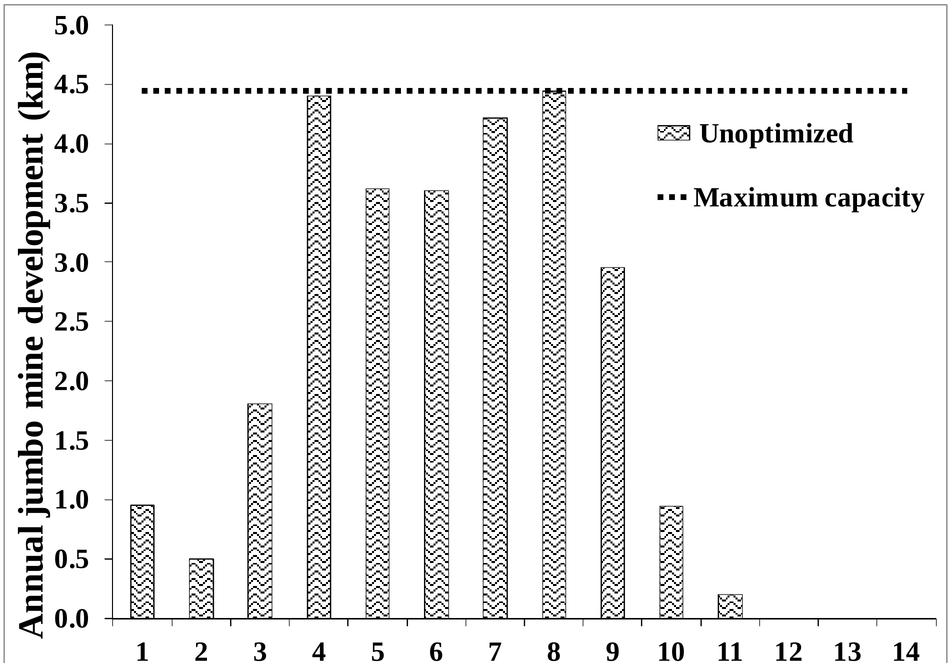


Figure 5-2Scenario A: Annual mine development profile of the unoptimized schedule.

The annual ventilation raise development profile consolidated from the raise bore operational resource category is shown in Figure 5-3. For each year, the annual ventilation raise length was significantly lower than the maximum capacity; only half of the maximum capacity was utilized, in any year, at best. The allocated capacity was 8.8 times higher than the total raise bore development length over the life of prospect. This indicates that the raise bore development resource was underutilized in this unoptimized mine schedule.

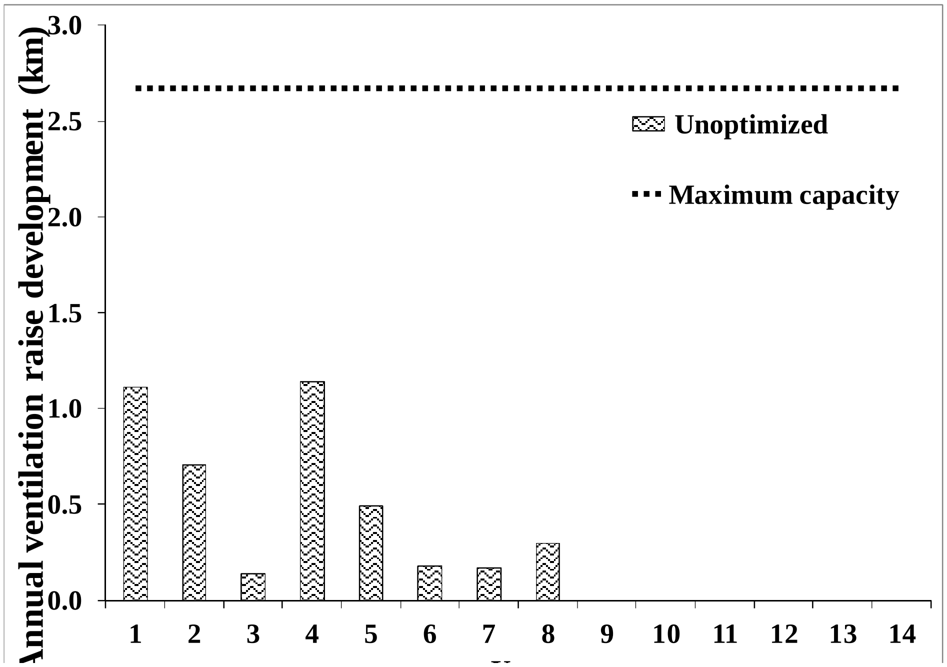


Figure 5-3Scenario A: Annual raise development profile of the unoptimized schedule.

5.1.2.3 Annual cash flow and NPV

Figure 5-4 shows that the discounted cash flow of the prospect for the unoptimized schedule reaches a breakeven point in the ninth year of operation. The breakeven point is the time at which the capital investments in the project are recovered. The cash flow profile shows inconsistencies between year five and eight. The inconsistencies illustrate that for the unoptimized schedule, the stope sequence did not generate enough revenue during the early phase of production.

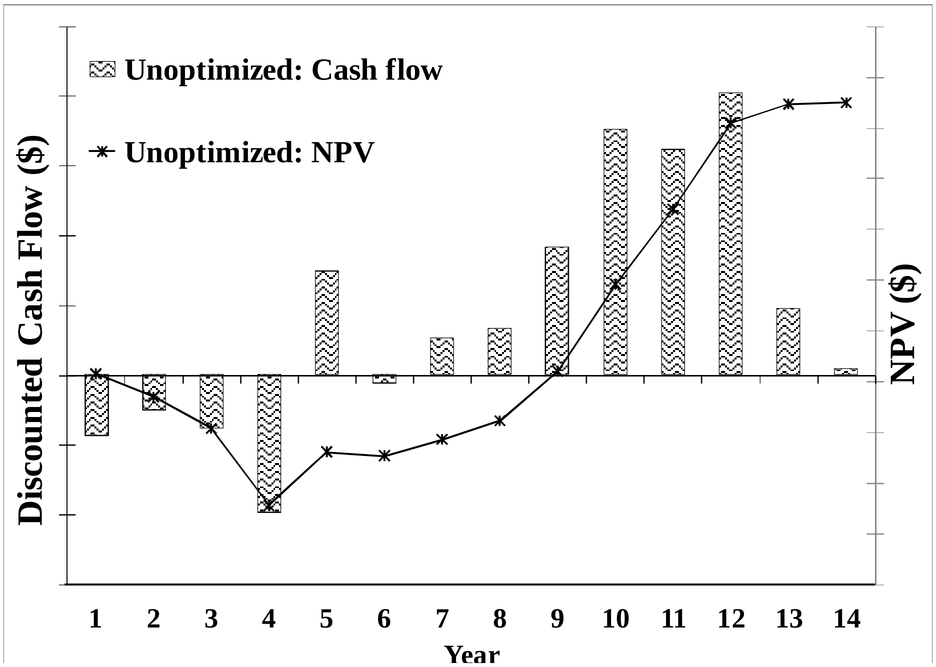


Figure 5-4Scenario A: Annual cash flow and NPV of the unoptimized schedule.

5.1.3 Interpretation of the results

The annual mine development profile for an unoptimized schedule shows that the given annual capacity of the jumbo drill for the mine development was higher than was required throughout the life of the mine. All mine development was completed in the eleventh year, four years earlier than the end of mine life. Throughout the mine life, the development under the raise bore category did not achieve half of the available capacity. The annual operational resource capacities thus need to be revised. Results in section 5.1.2showed that, among all operational resources, the key restrictive constraint was hoisting capacity. The cash flow profile distinctly shows the extraction of less valuable stopes from year six to year eight. Mining of these stopes did not add appreciable value to the cash flow. It is noticeable that in year six, jumbo drill and raise bore development scheduled was lower than in adjacent producing years, and ore production tonnes were at maximum capacity. Cash flow was negative and demonstrated that mined stopes were not being selected with profitability in mind.

5.2 Scenario A: SOT optimized schedule

For the base case schedule, SOT was applied to find an *optimized* schedule. The maximum deployment of operational resources and prior stoping of high mineral grades stopes may improve the profitability of the mine project (Fava *et al*., 2012). Optimization was also subject to *just-in-time* development. The heuristic used initially for the optimization process was ‘rank then stope mineral weight’.

5.2.1 Annual ore production

In the optimized schedule, during the initial phase of the mine, ore production was higher than the unoptimized schedule to some extent. As for the unoptimized schedule, ore production achieved the given maximum capacity, as seen in Figure 5-5. From the ore production tonnage, other than years 4 and 14, no appreciable difference between the optimized and unoptimized schedule was evident.

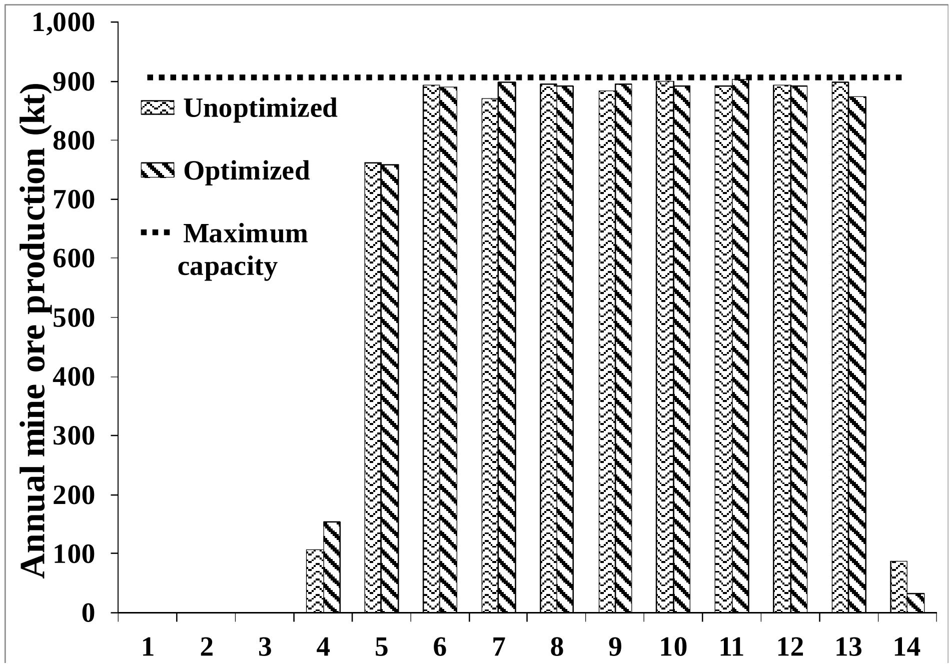


Figure 5-5 Scenario A: Comparison of annual ore production between the unoptimized and optimized schedules.

5.2.2 Annual mine development

A comparison between the optimized and unoptimized schedule for development under the jumbo operational resource category is shown in Figure 5-6. It shows that in the optimized case, mine development was deferred until it was completed '*just-in-time*'. This has a positive effect on NPV because development costs are deferred to later years where present value factor is lower. However, utilization of the jumbo drill for the mine development was variable and at no time does it reach the threshold capacity. In the optimized case, mine development occurred up to the end of the prospect. For the development under the raise bore operational resource, development of ventilation raise was delayed for the initial two years again due to the application of the '*just-in-time*' policy. In the 4th year, raise bore operational resource utilization came close to the maximum capacity, but for the remaining years, it was well below the given capacity (Figure 5-7).

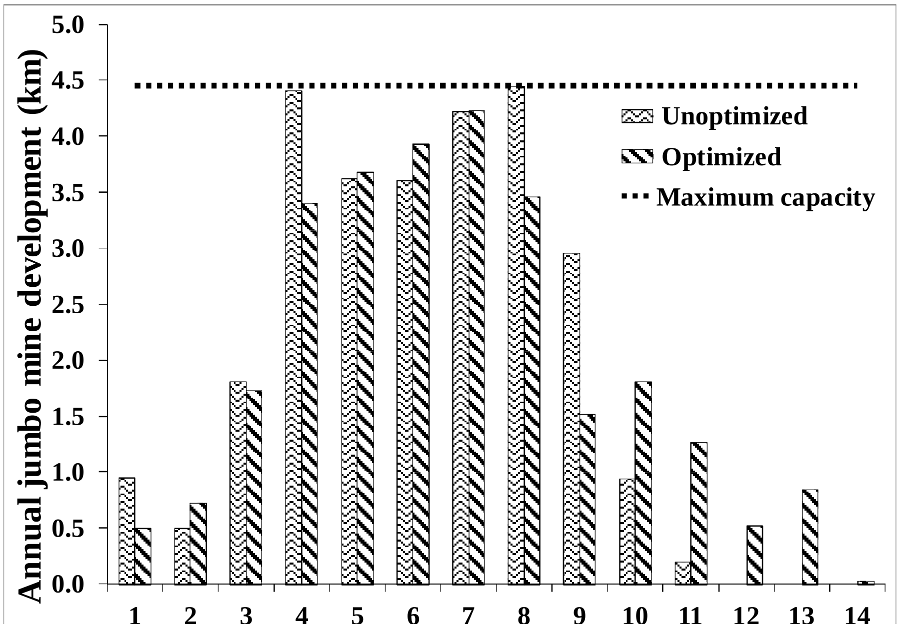


Figure 5-6 Scenario A: Comparison of annual mine development between the unoptimized and optimized schedules.

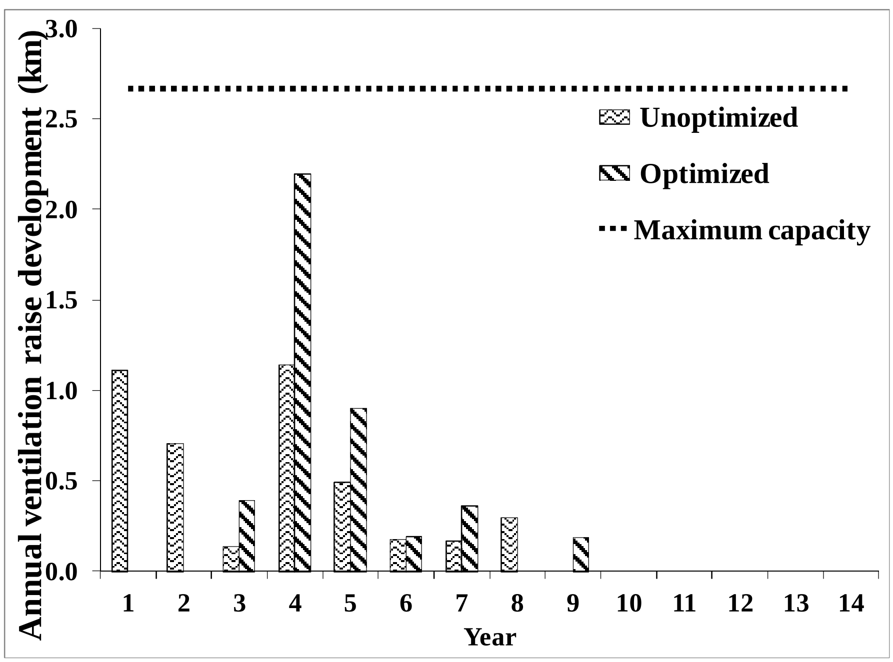


Figure 5-7 Scenario A: Comparison of annual raise development between the unoptimized and optimized schedules.

5.2.3 Annual cash flow and NPV

Figure 5-8 shows the annual discounted cash flow and the NPV of the optimized schedule, with an improvement of 26.9% as compared to the unoptimized schedule. The optimized schedule crossed the breakeven point three years earlier than the unoptimized schedule. The NPV difference between the unoptimized and optimized schedule corresponds to the results shown in the previous section. *Just-in-time* development and prioritizing the stopes that generate higher revenue account for the improvements.

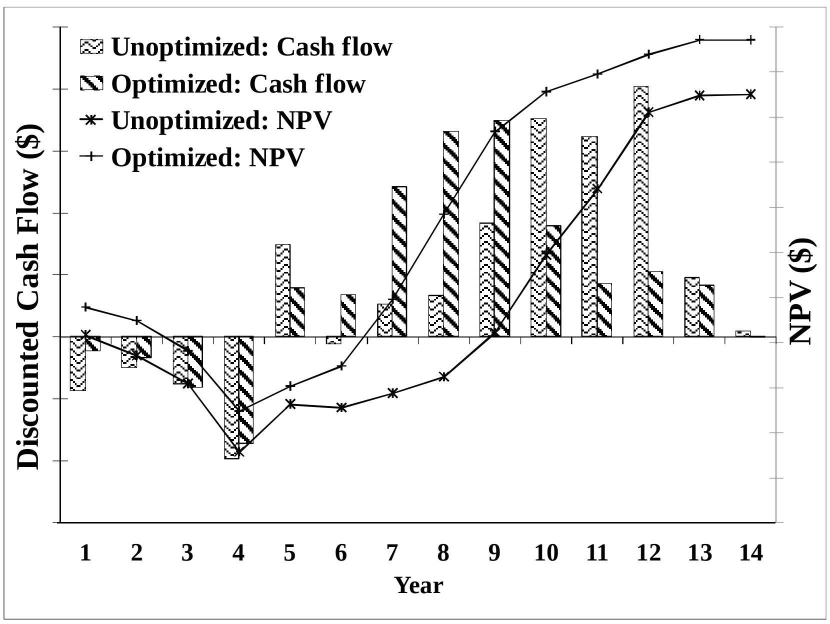


Figure 5-8 Scenario A: Comparison of annual cash flow and NPV between the unoptimized and optimized schedules.

5.2.4 Comparison between EPS® schedules and SOT optimized schedules

An additional comparison was made between EPS® schedules and SOT optimized schedules to evaluate the impact of '*just-in- time'* development and stoping priority on the basis of high revenue. Figure 5-9 shows the NPV of all six schedules, normalized to the value of the EPS® default schedule. The schedules created using EPS® were: i) default schedule, ii) default schedule with '*just-in-time*', iii) default schedule with '*high grading'*, and iv) default schedule with both '*just-in-time*' and *'high grading'*. Schedules reported for SOT were: i) optimized and ii) optimized with *'sliding'*. For the default schedule, EPS® '*just-in-time*' increased the project value by 4%. The results show '*high grading'* is not a good strategy for scheduling while using EPS®. The SOT optimized schedule results show a 14% improvement in the NPV due to schedule optimization through SOT and a further 13% improvement from *sliding*. The EPS® '*just-in-time'* is not effective when multiple operation resources are incorporated into mine activities.

This analysis was undertaken in order to establish the policies affecting schedule value that should apply in order to make a fair comparison of performance between established scheduling and scheduling using SOT. The fairest comparison is probably between EPS®+JIT and SOT + *sliding*. However, due to the inconsistency of the JIT policy implementation in EPS® with the scenarios of higher complexity, a decision to take the EPS® default as the base case value was taken, and this measure was applied consistently for all subsequent scenarios.

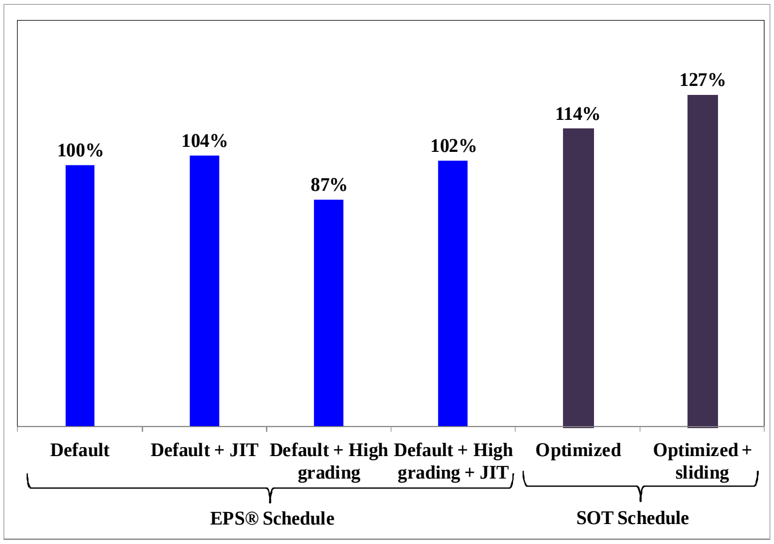


Figure 5-9 Scenario A: The NPV difference in percentage between EPS® schedule and SOT optimized schedules

5.2.5 Time for SOT optimization

To find an optimized schedule, an initial population of sequences of activities was generated randomly. The initial population for a learning run can be augmented by the addition of activity sequences that are probably of high value relative to randomly initialized sequences. These are called ‘seeds’, which are established from use of one or more of the heuristics listed in Table 3-2, for alternatively, from the results of a prior phase of learning. In the case of the Scenarios A to D of this study, the size of the population used was 20.

To improve the NPV associated with the population, selection, crossover and mutation and evaluation processes repeatedly operated on the population (following the algorithm flow chart of Figure 3-2) until the NPV of the fittest member of the evolving population was considered to have converged. This was when no improvement in the NPV occurred above a defined threshold of $1,000 over one generation of the population. Before every evaluation step, each of the activity sequences in the population were ‘translated’ to schedules (Sequence2Schedule) and additional operators optionally applied to the schedules (e.g. sliding). At the conclusion of this learning process, the population of sequences was re-initialized with random values plus the seed, and the evolutionary learning process applied, completely, again. The term applied to refer to this second, and subsequent processes, is called a ‘reset’. It has become standard practice to conduct a large number of resets with SOT. For Scenarios A to D, 200 resets (independent evolutionary learning trials) were undertaken, and the converged value of the NPV recorded for each reset. These are shown as the Phase 1 resets in Figure 5-10 (and the set of results appears to be bimodally distributed between two different ‘clusters’ of results). At the conclusion of Phase 1, the best candidate found from this Phase was used to seed the population for a second Phase of 200 resets of learning. The results of the overall process are presented in Figure 5-10.

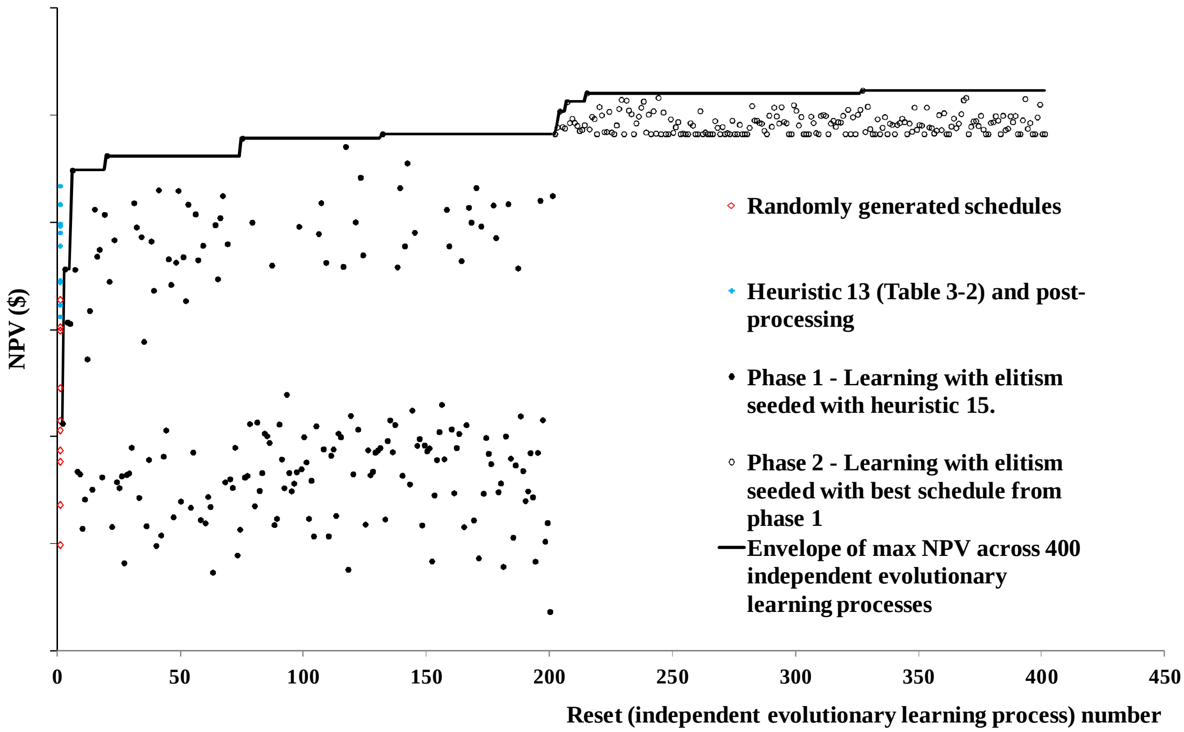


Figure 5-10 Scenario A: Values of the best schedule in a population after evolutionary learning for 2 learning phases each comprising 200 resets. Phase 1 – Seeded with heuristic 15. Phase 2 – Seeded with best schedule from Phase 1

5.2.6 Interpretation of the results

The use of SOT resulted in one best optimized schedule out of 187,500 schedules explored. To design and evaluate this number of potential schedules would take a human a great deal of time, a task human planning could not achieve. For the optimized schedule, the annual ore production profile was similar to that of the unoptimized schedule but in the optimized schedule, mining priority was given to the stopes with higher revenue, which increased the NPV. The annual profile for the mine development exhibits under-utilization of the given development equipment capacity in both the optimized and unoptimized cases of Scenario A. However, in the optimized schedule, mine development focuses on access to higher revenue stopes. This deferring of capital expenses lowers the present value factor and boosts the discounted cash flow.

5.2.7 Comparison of the mine sequence

Comparing the unoptimized and optimized schedules is a useful way to decode the information in the optimized schedule. By comparing the schedule at different phases, one can identify the sequence of stoping and mine development that results in the higher NPV. Examination of the optimized schedule confirmed that SOT benefits arose by selecting stopes with higher revenue factors and the '*just-in-time*' development policy.

Table 5-1 shows the developments and ore production at the breakeven point for both cases. The results show that in the optimized schedule, 26.7% less ore production was required to reach the breakeven point of the prospect and that breakeven occurred 2.5 years (130 weeks) earlier than in the unoptimized schedule.

The stope mine sequence during the life of the mine is shown in Figure 5-11 for the unoptimized schedule. In Figure 5-12 and Figure 5-13 stope mine sequence is shown for the optimized schedule. The numbers on the diagrams show the mining order of the 158 stopes in each case. Examination of the diagrams reveals that sequence organization, to some extent, has been modified in the optimized schedule.

Table 5-1 Scenario A: Comparison of mine development and ore production at breakeven point between the unoptimized and optimized schedules

Scenario A	Total	Unoptimized	Optimized	Difference
Jackleg (m)	100%	100.0%	74.2%	25.8%
Jumbo (m)	100%	98.5%	66.9%	31.6%
Raise bore (m)	100%	100.0%	95.6%	4.4%
Ore (tonne)	100%	61.0%	34.4%	26.7%
Number of stopes	158	92	62	30
Breakeven year		9.5	7.0	2.5
Mine life (Year)		13.33	13.17	0.17

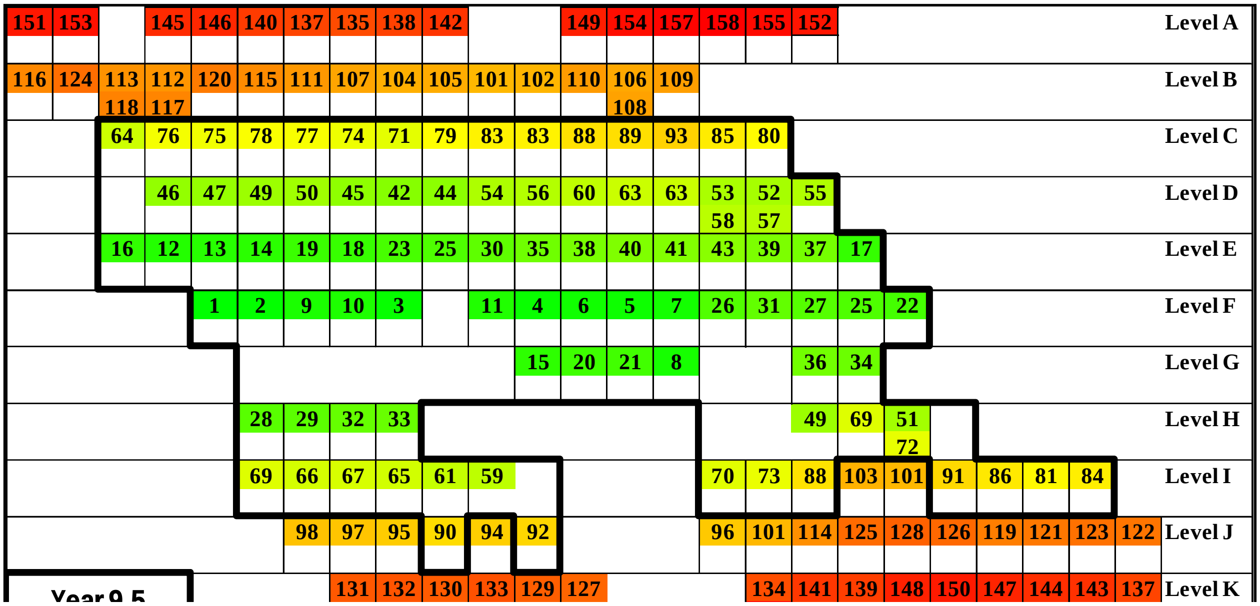


Figure 5-11 Scenario A: Unoptimized schedule stope sequence for the life of mine and 92 stopes mined out at the breakeven point

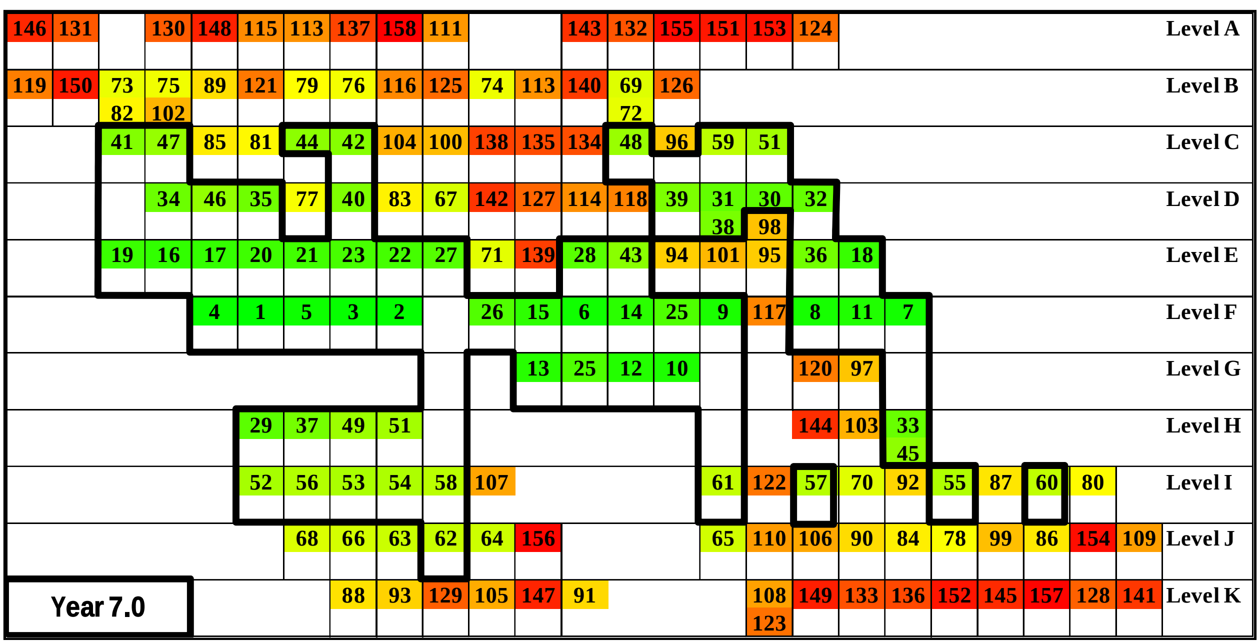


Figure 5-12 Scenario A: Optimized schedule stope sequence for the life of mine and 62 stopes mined out at breakeven point

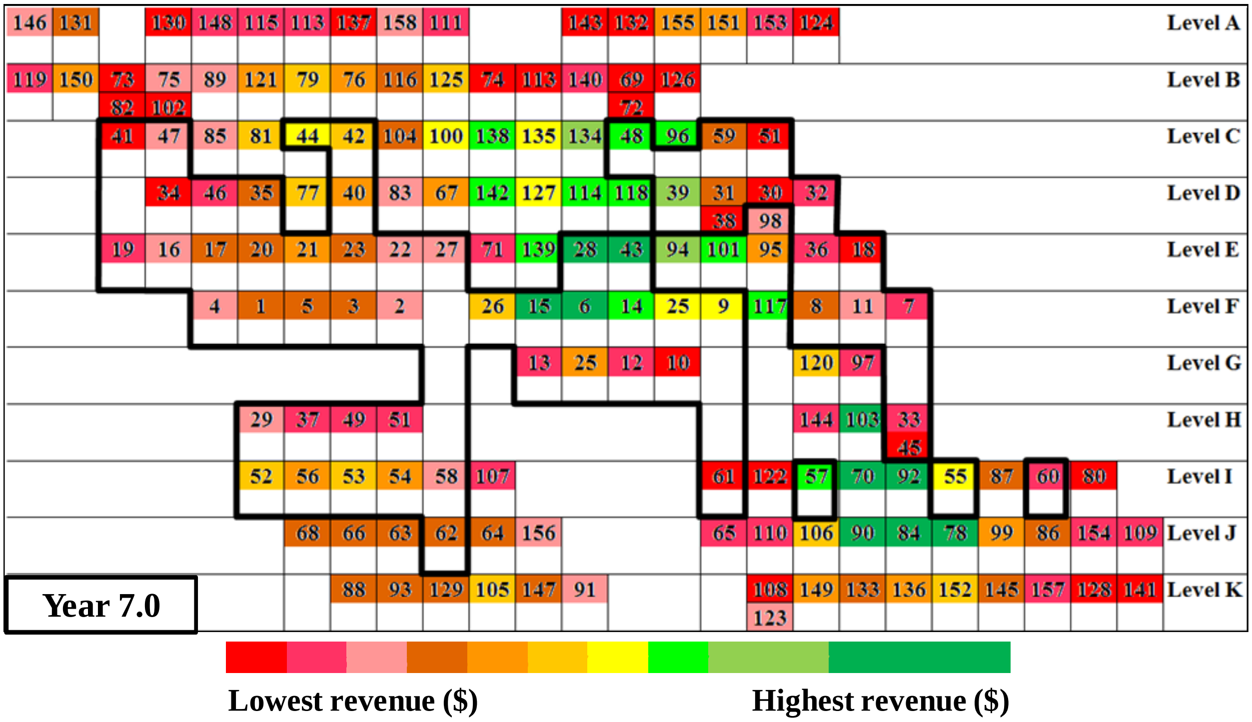


Figure 5-13 Scenario A: Optimized schedule stope sequence with undiscounted stope revenue

6 Mine schedule optimization through SOT

6.1 Scenario B: Mine schedule with ventilation constraint

For Scenario A, two principal types of constraints were applied: (i) operational resource constraints, and (ii) precedence constraints. In the forthcoming scenario, the exercises demonstrate the effect of additional constraints on the mine schedule and prospect value. This section considers the effect of ventilation constraints first.

Ventilation is one of the key constraints for underground mines. For the Scenario B, the investigation was based on incorporating ventilation resource capacity (m^3/s) as an optimization constraint. The computation included the extent and depth of the mine, the stoping and extraction systems and the size of the development openings.

6.1.1 Comparison of performance indicators

Optimization using SOT was undertaken with the same convergence criteria and parameters as for Scenario A, and took 7.1 hours to complete. With a higher complexity of scheduling problem when fewer solutions exist, SOT did take shorter period of time compared to manual scheduling processes. When the mine schedule was constrained considerably with ventilation airflow quantity, as shown in Figure 6-1, for both the unoptimized and optimized schedule, the ore production quantity was comparable; however, the annual ore production was 42% of the maximum threshold annual capacity. In addition, the optimized schedule prioritized to the stopes with higher revenues.

The differences of mine development and ventilation raise development between the unoptimized and optimized schedules are shown in Figure 6-2 and Figure 6-3 respectively. The optimized schedule has given preference to the productive developments and defers non-immediately productive development according to the '*just-in-time*' policy. As shown in Figure 6-4 for both the unoptimized and optimized schedule, the ventilation capacity was completely utilized to support development and ore production fleets, all of which compete for air. The NPV and cash flows shown in Figure 6-5 illustrate that ore production tonnes were similar in the unoptimized and optimized schedule, however the optimized mine sequence increased the NPV by 35%.

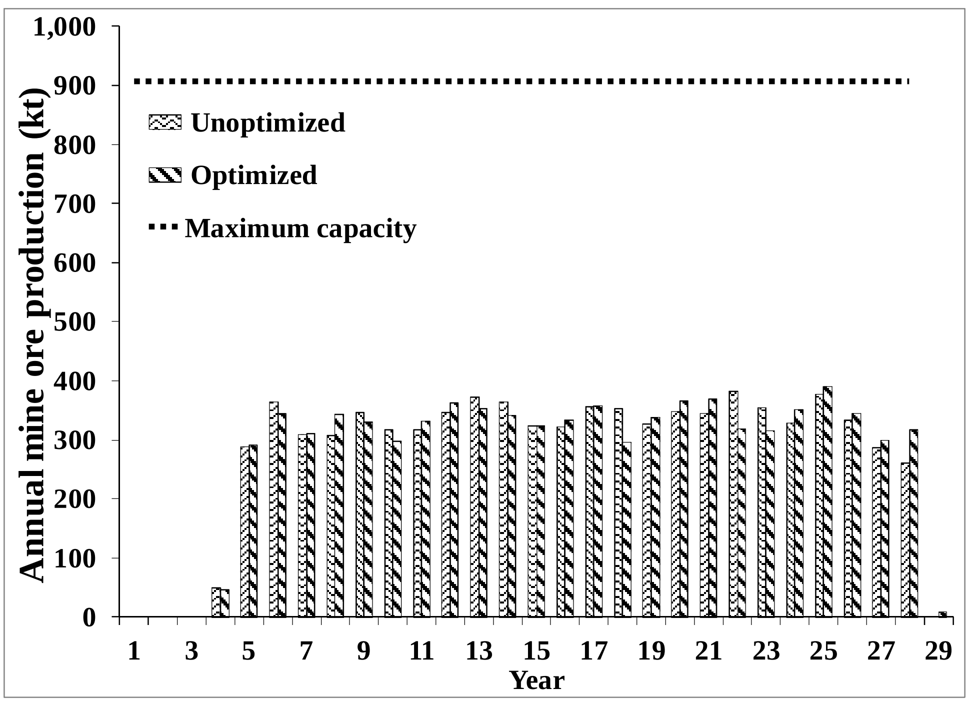


Figure 6-1Scenario B: Comparison of annual ore production between the unoptimized and optimized schedules (ventilation constrained)

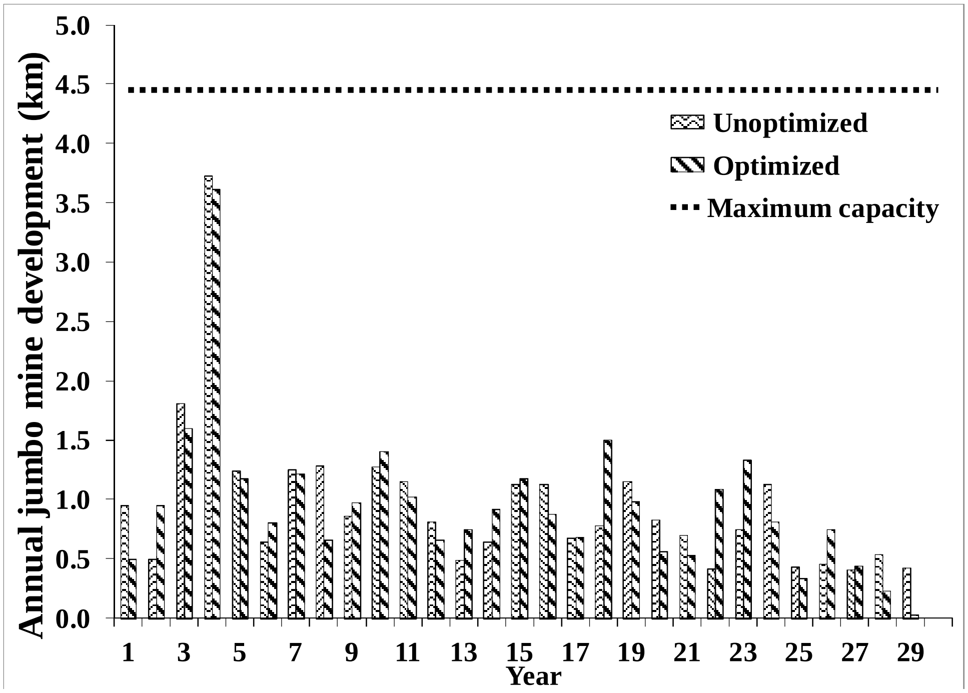


Figure 6-2 Scenario B: Comparison of annual mine development between the unoptimized and optimized schedules (ventilation constrained).

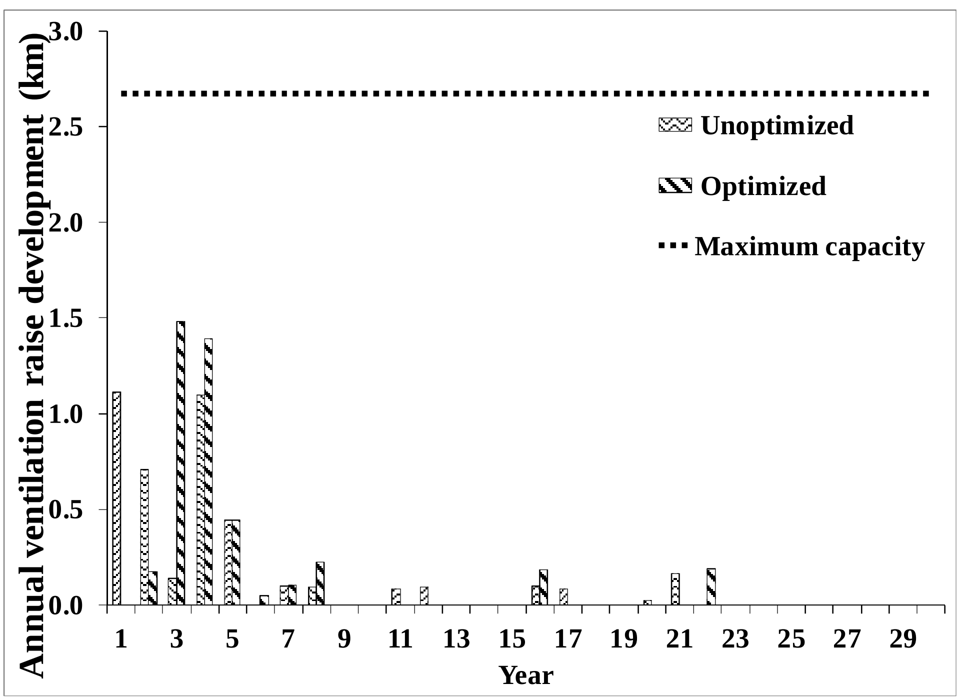


Figure 6-3Scenario B: Comparison of annual raise development between the unoptimized and optimized schedules (ventilation constrained).

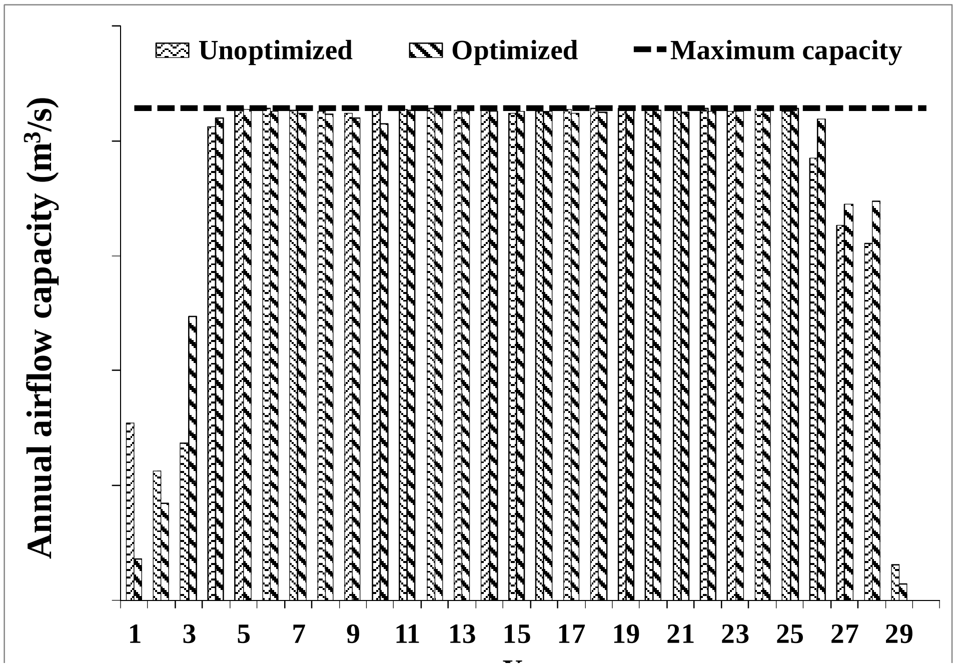


Figure 6-4Scenario B: Comparison of annual airflow utilization between the unoptimized and optimized schedules (ventilation constrained).

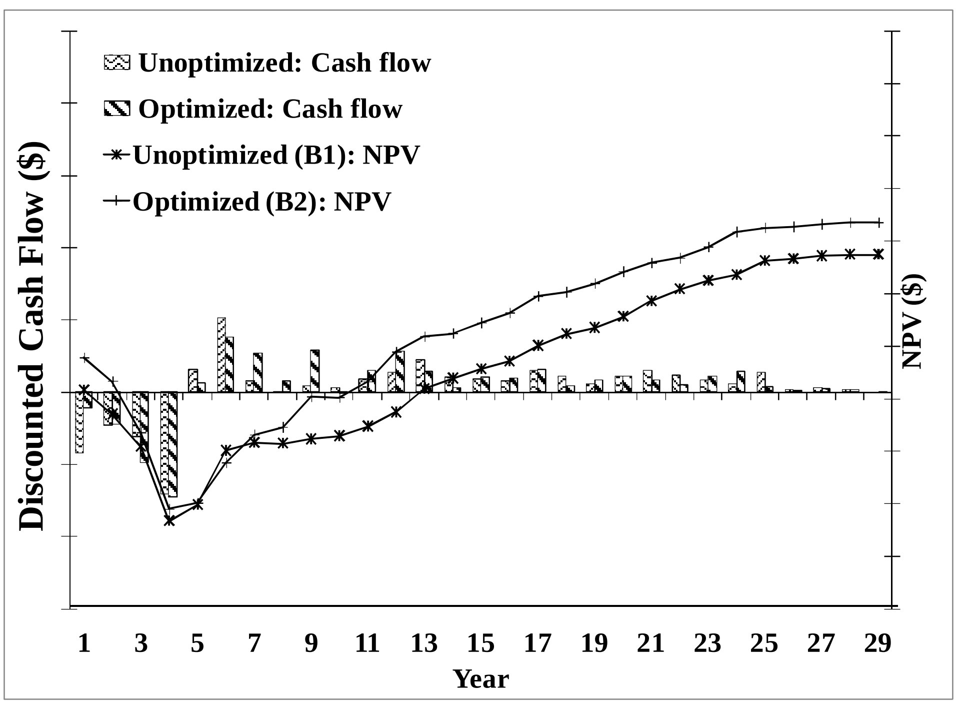


Figure 6-5Scenario B: Comparison of annual cash flow and NPV between the unoptimized and optimized schedules (ventilation constrained).

6.1.2 Interpretation of the results

With the ventilation constrained, the annual ore production was approximately 42% of the maximum capacity. In the optimized schedule, the optimization procedure delayed the unnecessary development to reduce the discounted cash flow arising from development costs, which adds value to the prospect. Due to an insufficient ventilation capacity, it was not possible to utilize the whole capacity of the operational resources. The results show that the specified capacity of the ventilation system was insufficient and needs to be revised. In Chapter 7, results of an extended investigation are shown regarding the optimum ventilation capacity that should be used for the prospect.

6.1.3 Comparison of the mine sequence

Results of the unoptimized and optimized schedule have shown that with regard to quantity, the cumulative ore production and development of Scenario B were similar to those of Scenario A at the breakeven point. However, due to the ventilation constraint, the ore production and development rates were reduced, which delayed the breakeven point. Table 6-1 shows the development and ore production at the breakeven point for both the unoptimized and optimized cases. The results, obtained from the optimized schedule, show that in addition to mine development for different operational resource categories, there is also 24.8% less ore production required for breakeven. The breakeven point of the mine was 4.8 years (248 weeks) earlier in the optimized schedule than in the unoptimized schedule. In comparison to Scenario A, breakeven occurs 4 years later for both unoptimized and optimized schedules.

The stope mine sequence during the life of the mine is shown in Figure 6-6for the unoptimized schedule. In Figure 6-7 and Figure 6-8, stope mine sequence is shown for the optimized schedule. The sequence organization to some extent has been modified in the optimized schedule. These observations have shown that the unoptimized sequence took significantly longer to mine the same number of stopes than the optimized sequence.

Table 6-1 Scenario B: Comparison of mine development and ore production at breakeven point between the unoptimized and optimized schedules

Scenario B	Total	Unoptimized	Optimized	Difference
Jackleg (m)	100%	73.7%	60.9%	12.8%
Jumbo (m)	100%	70.9%	53.5%	17.4%
Raise bore (m)	100%	95.6%	91.2%	4.3%
Ore (tonne)	100%	75.8%	51.0%	24.8%
Number of stopes	158	86	54	32
Breakeven year		16.9	12.2	4.8
Mine life (Year)		28.92	28.08	0.84

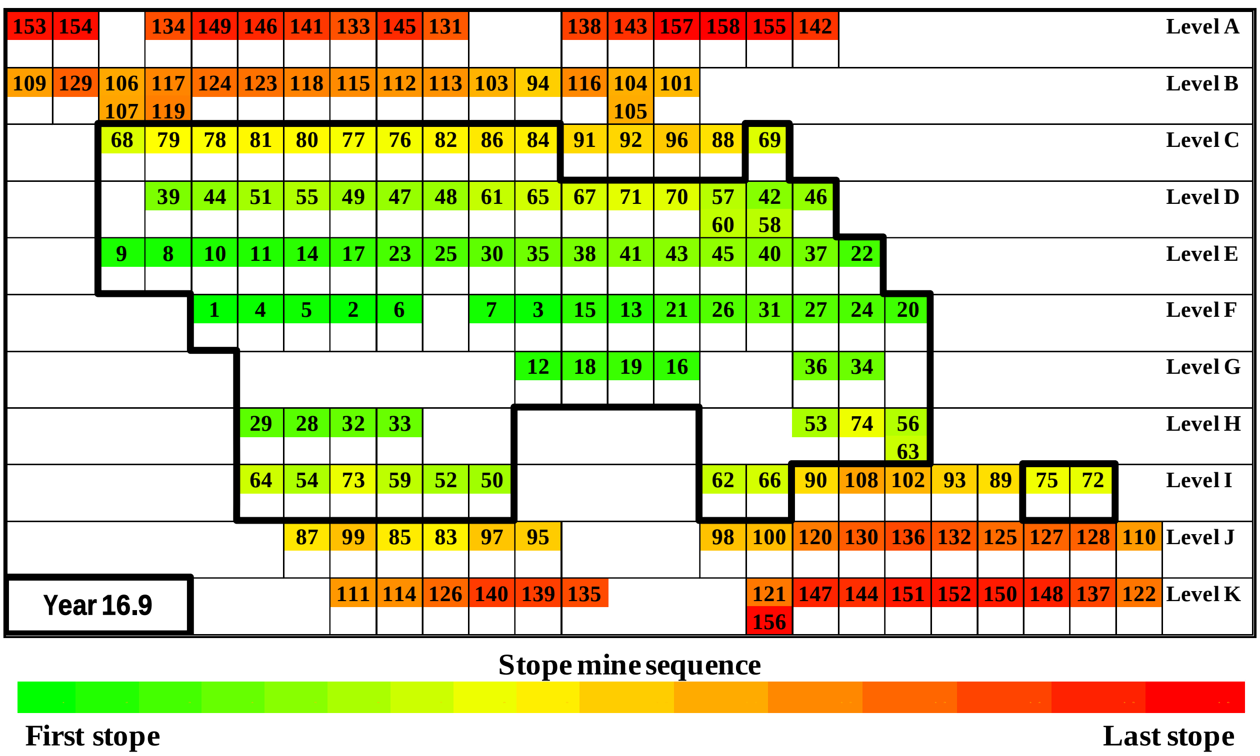


Figure 6-6Scenario B: Unoptimized schedule stope sequence for the life of mine and 86 stopes mined out at breakeven point

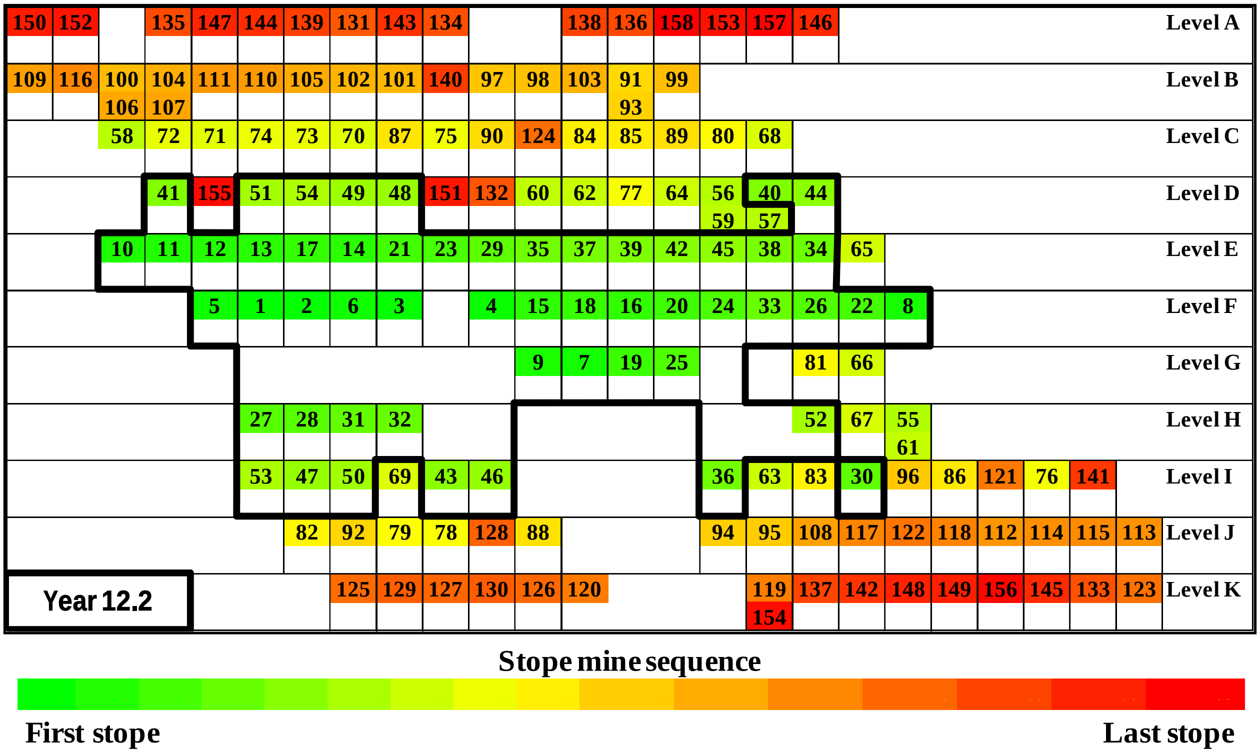


Figure 6-7Scenario B: Optimized schedule stope sequence for the life of mine and 54 stopes mined out at breakeven point

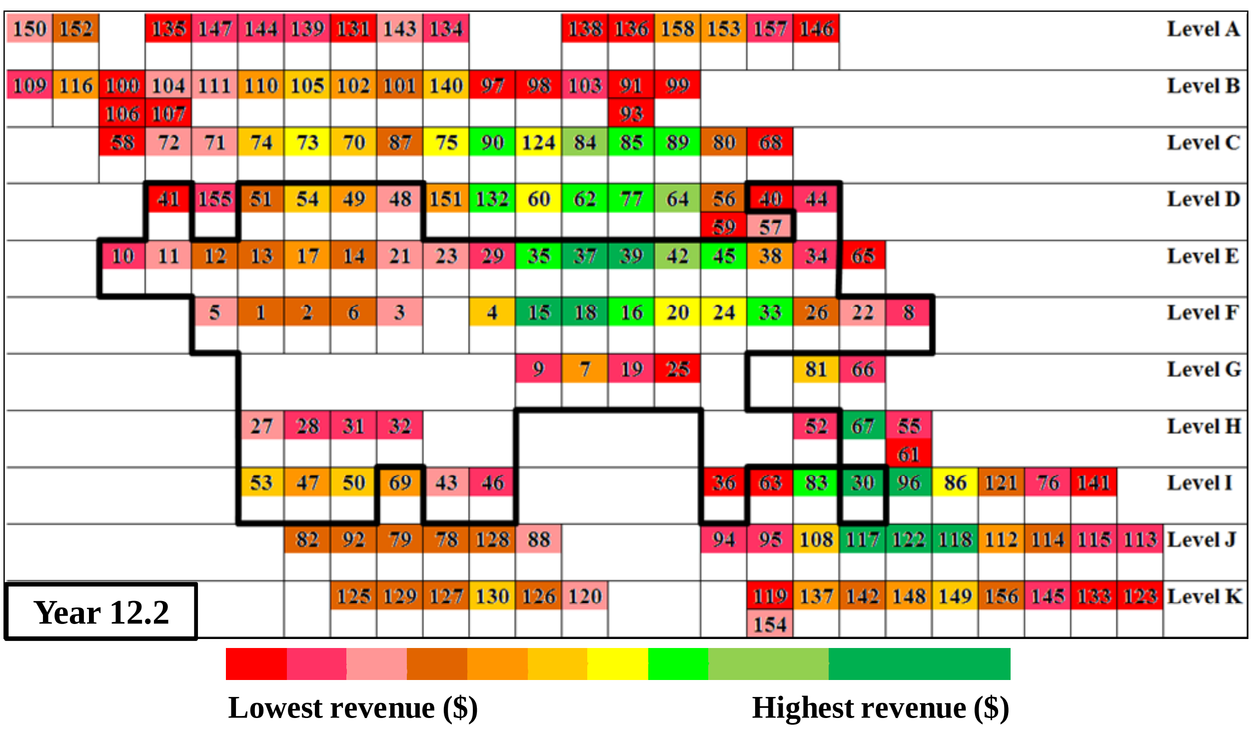


Figure 6-8 Scenario B: Optimized schedule stope sequence with undiscounted stope revenue

6.2 Scenario C: Mine schedule with geotechnical constraint

Scenario C incorporates geotechnical constraints on the mine schedule. The methodology for incorporating the geotechnical constraint involved tactical and strategic design as described in section 4.5.The tactical design approach was to pursue the ‘chevron’ pattern and primary and secondary stope sequence (Henning and Mitri, 2007; Villaescusa, 2003).The strategic design approach was to use the tactical design repeatedly for Zone A, Zone B and the sill pillar. This study included creating additional stope precedence links through Mine2-4D ® and EPS® software. The stope predecessor links thus permitted the geotechnical constraints and other defined adjacencies. The geotechnical constraints significantly restricted the search space for schedule optimization.

6.2.1 Comparison of performance indicators

Optimization using SOT was undertaken with the same convergence criteria and parameters as for Scenario A, and took 14.7 hours to complete. Figure 6-9compares the ore production profile between the unoptimized schedule and the optimized schedule. The prospect life was extended by 6 years compared to Scenario A, because the permissible geotechnical constrained utilization of the full capacity of the operational resources. The life of the prospect in the optimized schedule is four years shorter than the unoptimized schedule, since the ore production in the optimized schedule was less variable and higher than that of the unoptimized schedule. Figure 6-10 and Figure 6-11compare the mine development between the unoptimized and optimized schedules for the operational resources: jumbo drill and raise bore. For the optimized schedule, mine development under the jumbo drilling category was delayed, particularly because development for non-productive stopes was deferred to later in the schedule when it was required '*just-in-time*'. The earlier and high revenue ore production and *just-in-time* development is reflected in the discounted cash flow and NPV curves as shown in Figure 6-12.A higher NPV was realized sooner in the optimized schedule compared to the unoptimized schedule.

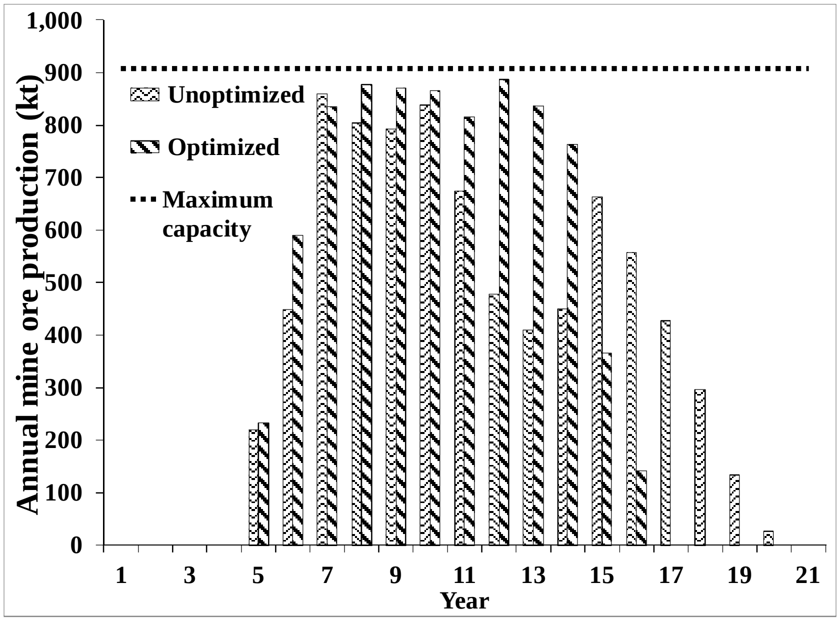


Figure 6-9Scenario C: Comparison of annual ore production between the unoptimized and optimized schedules (geotechnically constrained)

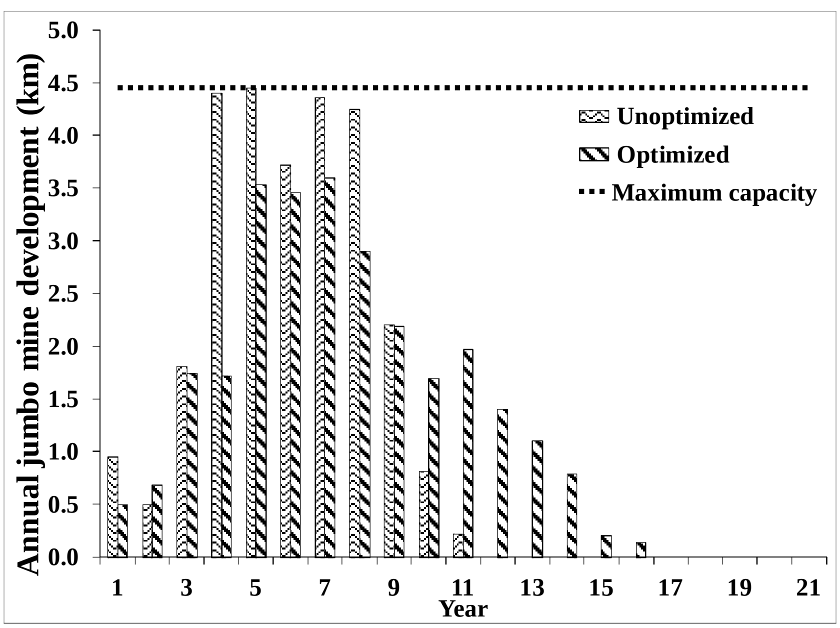


Figure 6-10Scenario C: Comparison of annual mine development between the unoptimized and optimized schedules (geotechnically constrained)

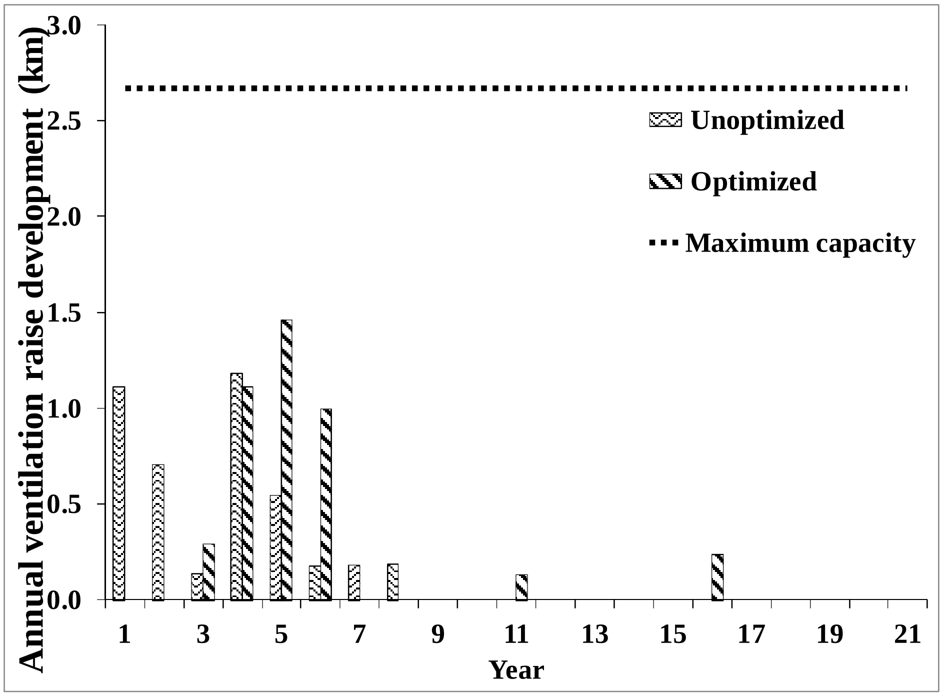


Figure 6-11Scenario C: Comparison of annual raise development between the unoptimized and optimized schedules (geotechnically constrained)

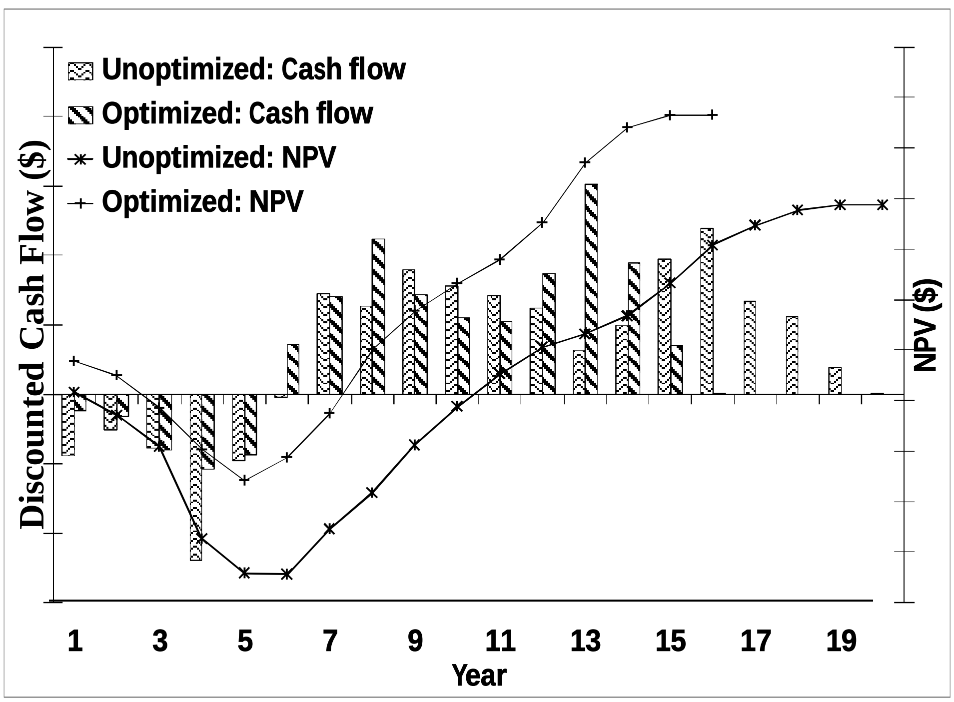


Figure 6-12Scenario C: Comparison of annual cash flow and NPV between the unoptimized and optimized schedules (geotechnically constrained)

6.2.2 Interpretation of the results

In the unoptimized schedule, due to geotechnical constraint, ore production was variable and delayed due to stope precedence logistics and therefore, the prospect life was increased by four years in comparison to the optimized schedule. The development was completed earlier and added higher discounted cost, which reduced the NPV. Even though the ventilation constraint was not considered, ore production still could not achieve the maximum capacity.

6.2.3 Comparison of the mine sequence

While comparing the results of the unoptimized and optimized schedule, the effects of optimization were evident. Since Scenario C was geotechnically constrained, the stope sequence was quite restrictive and significantly impacted the orebody value, in comparison to the other scenarios that were explored. Table 6-2 shows the development and the ore production at breakeven point for both cases. It shows that in addition to less mine development, there was also 31.5% less ore production at the breakeven point of the optimized schedule, which occurred3.9 years (204 weeks) earlier than that of the unoptimized schedule. Geotechnical constraints affected the ore production, therefore, in the optimized schedule, priority of the higher revenue stopes and mine development was completed *just-in-time*. The stope mine sequence during the life of the mine is shown in Figure 6-13for the unoptimized schedule. Figure 6-14and Figure 6-15show the relative order of stope sequence in the mine, and indicate that sequence organization has been modified in the optimized schedule.

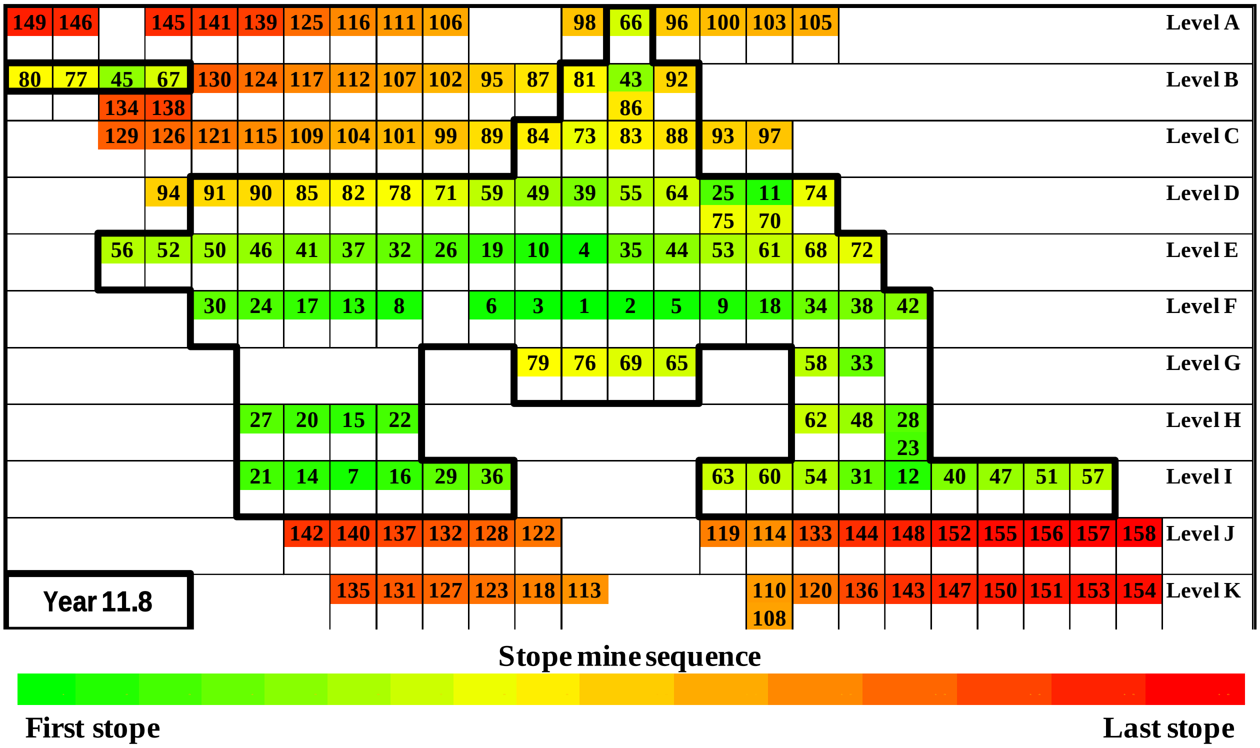


Figure 6-13Scenario C: Unoptimized schedule stope sequence for the life of mine and 92 stopes mined out at the breakeven point

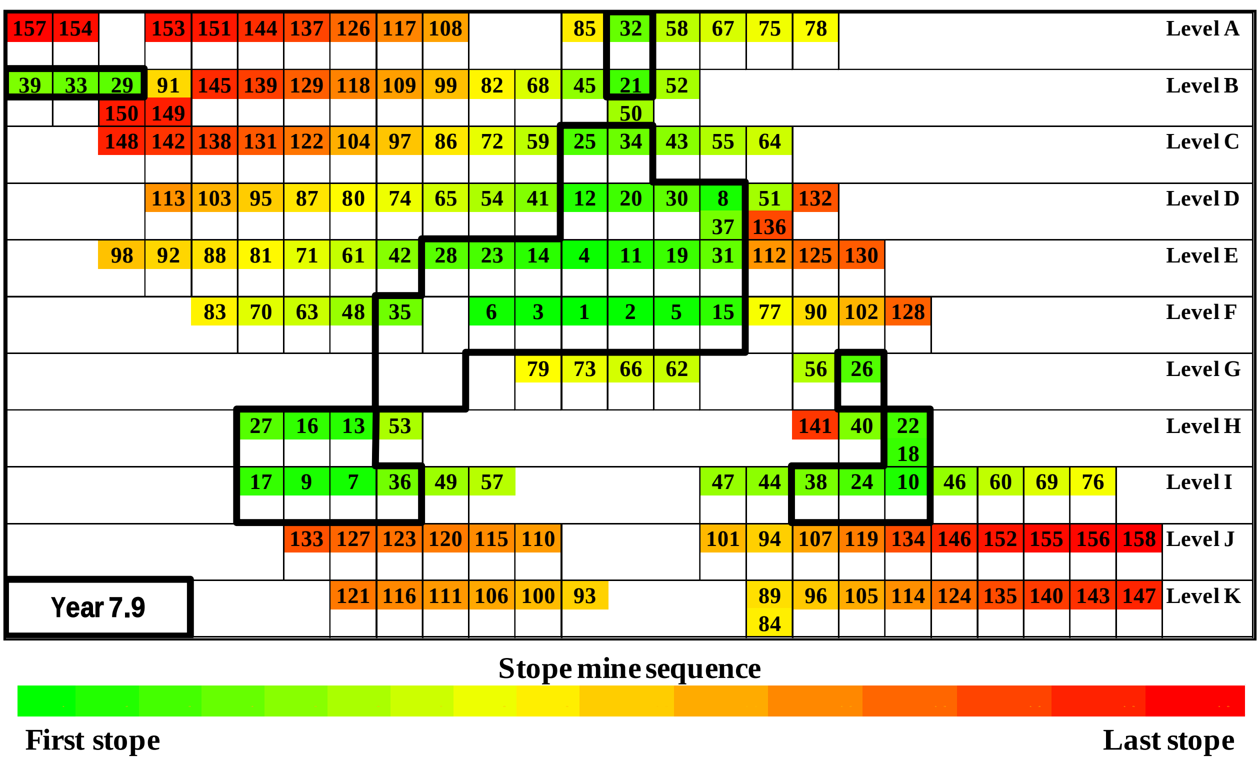


Figure 6-14Scenario C: Optimized schedule stope sequence for the life of mine and 39 stopes mined out at the breakeven point

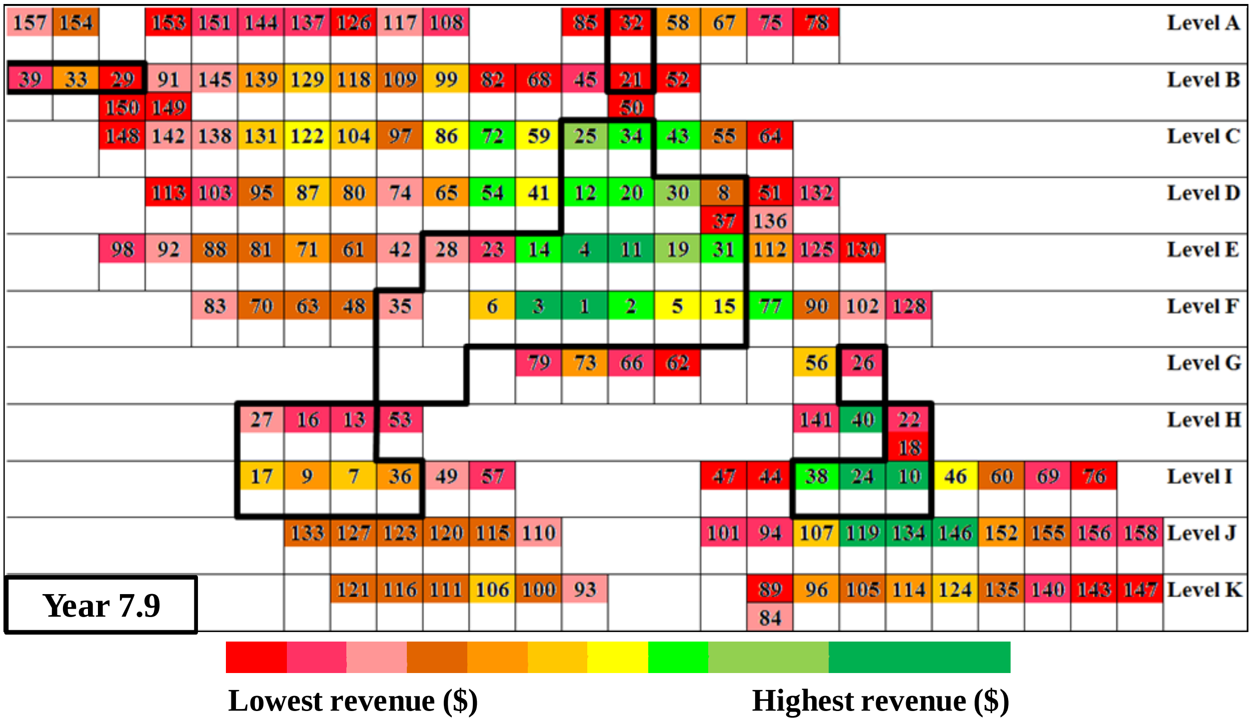


Figure 6-15 Scenario C: Optimized schedule stope sequence with undiscounted stope revenue.

Table 6-2 Scenario C: Comparison of mine development and ore production at the breakeven point between the unoptimized and optimized schedules

Scenario C	Total	Unoptimized	Optimized	Difference
Jackleg (m)	100%	100.0%	87.6%	12.4%
Jumbo (m)	100%	100.0%	65.6%	34.4%
Raise bore (m)	100%	100.0%	91.2%	8.8%
Ore (tonne)	100%	62.8%	31.3%	31.5%
Number of stopes	158	92	39	53
Breakeven year		11.8	7.9	3.9
Mine life (Year)		19.3	15.7	(3.7)

6.3 Scenario D: Mine schedule with geotechnical and ventilation constraints

Scenario B and C produced different schedules because the geotechnical and ventilation constraints were applied individually. In Scenario D, both geotechnical and ventilation constraints were applied simultaneously.

6.3.1 Comparison of performance indicators

Optimization using SOT was undertaken with the same convergence criteria and parameters as for Scenario A, and took 7.1 hours to complete. As shown in Figure 6-16, the optimized schedule mine life was four years shorter than for the unoptimized schedule. The optimized schedule produced a consistently higher ore production than the unoptimized schedule throughout the mine life. The addition of the ventilation constraint resulted in a drop in the annual ore production one third of full capacity for both optimized and unoptimized schedules. The mine development was consistently delayed and distributed throughout the mine life in the unoptimized schedule. The jumbo development is shown in Figure 6-17 and raise bore development is shown in Figure 6-18. In Figure 6-19, the ventilation capacity (m^3/s) was fully utilized for both studies. When ventilation and geotechnical constraints were collectively applied in Scenario D, the NPV changed significantly for the unoptimized schedule, as shown in Figure 6-20. This figure also shows that there was a significant difference in the NPV between the optimized and unoptimized schedules.

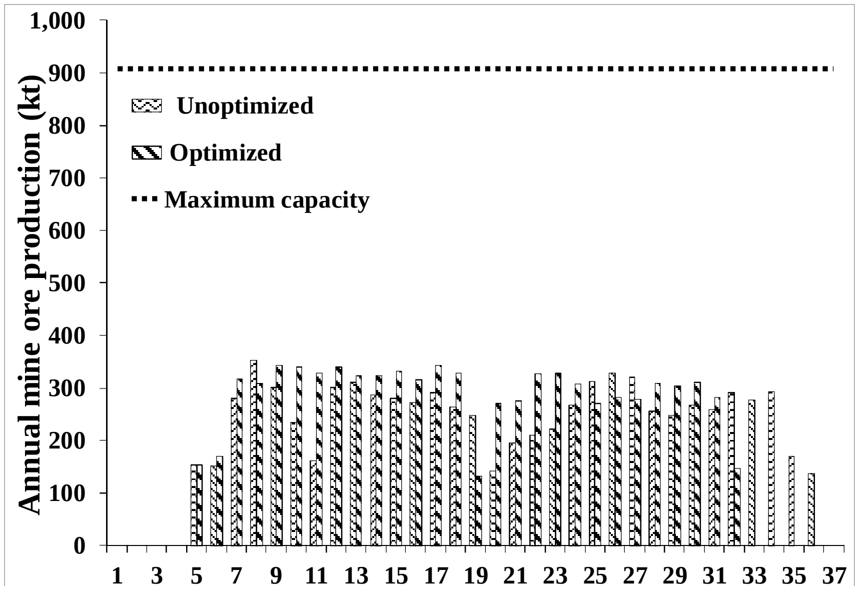


Figure 6-16 Scenario D: Comparison of annual ore production between the unoptimized and optimized schedules (ventilation and geotechnically constrained).

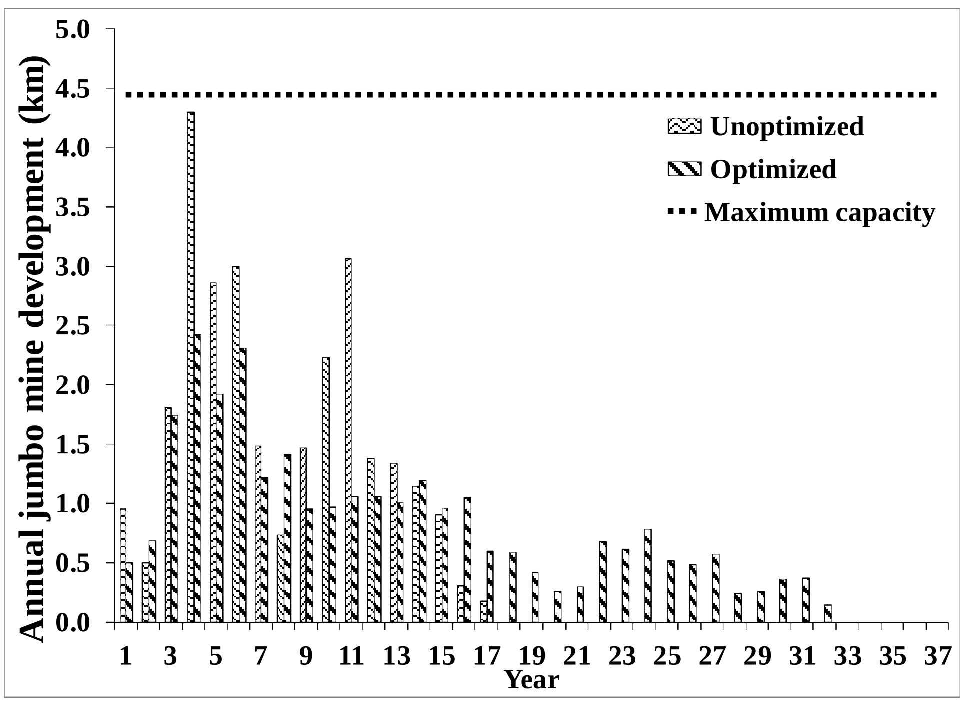


Figure 6-17 Scenario D: Comparison of annual mine development between the unoptimized and optimized schedules (ventilation and geotechnically constrained).

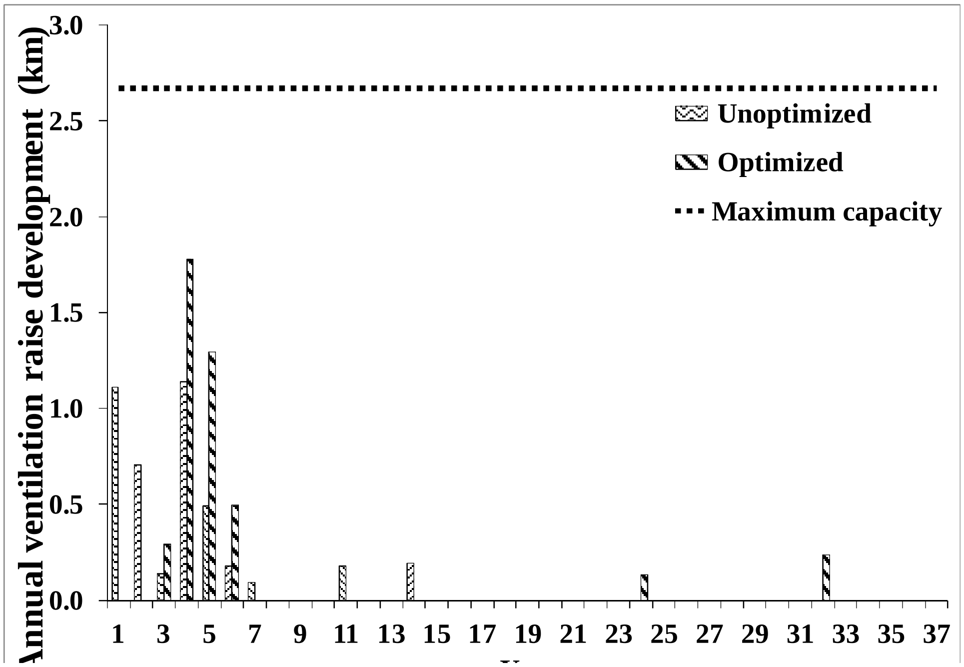


Figure 6-18 Scenario D: Comparison of annual raise development between the unoptimized and optimized schedules (ventilation and geotechnically constrained).

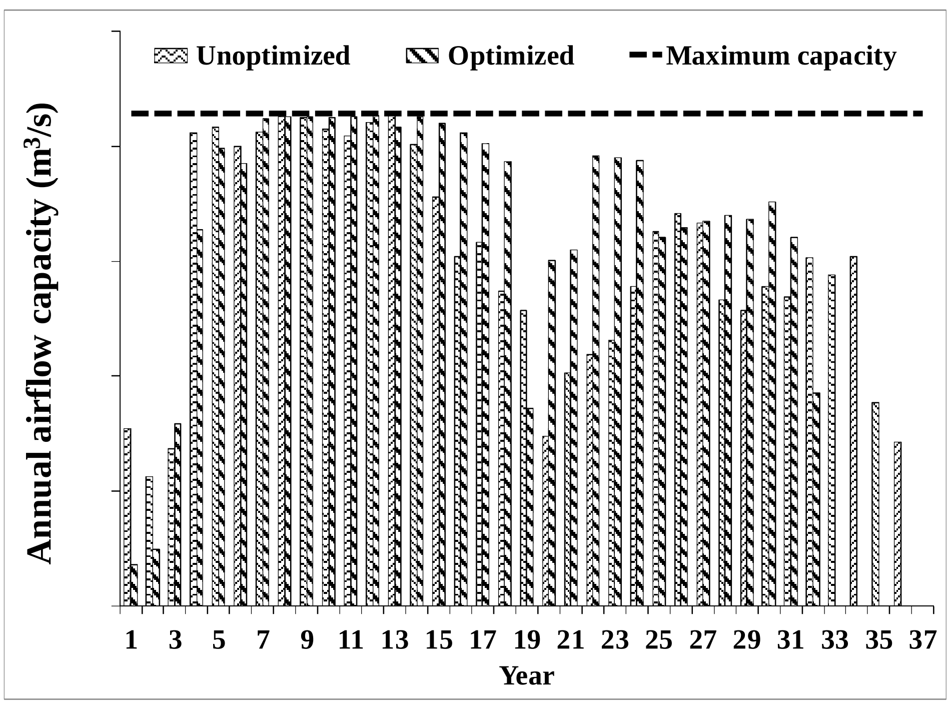


Figure 6-19 Scenario D: Comparison of annual airflow utilization between the unoptimized and optimized schedules (ventilation and geotechnically constrained).

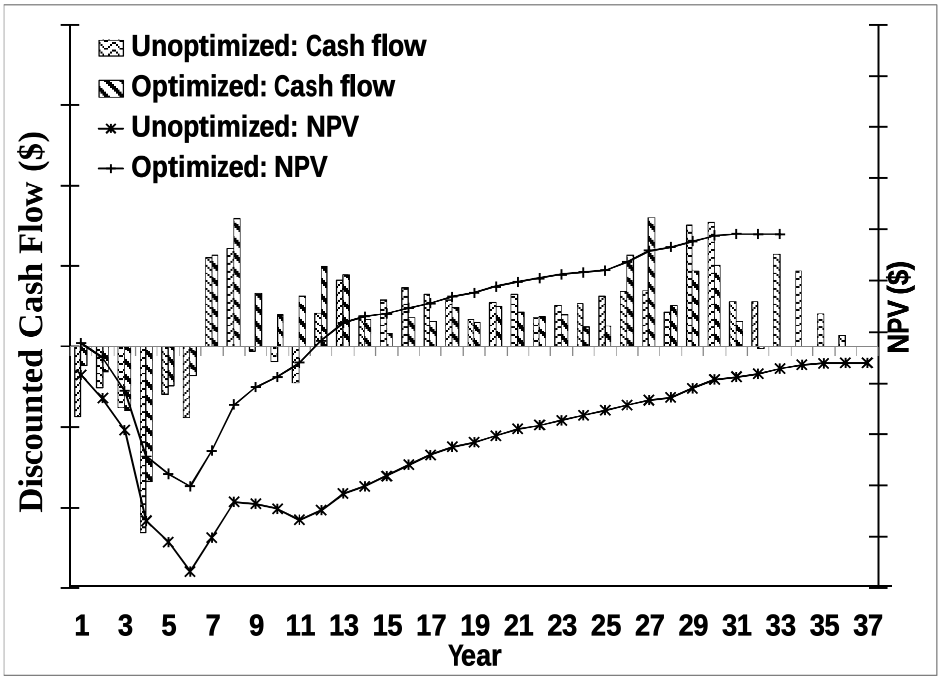


Figure 6-20 Scenario D: Comparison of annual cash flow and NPV between the unoptimized and optimized schedules (ventilation and geotechnically constrained).

6.3.2 Interpretation of the results

Due to the ventilation constraint, the ore production profile of both studies dropped to one third of the full capacity. The ventilation constraint had a greater negative impact on the production schedule than the geotechnical constraint. The NPV difference between unoptimized and optimized schedule was significant. The optimized schedule illustrated a higher degree of complex constraints and improved the mine value.

6.3.3 Comparison of the mine sequence

Scenario D was constrained by geotechnical and ventilation constraints; however, the optimized schedule is the more realistic approach for a mine sequence. Table 6-3 shows the development and ore production; however, the breakeven point was achieved only for the optimized schedule. The results in the optimized schedule shows that, in addition to mine development for different resource categories, there is 50.7% less ore produced. Due to the applied constraints, the unoptimized schedule never achieved the breakeven point, while it was achieved with the optimized schedule in the thirteenth year. Figure 6-21, Figure 6-22and Figure 6-23show the stope sequence of the mine. The sequence of the optimized schedule has been updated, unlike the unoptimized schedule, and after excavation of forty-six stopes, the schedule obtained a breakeven point.

Table 6-3 Scenario D: Comparison of mine development and ore production at breakeven point between the unoptimized and optimized schedules

Scenario D	Total	Study D1	Study D2	Difference
Jackleg (m)	100%	100.0%	60.9%	39.1%
Jumbo (m)	100%	100.0%	61.4%	38.6%
Raise bore (m)	100%	100.0%	91.2%	8.8%
Ore (tonne)	100%	100.0%	49.3%	50.7%
Number of stopes	158	158	46	112
Breakeven year			12.5	
Mine life (Year)		35.75	31.7	4.0

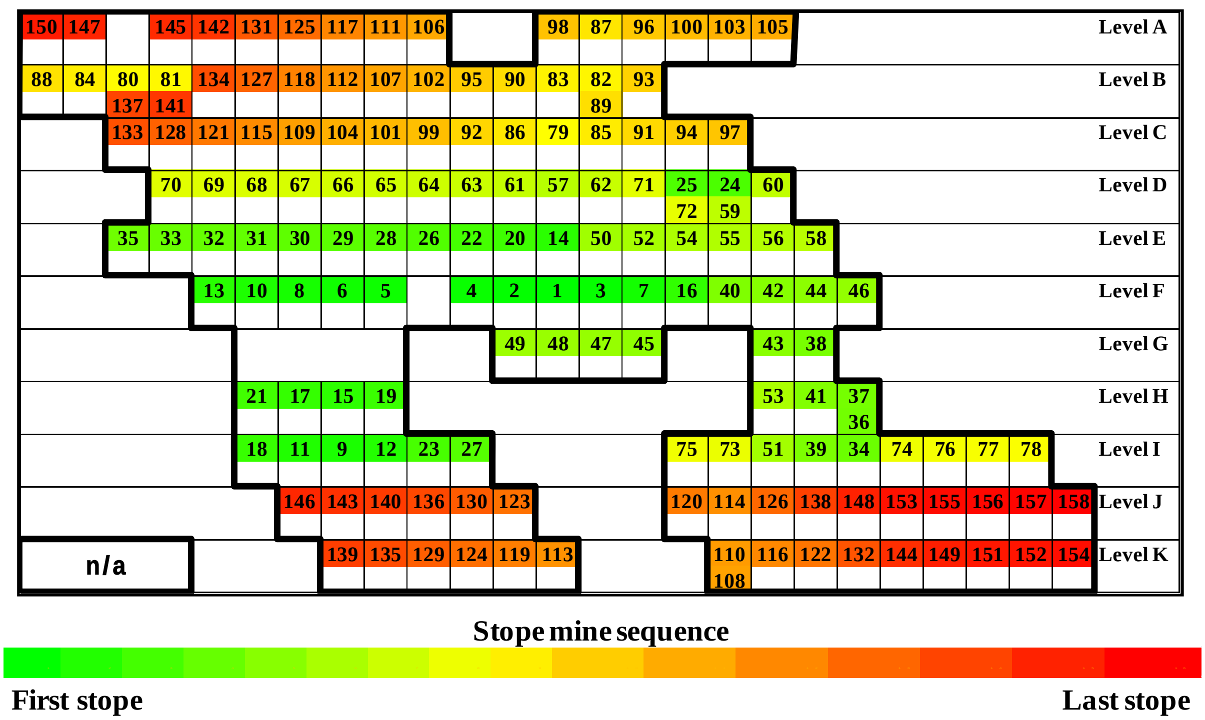


Figure 6-21Scenario D: Unoptimized schedule stope sequence for the life of mine and 158 stopes mined out at breakeven point

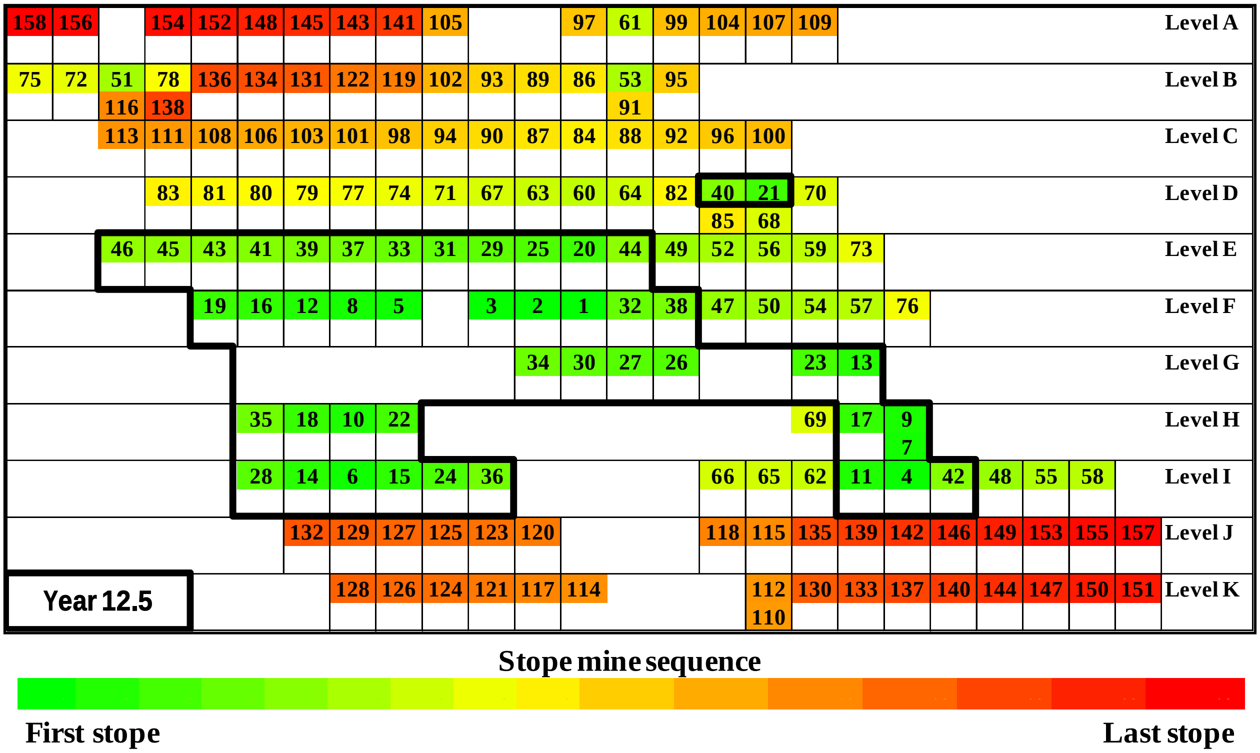


Figure 6-22Scenario D: Optimized schedule stope sequence for the life of mine and 46 stopes mined out at breakeven point

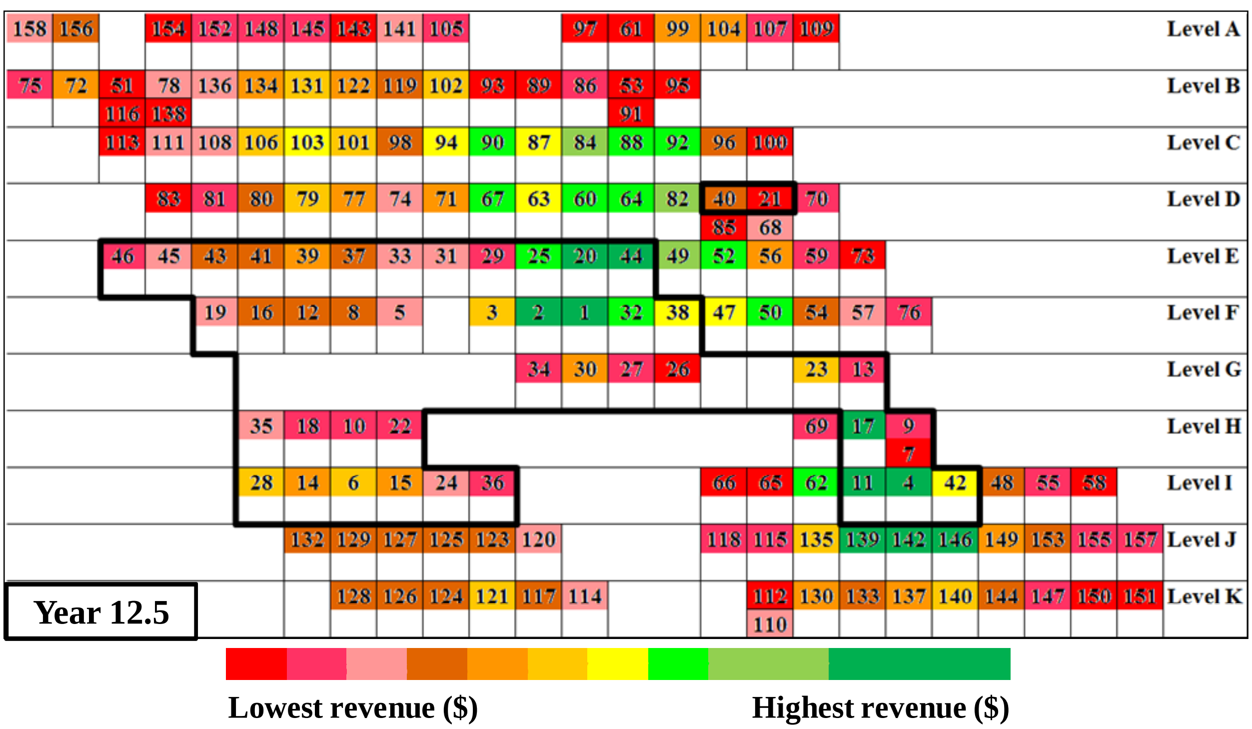


Figure 6-23 Scenario D: Optimized schedule stope sequence with undiscounted stope revenue.

6.4 Summarized results for all scenarios

The project NPV is summarized graphically for all the scenarios mentioned in Chapters4 and 5in Figure 6-24.The summary indicates that the opportunity to improve project value is directly proportional to the project complexity and degree of additionally applied constraints, as was expected. The results from the optimized schedules for Scenario B, C and D show that the ventilation constraint has foremost negative impact on the NPV of the mine. Table 6-4 summarizes the NPV improvement as a percentage of the unoptimized case for each scenario. In each case, the use of SOT has improved the prospect value significantly. For each scenario, there was roughly equal contribution to project value of '*sliding*' and GA driven optimization.

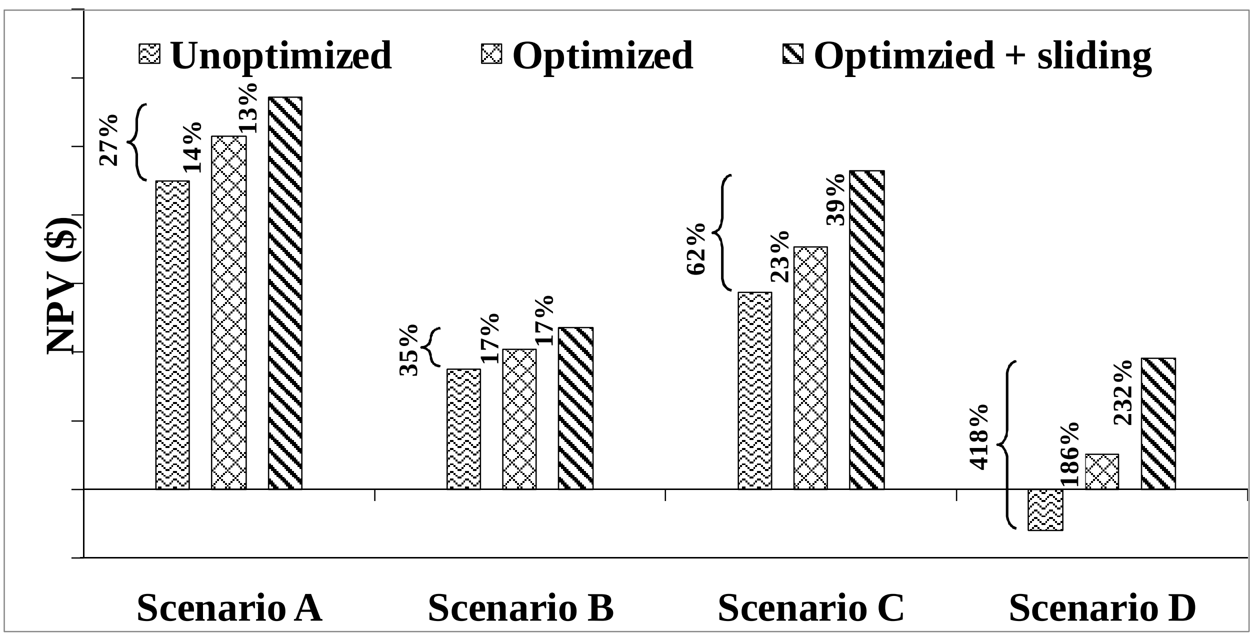


Figure 6-24 NPV of different scenario for the optimized and unoptimized schedules

Table 6-4 Net present values and differences between optimized and unoptimized schedules from different scenarios.

Scenario	Schedule	Mine life (years)	Difference in NPV (%)	Contribution of improved NPV	
				'sliding'	GA driven optimization
A	Unoptimized	13.3	27%	53%	47%
	Optimized	13.2			
B	Unoptimized	28.9	35%	52%	48%
	Optimized	28.1			
C	Unoptimized	19.8	62%	38%	62%
	Optimized	15.7			
D	Unoptimized	35.8	418%	45%	55%
	Optimized	31.7			

Based on the combinations of geotechnical and ventilation constraints, four different scenarios A, B, C and D were generated as illustrated in Figure 1-1. For each individual scenario, investigations were carried out and the outcomes were compared in terms of ore production, development and NPV. Table 6-5shows the computational time taken for different scenarios to be optimized.

SOT requires only a few hours of effort to test a large number of schedules on a desktop computer. Thus, the speed of evaluation of scenario revisions requires a few hours of additional effort. Conventional scheduling practices are no less complex, but are tedious and time consuming, as they are manual.

Table 6-5 Number of SOT optimized schedules and duration for different scenarios

Scenario	Number of schedules	Computational time (hours)
A	129,800	38.5
B	16,840	7.1
C	56,320	14.7
D	27,880	7.1

7 Extended assessments

7.1 Scenarios with flex of operating cost

An important factor to take into account in this study is the effect of varying operating costs on the robustness of the optimized schedule. Operating costs were systematically flexed for stoping and all development operational resources for each scenario, as presented in Chapter 5 and 6. The effect on the prospect NPV is illustrated in Figure 7-1. The NPV of the prospect changes significantly in each scenario between the optimized and unoptimized schedules. Figure 7-2 shows the difference between the NPV of the optimized schedules. These graphs illustrate that 10% variance in the operating cost variance changes the project value from 30% to 60%. A change in operating cost not only affects the project NPV but also the entire mining schedule.

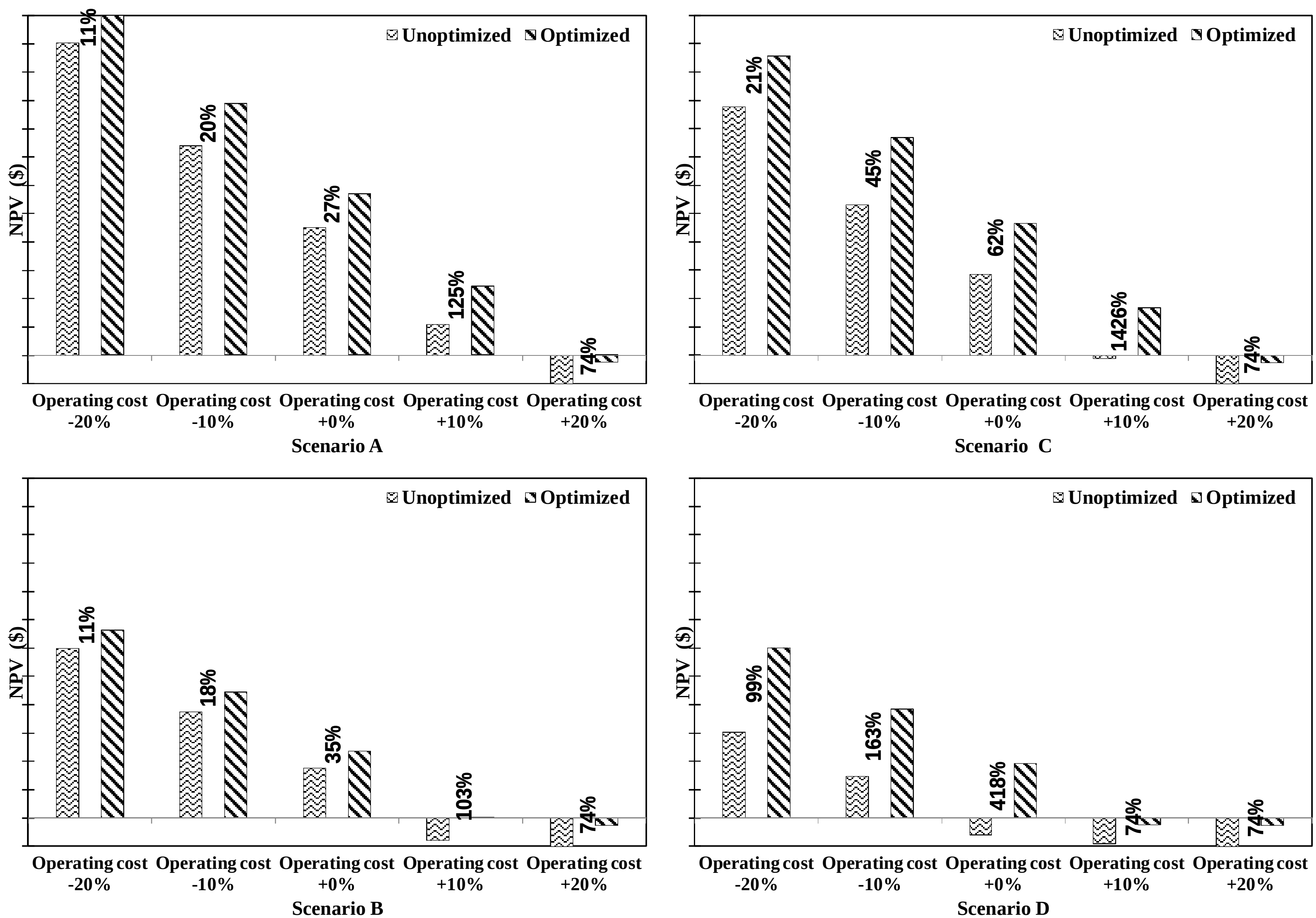


Figure 7-1 At variance of 10% operating cost, NPV of unoptimized and optimized schedules for all scenarios

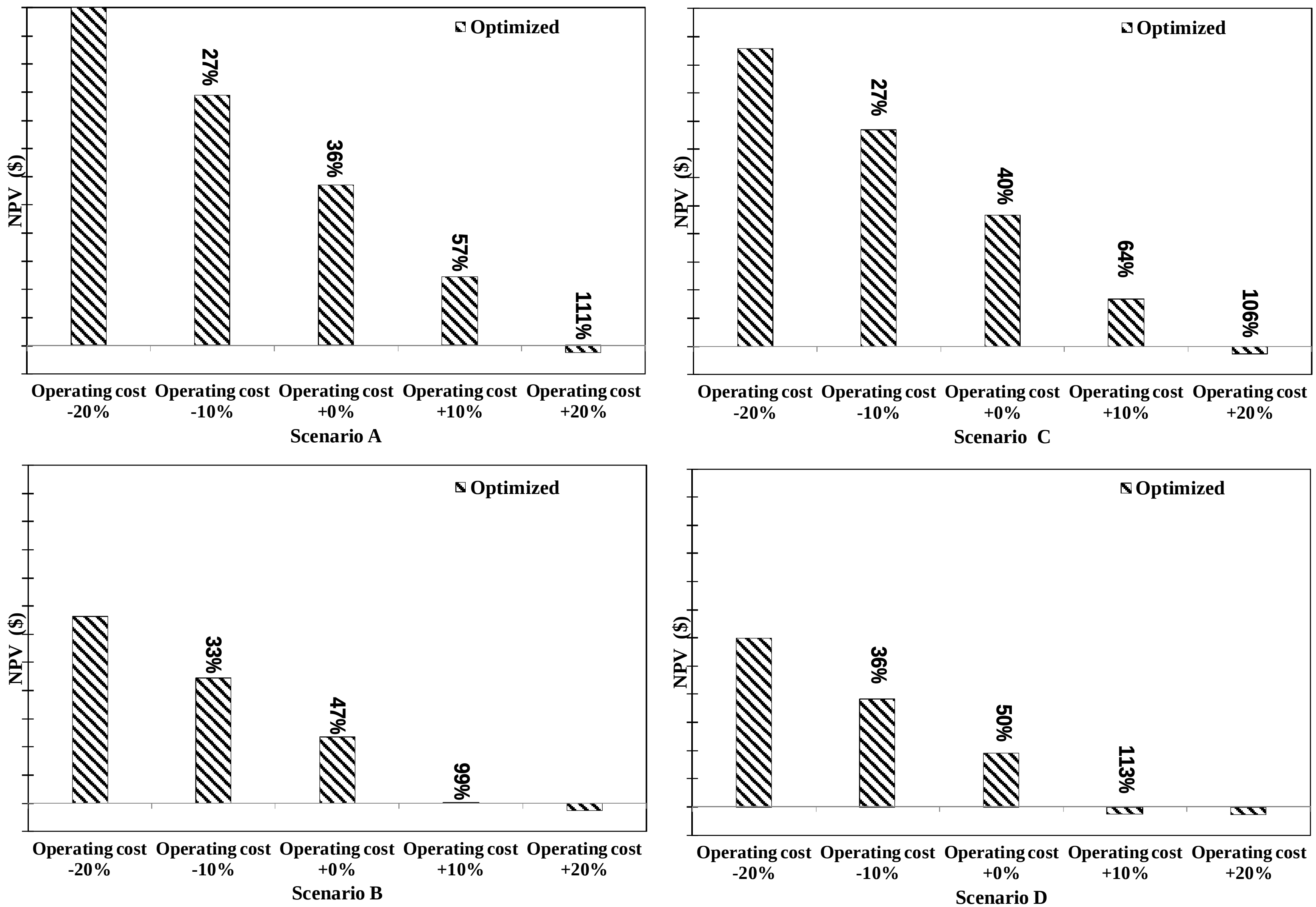


Figure 7-2At variance of 10% operating cost, difference of the NPV percentage for the optimized schedules for all scenarios

7.2 Scenario B: Alteration of ventilation constraint

From the results of the scenarios A-D, it was identified that ventilation is a key constraint for the prospect. To achieve improved value for the project, it is necessary to enhance the ventilation capacity. Scenario B was optimized with selected ventilation capacity, then one and a half of the capacity and twice the capacity. The purpose of this exercise was to find a ventilation capacity that allows the schedule to achieve the maximum hoisting capacity. Results of ore production, development and NPV are shown in Figure 7-3, Figure 7-4, Figure 7-5 and Figure 7-6. The results show that twice the ventilation capacity of the base case is required to maximum utilization of the operational resource.

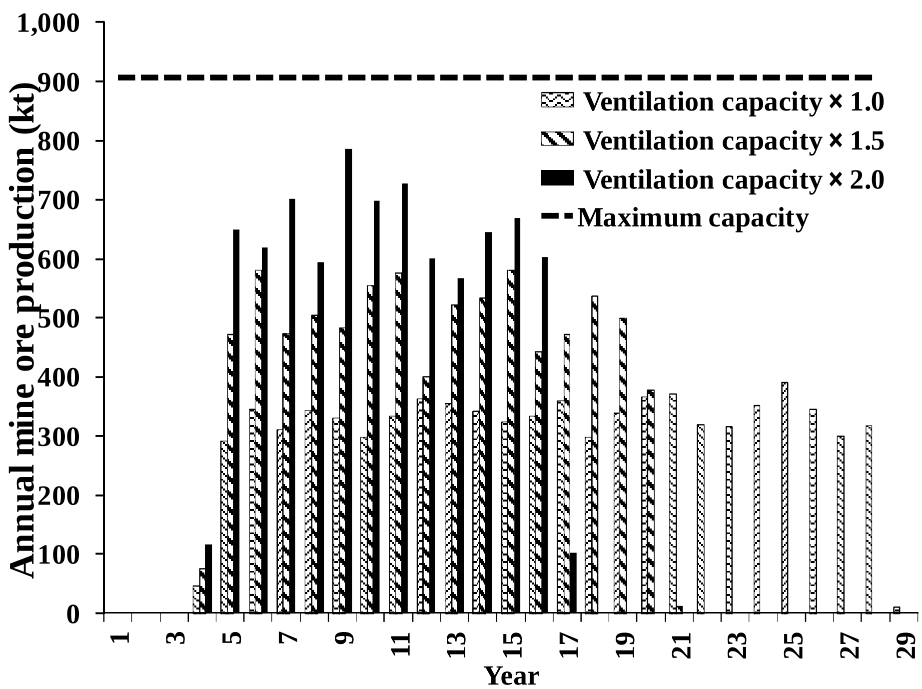


Figure 7-3 Optimized schedules for annual ore production at various ventilation capacities

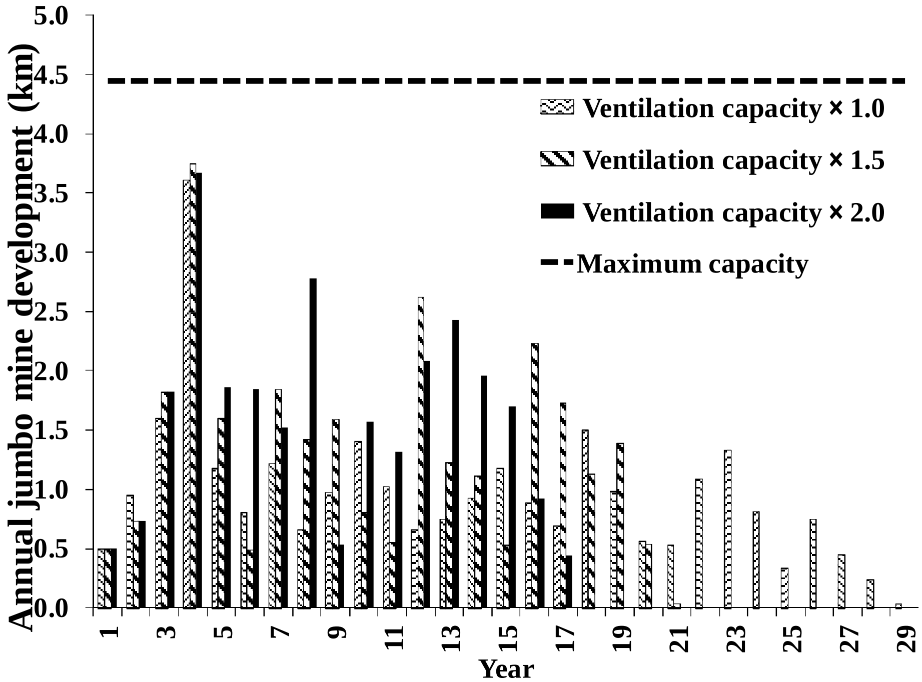


Figure 7-4Optimized schedules for annual mine development at various ventilation capacities

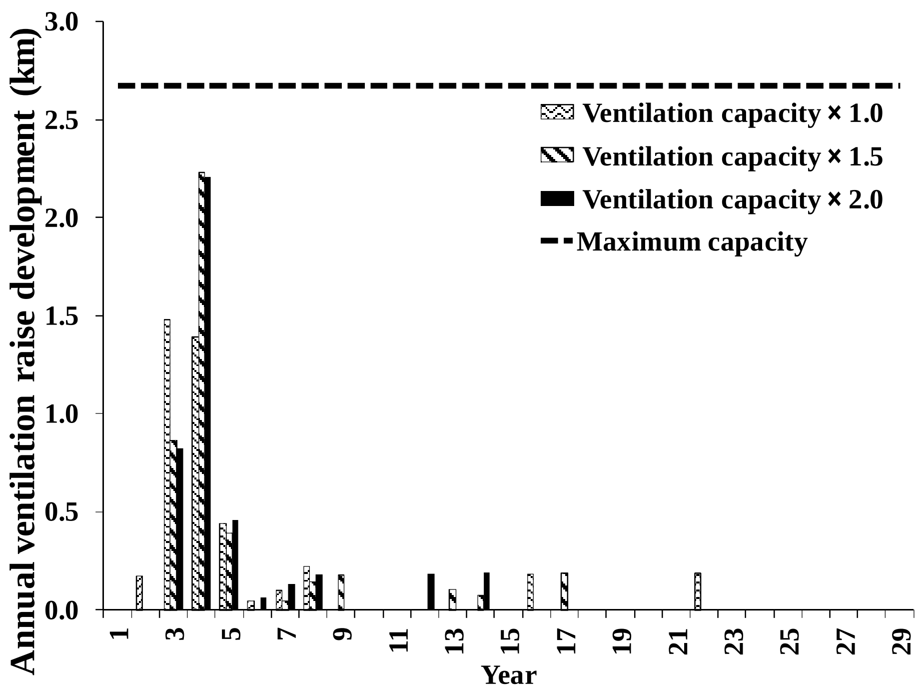


Figure 7-5Optimized schedules for annual ventilation raise development at various ventilation capacities

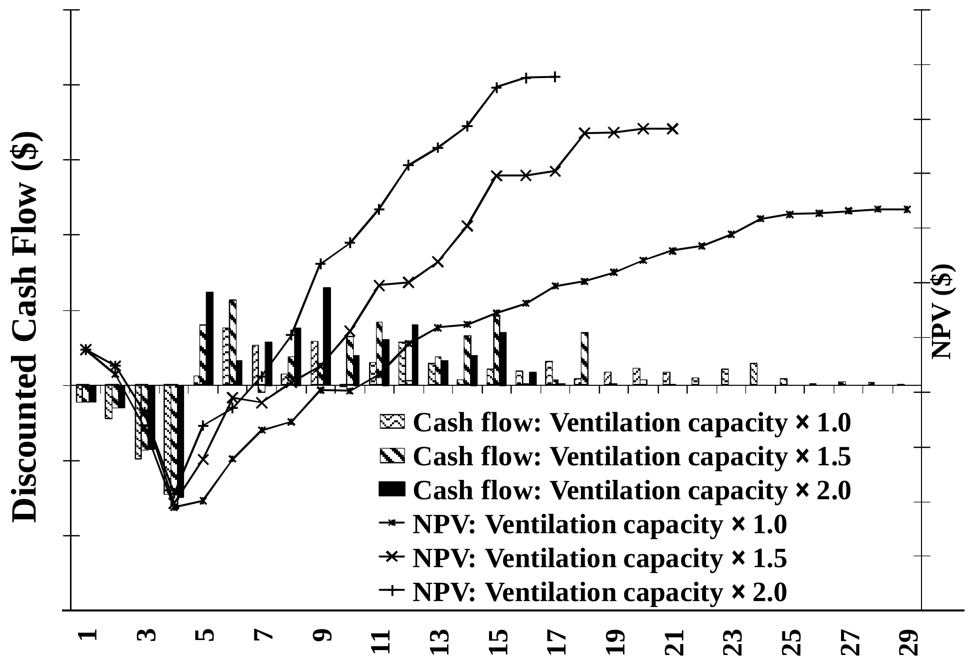


Figure 7-6Optimized schedules for annual cash flow and project value at various ventilation capacities

Table 7-1 The NPV and mine life with different ventilation capacities

Scenario	Ventilation capacity	Mine life (years)	Times increased project value
	1.0	28.1	1.00
B	1.5	20.2	1.63
	2.0	16.5	2.03

7.3 Conclusion

Results from the extended assessments show that in each case of increased ventilation capacity, there was improvement in the maximum use of operational resource and project value. These scenarios also help to estimate project life and project viability. These results can assist the mine project evaluation process. The increased project values from higher ventilation capacities are not the true project value however, it could help to evaluate a scenario when the capital cost for the higher ventilation capacity would be incorporated.

8 Summary and future work

8.1 Summary

SOT optimized the mine schedule with geotechnical, ventilation and operational resource constraints. This study accentuated that the optimized schedules increased profitability while meeting the other goals of the project such as effective utilization of operational resources capacities. The base case schedule was considered to study maximum potentiality and decide on the most beneficial stope sequence to initialize excavation. The optimized schedule from Scenario A has a significant upside potential, when no ventilation and geotechnical constraints were applied. Geotechnical and ventilation constraints were applied to Scenarios B, C and D, which had a negative effect on scheduling flexibility. The geotechnical constraint was used to ensure a practical stoping sequence while the ventilation constraint was implemented based on stope tonnes. The results show that the ventilation constraint has a significant negative impact on the project NPV.

The different scenarios with geotechnical and ventilation constraints showed that scheduling flexibility was affected. The results show a significant difference between the NPV of the optimized and unoptimized schedules for all scenarios, with the optimized schedules having a more favorable NPV than the unoptimized schedules.

The NPV of the mine increased by 26.9% in Scenario A because there were no geotechnical and ventilation constraints. The ventilation constraint was incorporated in Scenario B, and the NPV of the optimized schedule increased by 34.7% over the unoptimized schedule. To ensure that stoping sequences were more realistic, Scenario C was geotechnically constrained. The NPV of the optimized schedule increased by 62.0% over the unoptimized schedule. Both ventilation and geotechnical constraints were incorporated in Scenario D to reflect a more realistic mining operation. For Scenario D, the unoptimized schedule NPV was negative and the optimized schedule improved the NPV by 418.3%, making the project financially feasible.

The results of Scenario B and D demonstrate the significance of the ventilation constraint, as it also prevents utilization of other operational resources to their full capacity. The NPV difference between Scenario A and C shows that if the geotechnical constraint cannot be relaxed, there will likely be some amount of flexibility in how they are applied. Investigation of whether a geotechnically feasible schedule exists that can capture some of this upside potential could be undertaken in future research.

The speed with which SOT re-evaluated the project value was easily undertaken with the application of new constraints. This study also demonstrated that SOT permitted the rapid re-assessment of project value for new constraint scenarios. The results obtained through this study were encouraging. Overall, they showed that automated schedule optimization using SOT added value to a mining project every time a different scenario was applied.

The optimized schedule assists in analyzing mining strategies and examines the effect of changing the mining operation. An optimized schedule allows for the evaluation of future actions against specific goals and identifies an appropriate course of action from the available alternatives. Therefore, an optimized schedule improves confidence for planning and forms the basis for improved decision making, which in turn contributes to better mining performance and higher profitability.

SOT provides significant potential performance benefits to underground mining operations including (i) long-term planning decisions, (ii) optimization of mine activities, (iii) effective utilization of operational resources, (iv) efficient stoping and extraction strategies, (v) consistent accomplishment of ore production targets, and (vi) competency to rapidly re-optimize with new and improved information.

The SOT solution adds value to the schedule through (i) accelerated ore production from high revenue stopes, (ii) delaying unnecessary mine development, (iii) circumventing cost-added alternatives for stoping and (iv) consistent operational resource management. Each mining activity has a physical dimension or a time dimension. Subsequently, each of these mining activities is connected with dependencies. SOT optimized the sequence of these activities in a chronological and feasible order in a very short period of time. Taking into account the discounting factor, while development activities are delayed until needed and activities that generated revenue are executed in early phase of mine, the application of SOT added value to the mine project.

8.2 Future work

The mine was shown to have a significant upside potential with the unconstrained schedule. It may be worthwhile to investigate whether a geotechnically feasible schedule exists that could capture some of this potential.

Further comprehensive financial inputs are required to specify the rates and costs for individual categories of mine operations at different locations and levels. For the revenue calculation, the mineral prices have to be confirmed and updated to compute equivalent pre-calculated revenue.

The ventilation constraint negatively affected the production capacity, thus an additional allocation of ventilation capacity might improve NPV. However, this depends on the additional operating cost and capital investment required for ventilation capacity expansion. Furthermore, optimization of the ventilation circuit at the initial stage of the mine could reduce overall costs. The control of primary ventilation circuits in the mine requires careful planning from the design stage and throughout the operating life of the mine. It was observed that as part of the initial design of the mine, simulation of the ventilation network could help to improve revenue.

The degree of impact of each constraint is different in different mines; each underground mine presents a unique scheduling problem to solve. For example, numerous reasons arise in the course of execution of a mining plan that precludes the adoption of a standard mining scheme. In all but the most massive disseminated ores, level spacing, stope width, pillar dimensions, etc must be varied as the orebody disposition becomes apparent through mining.

References

Ackley, D.H., 1987. A connectionist machine for genetic hillclimbing. Kluwer Academic Publishers.

Aycock, J., 2003. A brief history of just-in-time. ACM Computing Surveys, Volume 35, No. 2, pp. 97–113.

Bai, X., Marcotte, D., Simon, R., 2014. A heuristic sublevel stope optimizer with multiple raises. The journal of the southern African institute of mining and metallurgy, Volume 114, pp. 427–434.

Ballington, I., Bondi, E., Hudson, J., Lane, G., Symanowitz, J., 2004. A practical application of an economic optimisation model in an underground mining environment, AusIMM Conference: Ore Body Modelling and Strategic Mine Planning, Perth., pp. 211-220

Blattman, M.J., 2003. Creation of an underground mine development sequencing optimizer. SME Annual meeting. Cincinnati, Ohio, Preprint 03-064, pp.1–8.

Bley, A., Terblanche, S., 2011. An improved formulation of the underground mine scheduling optimization problem when considering selective mining. Optimization Online, Centre for Business Mathematics and Informatics, North-West University (Potchefstroom), South Africa.http://www.optimization-online.org/DB_HTML/2012/11/3687.html

Blum, C., Chiong, R., Clerc, M., Jong, K.A.D., Michalewicz, Z., Neri, F., Weise, T., 2012. Evolutionary optimization, in: Variants of Evolutionary Algorithms for Real-World Applications. pp. 1–29.

Brake, D.J., Nixon, T., 2008. Correctly estimating primary airflow requirements for underground metalliferous mines. Proceedings of the 10th underground operators conference, Launceston, Tasmania. pp. 1–6.

Brazil, M., Lee, D.H., Rubinstein, J.H., Thomas, D.A., Weng, J.F., Wormald, N.C., 2002. A network model to optimise cost in underground mine design. Transactions-South African Institute of Electrical Engineers Volume 93, pp. 97–103.

Burjorjee, K.M., 2013. Explaining optimization in genetic algorithms with uniform crossover, in: Proceedings of the Twelfth Workshop on Foundations of Genetic Algorithms XII. ACM, pp. 37–50.

D’Angelo, D., Gardner, P., 2008. Going deeper – has your mine plan fully considered ventilation? in: Tenth Underground Operators’ Conference. Carlton, Vic. : Australasian Institute of Mining and Metallurgy, Launceston, Tasmania, pp. 109–114.

Dao, S., Marian, R., 2011. Optimisation of Precedence-constrained Production Sequencing and Scheduling Using Genetic Algorithms. Proceedings of the International MultiConference of Engineers and Computer Scientists Hong Kong. Newswood Limited pp. 59-64

De Jong, K.A., 1975. An analysis of the behavior of a class of genetic adaptive systems. University of Michigan, Ann Arbor, MI, USA. Technical report No. 185 pp. 48-91

Denby, B., Schofield, D., 1995. The use of genetic algorithms in underground mine scheduling, in: Proceedings of the 25th International Symposium Application of Computers Mineral Industries. pp. 389–394.

Eberhart, R.C., Kennedy, J., 1995. A new optimizer using particle swarm theory, in: Proceedings of the Sixth International Symposium on Micro Machine and Human Science. New York, NY, pp. 39–43.

Eivazy, H., 2013. SOT problem statement. Unpublished internal research. MIRARCO, Sudbury, Canada.

Engelbrecht, A.P., 2006. Fundamentals of computational swarm intelligence. John Wiley & Sons.

EPS, 2014. Enhanced Production Scheduler (EPS) [WWW Document]. URL http://www.minerpsolutions.com/en/software/planningsched/EPS.aspx

EPS V2, 2012. , Leveling Help. EPS v2 © 2013 Sirius Consulting.

Fava, L., Goforth, D., Van Wageningen, A., Dunn, P., Cameron, C., Muldowney, D., 2005. A parallel composite genetic algorithm for mine scheduling, in: 9th IASTED International Conference on Artificial Intelligence and Soft Computing, ASC 2005, September 12, 2005 - September 14, 2005, Proceedings of the 9th IASTED International Conference on Artificial Intelligence and Soft Computing, ASC 2005. Acta Press, pp. 245–250.

Fava, L., Maybee, B., Millar, D., 2012. Decision support for an underground gold mining operation - A case study using the schedule Optimisation tool, in: 3rd Conference on Project Evaluation 2012, May 24, 2012 - May 25, 2012, Australasian Institute of Mining and Metallurgy Publication Series. Australasian Institute of Mining and Metallurgy, pp. 41–48.

Fava, L., Millar, D., Maybee, B., 2011. Scenario evaluation through Mine Schedule Optimisation. In Proceedings of the 2nd International Seminar on Mine Planning, Gecamin, Santiago, pp. 1-10

Fava, L., Saavedra Rosas, J., Tough, V., Haarala, P., 2013. Heuristic optimization of scheduling scenarios for achieving strategic mine planning targets. Presented at the 23rd World Mining Congress, Canadian Institute of Mining, Metallurgy and Petroleum.

Floudas, C.A., Lin, X., 2005. Mixed integer linear programming in process scheduling: Modeling, algorithms, and applications. Annals of Operations Research Volume 139, pp. 131–162.

Foster, J.D., Berry, A.M., Boland, N., Waterer, H., 2014. Comparison of Mixed-Integer Programming and Genetic Algorithm Methods for Distributed Generation Planning. IEEE transactions on power systems, Volume 29, No. 2, pp. 833-843

Gamble, B., 2007. Risk analysis and decision-making – a case study, Presented at the Project Evaluation 2007, The Australasian Institute of Mining and Metallurgy, Melbourne, pp. 19–32.

Gershon, M.E., 1985. Developments in computerized mine production scheduling. in: SME-AIME Annual Meeting., Preprint - Society of Mining Engineers of AIME, Littleton, CO, USA, Transactions Volume 28, pp. 1801-1804

Goldberg, D.E., 1985. Dynamic system control using rule learning and genetic algorithms., in: International Joint Conference on Artificial Intelligence. Volume 85, pp. 588–592.

Hall, B., 2007. Evaluating all the alternatives to select the best project strategy, in: Project Evaluation Conference 2007, June 19, 2007 - June 20, 2007, Australasian Institute of Mining and Metallurgy Publication Series. Australasian Institute of Mining and Metallurgy, pp. 53–64.

Hartmann, S., 1998. A competitive genetic algorithm for resource-constrained project scheduling. Naval Research Logistics (NRL) Volume 45,Issue 7, pp. 733–750.

Hazewinkel, M., 2001. Steiner tree problem. Encyclopedia of Mathematics Springer ISBN 978-1556080104

Heinz, S., Beck, J.C., 2012. Reconsidering mixed integer programming and MIP-based hybrids for scheduling, in: Integration of AI and OR Techniques in Constraint Programming for Combinatorial Optimization Problems. Springer, pp. 211–227.

Henning, J.G., Mitri, H.S., 2007. Numerical modelling of ore dilution in blasthole stoping. International Journal of Rock Mechanics and Mining Sciences. Volume 44, Issue 5, pp. 692–703.

Holland, J.H., 1975. Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control and artificial intelligence. U Michigan Press.

Howes, M.J., 2013. Ventilation and Cooling in Underground Mines [WWW Document]. URL http://www.ilo.org/oshenc/part-xi/mining-and-quarrying/item/604-ventilation-and-cooling-in-underground-mines (accessed 2.3.14).

Jang, H., Topal, E., 2014. A review of soft computing technology applications in several mining problems. Applied Soft Computing Volume 22, pp. 638–651. doi:10.1016/j.asoc.2014.05.019

Kawahata, K., Schumacher, P., Hufford, R., 2013. Mine production scheduling optimization at Newmont's Twin Creeks Mine. Mining Engineering, Volume 65, pp. 49–54.

Kennedy, J., 2010. Particle swarm optimization, in: Encyclopedia of Machine Learning. Springer, pp. 760–766.

Kok, D., Lane, G.R., 2012. Case study: using software optimization techniques for the optimal allocation of equipment in a mechanized underground mining environment, in: A Catalyst for Change. Presented at the Fifth International Platinum Conference, Sun City, South Africa. pp. 35-48.

MacMillan, A., Ross, A.G., 2004. Frontline planning and scheduling at INCO's copper cliff smelter complex. Journal of the Minerals, Metals and Materials Society Volume 56, Issue 12, pp. 28–28.

Martinez, M.A., Newman, A.M., 2011. A solution approach for optimizing long-and short-term production scheduling at LKAB's Kiruna mine. European Journal of Operational Research. Volume 211, Issue 1, pp. 184–197.

Maybee, B., Fava, L., Dunn, P.G., Wilson, S., Fitzgerald, J., 2010a. Toward optimum value in underground mine scheduling. CIM Journal, Volume 1(3), pp. 176–182.

Maybee, B.M., 2010. A Risk-Based Evaluation Methodology for Underground Mine Planning. Phd Thesis, Laurentian University (Canada).

Michalewicz, Z., 1996. Genetic algorithms+ data structures= evolution programs. springer.

MineRP, 2014. Mine2-4D [WWW Document]. URL http://www.minerpsolutions.com/

MineSchedTM, 2010. Underground Scheduling GEOVIA. URL http://www. gemcomsoftware. com

Morrison, D., 1995. Fragmentation–the future. Proceeding Explo'95 pp. 11–18.

Mun, J., 2006. Modeling risk: Applying Monte Carlo simulation, real options analysis, forecasting, and optimization techniques. Volume 347 John Wiley & Sons.

Musingwini, C., Minnitt, R.C.A., Phuti, D., Makwara, F., 2003. Just-in-time development model for a sub-level caving underground mine in Zimbabwe. Journal of the South African Institute of Mining and Metallurgy Volume 103, Issue 3, pp. 187–191.

Nehring, M., Topal, E., Little, J., 2010. A new mathematical programming model for production schedule optimization in underground mining operations Journal of the South African Institute of Mining and Metallurgy Volume 110, Issue 8, pp. 437-446.

Newman, A.M., Rubio, E., Caro, R., Weintraub, A., Eurek, K., 2010. A review of operations research in mine planning. Interfaces Volume 40, Issue 3, pp. 222–245.

Pearl, J., 1984. Heuristics. Addison-Wesley Publishing Company Reading, Massachusetts.

Pei, J., Han, J., Wang, W., 2002. Mining sequential patterns with constraints in large databases, in: Proceedings of the Eleventh International Conference on Information and Knowledge Management. ACM, pp. 18–25.

Pezzella, F., Morganti, G., Ciaschetti, G., 2008. A genetic algorithm for the flexible job-shop scheduling problem, Computers & Operations Research, Volume 35, Issue 10, pp. 3202–3212.

Pop, P.C., Matei, O., 2012. A genetic programming approach for solving the linear ordering problem, in: Hybrid Artificial Intelligent Systems. Springer, pp. 331–338.

Saavedra Rosas, J.F., 2009. A genetic optimizer for stochastic problems with applications to orebody uncertainty in mine planning. Phd Thesis, Laurentian University (Canada).

Sakalauskas, L., Felinskas, G., 2006. Optimization of resource constrained project schedules by genetic algorithm based on the job priority list. ISSN 1392–124X Information Technology And Control, Volume 35, Issue 4, pp. 412–418.

Sivanandam, S.N., Deepa, S.N., 2008. Genetic Algorithm Optimization Problems. Springer.

Smit, A., Lane, G., 2010. Mine optimization and its application using the Anglo Platinum Mine Optimisation Tool (APMOT), in: Platinum in Transition "Boom or Bust." Presented at the 4th International Platinum Conference, The Southern African Institute of Mining and Metallurgy, pp.317-328.

Smith, J.C., Taskin, Z.C., 2008. A tutorial guide to mixed-integer programming models and solution techniques. Optimization in Medicine and Biology, pp. 521–548.

Smith, M.L., 2007. Life of business optimisation – the mathematical programming approach, in: Project Evaluation 2007. Presented at the Project Evaluation 2007, The Australasian Institute of Mining and Metallurgy, Melbourne, pp. 139–146.

Stinnette, J., 2013. Establishing Total Airflow Requirements for Underground Metal/Non-metal Mines based on the Diesel Equipment Fleet. Master thesis, Queens University, Canada.

Torries, T.F., 1998. Evaluating Mineral Projects: Applications And Misconceptions Publisher: Society For Mining Metallurgy & Exploration, ISBN-13: 9780873351591.

Toth, P., Vigo, D., 2001. The Vehicle Routing Problem. Society for Industrial and Applied Mathematics.

Varendorff, R. von, 2003. Confidence in Mine Planning — The Role of Intelligent Technologies, in: Mine Planning and Equipment Selection. 23-25 April 2003, Kalgoorlie, Western Australia: Hosted by Curtin University of Technology, WASM, IJSM. AusIMM, Carlton, Victoria, pp. 35–40.

Villaescusa, E., 2003. Global extraction sequences in sublevel stoping, in: MPES 2003, Conference Kalgoorlie April 2003.

Wallace, K.G., 2001. General operation characteristics and Industry practices of mine ventilation systems, in: Proceedings of the 7th International Mine Ventilation Congress, Krakow, Poland. pp. 229–234.

Wang, H.-F., Wu, K.Y., 2003. Modeling and analysis for multi-period, multi-product and multi-resource production scheduling. Journal of Intelligent Manufacturing, Volume 14, Issue 3-4, pp. 297–309. doi:10.1023/A:1024645608673

Wong, C.K., Fung, I.W.H., Tam, C.M., 2010. Comparison of using mixed-integer programming and genetic algorithms for construction site facility layout planning. Journal of Construction Engineering and Management, Volume 136, Issue 10, pp. 1116–1128.

XPRESS Solver Engine [WWW Document], 2014. Solver. URL http://www.solver.com/xpress-solver-engine (accessed 8.20.14).

Yamada, T., Nakano, R., 1997. Job shop scheduling. Chapter 7, Genetic algorithms in engineering systems, IEE control engineering series Volume 55, pp. 134–134.

Yun, Q.X., Guo, W.W., Chen, Y.F., Lu, C.W., Lian, M.J., 2003. Evolutionary algorithms for the optimization of production planning in underground mines. Application of Computers and Operations Research in the Minerals Industries, South African Institute of Mining and Metallurgy, pp.311-314

Yun, Q.X., Liu, S.H., 2002. Genetic programming for the design of underground mining methods, in: APCOM 2002: 30 The International Symposium on the Application of Computers and Operations Research in the Mineral Industry, pp. 433–440.

Zaknich, A., 2006. Principles of adaptive filters and self-learning systems. Springer.

Zhanyou, H., Cai, W., Benfield, F., 2009. A mixed integer linear programming based short term planning tool, in: Application of Computers and Operations Research (APCOM 2009). Canadian Institute of Mining Metallurgy and Petroleum (CIM), Vancouver, Canada, Volume 1, pp. 1–10. ISBN 9781618399939.