Hierarchical mine production scheduling using discrete-event simulation

Eugene Ben-Awuah, Samira Kalantari
Yashar Pourrahimian, and Hooman Askari-Nasab
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Canada

Abstract

Mine planning involves different levels of decision-making depending on the time horizon under consideration. Long-term production plans determine the optimal sequence of mining and allocation of resources over a yearly time horizon, whereas short-term scheduling provides the feasible production schedules for every day operations. The main goal of this study is to develop a discrete-event simulation model to link long-term predictive mine plans with short-term production schedules in the presence of uncertainty. We have developed, verified and validated a discrete-event simulation model for open pit production scheduling with the SLAM simulation language. The simulation model proved to bridge the gap between a deterministic long-term yearly plan and a daily dynamic short-term schedule. The simulation model takes into consideration the constraints and uncertainties associated with mining and processing capacities, crusher availability, stockpiling strategy and blending requirements. The results of an iron ore open pit mine case study show that discrete-event simulation is a powerful tool in minimizing the discrepancies between long and short-term mine plans.

1. Introduction

Mine planning traditionally is categorized based on the time horizon of the planning periods or the acceptable ranges of accuracy for project evaluation. The conceptual mine plan establishes a basis for the main variables of the project and economic analysis of the potential viability of the mineral resource. If the project looks promising, a prefeasibility and feasibility study will follow to confirm the economic viability of the mineral project by selecting the effective mining and mineral processing methods and enough details to make a well-informed decision. Subsequently, a bankable feasibility study will obtain the capital required to bring the mine into production and this is followed by the operational planning stage, which is aimed at specifying the details about how the overall plan should be executed.

Life-of-mine production schedules define the complex strategy of ore, waste and overburden displacement over the mine life. The objective of long-term production scheduling is to determine the sequence of extraction and displacement of material in order to fulfill managements' goal within the existing economic and technical constraints. Pit optimization and cut-off analysis lead to definition of reserves and the subsequent long-term production scheduling is the backbone of short-term planning and day to day mining operations. The long-term production schedules resolve mine and processing plant capacity and their expansion potential.

There are well developed long-term mine planning techniques based on operations research and heuristic methods. These techniques aim at maximizing shareholder values by quantitative modeling of the primary drivers influencing project value. The main variables driving the mine plans are not limited to but can be categorized as: (i) economic factors such as market commodity price and costs, (ii) metallurgical and processing factors such as recoveries and throughput, (iii) mining parameters such as capacity, productivity, equipment performance, stockpiles, cut-offs and dilution, (iv) geotechnical factors such as overall pit slopes, batter angles, and hydrology, and (v) geological parameters such as tonnes, grades, continuity, and geological structures. In the mine planning context, many of these variables and their relationships are estimated and quantified. These deterministic estimations are used to optimize a life-of-mine schedule and are the basis of short-term plans. However, the main mine planning parameters articulated above are either stochastic processes that would add up to a sequence of random variables over time or are random fields, whose domain is a random function. These variables may be independent random variables, or exhibit complicated statistical correlations.

One of the major shortcomings of the mine planning methods mostly used in industry is treatment of stochastic input variables as deterministic parameters, which in turn results in over or underestimation of project value, impractical mine plans, and significant discrepancies between long and short-term predictive models with the actual outcomes. In mining the relationship between these parameters, decision variables and the physical and economic outcomes are complex and often non- linear. Models that are used for optimization must therefore capture the dynamics of the economic system in question as well as anticipate changes to the relationships between these variables.

The main purpose of this study is to develop, verify and validate a discrete-event simulation model to link long-term and short-term open pit production scheduling. The simulation model intends to bridge the gap between a deterministic long-term yearly plan and a daily dynamic short-term schedule. The simulation model takes into consideration the constraints and uncertainties associated with mining and processing capacities, crusher availability, stockpiling strategy and blending requirements. The objective of this project is to use simulation to minimize ore production variation and idling time of the crusher while satisfying all the mining, processing, stockpiling and grade constraints. To achieve the goals, the following tasks are followed: (i) optimal final pit limit design using Lerchs and Grossmann (1965) algorithm; (ii) long-term production scheduling with the objective of providing a uniform feed to the processing plant. Milawa balanced tool in Whittle software (Gemcom Software International, 2008) is used to generate a deterministic production schedule; (iii) development of a simulation model in Visual Slam (Pritsker and O'Reilly 1999). The deterministic long-term schedule developed in stage two is the input into the simulation model. We simulate the deterministic long-term schedule with uncertain variables such as mining capacity, crusher availability and downtimes, and stockpiling and blending requirements; (iv) comparison and analysis of the deterministic production schedule against the simulated schedule after introduction of production and processing uncertainties into the model.

The simulation model developed is to be used as a linkage between the strategic mine plans and the short-term schedule. The simulation tool will assist mine planers to simulate the developed deterministic long-term schedule with uncertain input variables. Simulation of the long-term schedule over the short-term discrete time periods (days or weeks) with stochastic variables will reveal the discrepancies between the targeted long-term plan and the possible outcomes in the real world. This information is very valuable since the long-term plans could be revised until practical and robust schedules are developed at the early stages of the mine life.

The results show that discrete-event simulation is a powerful tool in minimizing the discrepancies between long and short-term plans. The simulation model also could assess different scenarios of long-term mine plans where multiple elements, multiple processing paths, various blending constraints and complex stockpiling strategies are required. Simulation allows the analyst to capture both the positive or negative swings in the operations for all possible values of the uncertain variables and to experiment with several scenarios to get a better understanding of the system.

The next section of the paper covers the relevant literature to open pit production scheduling problem and utilization of discrete-event simulation in mining. Section 3 presents problem definition and assumptions, while Section 4 presents the simulation model description and the logic flow diagrams of the model. Section 5 presents the experimental design and the next section represents the discussion of results with the iron ore mining case study. Finally, Section 7 presents the conclusions followed by the list of references.

2. Relevant literature

Current production scheduling methods in the literature are not just limited to, but can be divided into heuristic methods, applications of artificial intelligence techniques, and operations research methods. Some of these algorithms are embedded into available commercial software packages.

One of the heuristic methods used in mine production scheduling was proposed by Gershon. XPAC AutoScheduler , a commercial mine scheduling software is based on Gershon's (1987) proposed heuristic approach. Gershon's (1987) algorithm generates cones upward from each block to approximate the shape of a pit and to determine whether or not the block in question could be part of the schedule. A list of exposed blocks and a ranking of those blocks based on what makes an exposed block more or less desirable to mine at the present time is updated through the algorithm with an index called the positional weight. This weighted function is used to determine the removal sequence.

Another popular heuristic used in strategic mine planning software, such as Whittle (Gemcom Software International, 2008) and NPV Scheduler (Datamine Corporate Limited, 2008) is based on the concept of parametric analysis introduced by Lerchs and Grossmann (LG). The LG algorithm provides an optimal solution to the final pit outline. There are unlimited numbers of strategies to reach the final pit. Each has a different discounted cash-flow. The optimal production schedule is the strategy that would maximize the discounted cash-flow and meets all the physical and economical constraints. The parametric analysis generates a series of nested pits based on varying the price of the product (revenue factor) and finding an optimal pit layout using LG algorithm. These nested pits then are used as a guideline to identify clusters of high grade ore and to determine the production schedule. The main disadvantage of heuristic algorithms are that the solution may be far from optimal and in mega mining projects, this is equal to huge financial losses.

Various models based on a combination of artificial intelligence techniques have been developed (Denby and Schofield, 1994; Denby et al., 1996; Tolwinski and Underwood, 1996; Askari-Nasab et al., 2005; Askari-Nasab, 2006; Askari-Nasab et al., 2007; Askari-Nasab and Szymanski, 2007; Askari-Nasab et al., 2008; Askari-Nasab and Awuah-Offei, 2009). In a sequence of publications we developed and tested the intelligent agent-based theoretical framework for open pit mine planning (Askari-Nasab et al., 2005; Askari-Nasab, 2006; Askari-Nasab et al., 2007; Askari-Nasab and Szymanski, 2007; Askari-Nasab et al., 2008) comprising algorithms based on reinforcement learning (Sutton and Barto, 1998) and stochastic simulation. This intelligent open pit simulator (IOPS) (Askari-Nasab, 2006) has a component that simulates practical mining push-backs over the mine life. An intelligent agent interacts with the push-back simulator to learn the optimal push-back schedule using reinforcement learning. The intelligent agent-based mine planning simulator, IOPS, was successfully used to determine the optimal push-back schedule of an open pit mine with a geological block model containing 883 200 blocks (Askari-Nasab and Awuah-Offei, 2009). A number of the artificial intelligence techniques, such as IOPS are based on frameworks that theoretically will converge to the optimal solution, given sufficient number of simulation iterations.

The main disadvantage however, is that there is no criteria to compare the solutions provided against the theoretical optimum.

Mixed integer linear programming (MILP) mathematical optimization have been used by different researchers to tackle the long-term open-pit scheduling problem (Caccetta and Hill, 2003; Ramazan and Dimitrakopoulos, 2004; Dagdelen and Kawahata, 2007). The MILP models theoretically have the capability to consider diverse mining constraints such as multiple ore processors, multiple material stockpiles, and blending strategies. The applications of MILP models result in production schedules generating near theoretical optimal net present values for mining ventures. The number of binary variables required in formulations presented by Caccetta and Hill (2003) and Ramazan and Dimitrakopoulos (2004) is equal to the number of blocks in the block model multiplied by the total number of scheduling periods. For a typical real size open pit scheduling problem, number of blocks is in the order of couple of hundred thousand to millions and the number of scheduling periods usually varies between twenty to thirty years for a life-of-mine schedule. Evidently, a problem of this size is numerically intractable with current state of hardware and commercial optimization solvers. Ramazan and Dimitrakopoulos (2004) presented a method to reduce the number of binary integer variables by setting waste blocks as linear variables. Setting waste blocks as linear variables will cause a block to be extracted in multiple periods, generating a schedule which is not feasible from practical equipment access point of view. Also, notable is the work by Dagdelen and Kawahata (2007), who applied the Lagrangian relaxation technique and sub-gradient methods to solve the mine production scheduling MILP problem.

Boland et al. (2007) extended the formulation of Caccetta and Hill (2003) based on strict temporal sequence of blocks rather than assigning blocks to periods of extraction. Boland et al. (2007) reduced the number of decision variables by eliminating a number of variables presented in Caccetta and Hill (2003) formulation prior to optimization. This was achieved by combining the block precedence constraints with the production constraints, aggregated over a sequence of time periods. The numerical results illustrated a decrease in computational requirements to obtain the optimal integer solution. Boland et al. (2009) have demonstrated an iterative disaggregation approach to using a finer spatial resolution for processing decisions to be made based on the small blocks, while allowing the order of extraction decisions to be made at an aggregate level. Boland et al. (2009) reported notable improvements on the convergence time of their algorithm. Boland et al. (2009) did not present enough information on their method of aggregation and assumed that some aggregation technique already exists.

Simulation has become established as one of the powerful techniques that can handle complex mining systems, which are stochastic in nature, change dynamically over time and space and operate within a variable economic environment (Panagiotou, 1999). Computer simulation is typically defined as either continuous or discrete-event simulation. Continuous simulation is concerned with modeling a system over time by representation of state variables changing continuously. However, discrete-event simulation deals with the modeling of systems that change their state based on the occurrence of events. The simulator changes the state variables at discrete time intervals and sets in motion new events at discrete points in time as each event is processed (Banks et al., 2010).

One of the first published work of discrete-event simulation of a mining operation is by Rist (1961). His model was about determination of the optimum number of trains to have on a haulage level in an underground molybdenum mine. Harvey (1964) expanded on Rist (1961) model by specifically using the GPSS language. During the 1960’s other investigators were attempting to build computer simulation models of mining systems with GPSS. Bauer and Calder (1973) pointed out the advantages of using the GPSS simulation languages for open pit operations. Steiker (1982) simulated an underground train haulage system using GPSS language. Sturgul and Smith (1993) simulated complex underground mining operations with GPSS/H software. Simulation has been applied in different areas of mining, mainly in connection with transportation systems, mining operation, mine planning and production scheduling (Basu and Baafi, 1999; Knights and Bonates, 1999; Konyukh et al., 1999; Panagiotou, 1999; Turner, 1999; Vegenas, 1999). Suglo et al. (2003) modeled three mining operations using Visual SLAM with AweSim software. These operations included a continuous surface miner-truck mining system in a strip coal mine, a continuous miner-shuttle car system, and hoist scheduling system both in an underground coal mine. Suglo et al. (2009) also studied the prospect of using at face slurry and continuous mining systems in oil sands. Interested readers are referred to Raj et al. (2009) for a detailed literature review on simulation models used in mining industry.

3. Problem definition

Long-term production schedule optimization is usually carried out with deterministic geological block models and estimated input parameters for mining and processing capacities, costs, prices, and recoveries. The generated schedules are optimized based on a fixed mining rate and processing plant availability and utilization with a constant production level. In reality, the mining rate is subject to deviations from the set target during the mine life. The processing plant availability and utilization is subject to plant breakdowns. These deviations from the optimized long-term production targets result in significant losses throughout the mine life, thereby deviating from the optimized net present value (NPV) of the operation.

Simulation models are major tools used to quantify uncertainties associated with production operations. The simulation model developed in this study seeks to address the problem of quantifying the effect of uncertainties associated with production and plant operations. The simulation model is to be used as a linkage between the strategic mine plan developed by Whittle software and the daily short-term schedule. The simulation tool developed will assist mine planers to simulate the developed deterministic long-term schedule with uncertain variables such as mining and processing capacities, equipment availability and utilization, crusher availability and downtimes, and stockpiling and blending requirements. Simulation of the long-term schedule over the short-term discrete time periods (days or weeks) with stochastic variables will reveal the discrepancies between the targeted long-term plan and the possible outcomes in the real world. This information is very valuable since the long-term plans could be revised until practical and robust schedules are developed at the early stages of the mine life.

After generating the long-term production plan, the resulting schedule and economic block values are used as the input source data for the simulation model where production and processing plant uncertainties are introduced and their resulting effect on the schedules and NPV are analyzed and compared to the original results from long-term schedule. The objective of this project is to use simulation to minimize ore production variation and idling time of the crusher while satisfying all the mining, processing, stockpiling and grade constraints.

Fig. 1 is a schematic diagram of the proposed mining operation circuit. The circuit starts from the pit operation where the material is being mined and transported to the crusher. The material is dumped directly into the crusher and no waiting time is allowed at the crusher. Hence, when the crusher is busy, the ore is sent to a stockpile where it is kept until the stockpile reaches the minimum required capacity and then crushing starts. The ore has two main rock-types which cannot be processed at the same time; therefore these rock-types have separate stockpiles. One rock-type is processed at a time, and the two rock-types after processing are blended together to achieve the requirement of the processing plant. As a result of this crushing requirement, a Visual SLAM sub-network is built to simulate the crushing schedule which runs with the main production network model processing one rock-type at a time with a change over time and requirement based on stockpile capacity and the rock type being mined. Another Visual SLAM sub-network is built to implement the stockpile management system required to run with the crushing schedule sub-network.

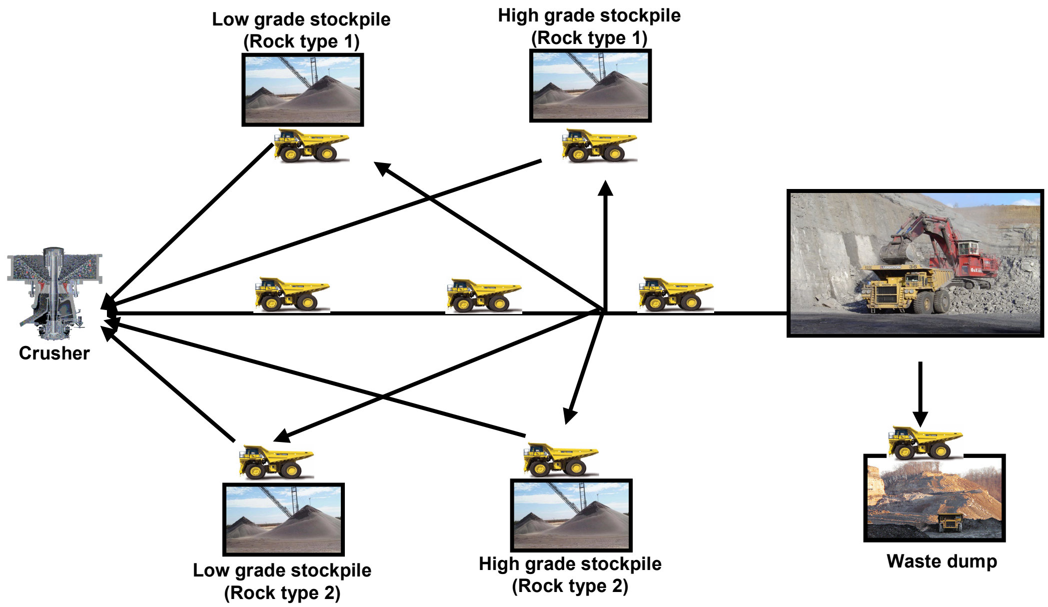

Fig. 1. Schematic diagram of proposed mining operation.

The simulation model will analyze the following variables in each period of the long-term schedule.

- The tonnage of ore and waste,
- The tonnage and average grade of MWT at the crusher,
- The tonnage and average grade of MWT directly sent to the crusher,
- The tonnage and average grade of MWT sent to stockpile 1 and stockpile 2,
- The tonnage and average grade of MWT sent from stockpile 1 and stockpile 2 to the crusher,
- How the crusher alternates between stockpile 1 and stockpile 2,
- The downtime (including idling time) of the crusher,
- The utilization of the crusher,
- The net present value,
- The appropriate mining and crushing rate for the blocks,
- The mine life.

4. Model description

The summary of the proposed mining operation process is as follows:

- One rock-type is milled at a time.
- The other rock-type is sent to the stockpile.
- The mill is fed directly from the mine and the stockpile.
- There is some downtime for the crusher to switch between rock-types.

In developing the model the following factors were considered: (i) the time used in hauling material from the pit to the crusher was not considered in the analysis; (ii) the production and crushing rate was considered to be very important in the analysis; (iii) the data from the blocks are carried by an entity as its attributes, and using the Visual SLAM with AweSim these attributes are employed to obtain the final production statistics; (iv) it is assumed that the crusher cannot process the two rock types at the same time; therefore a change over time is required which also takes care of crusher breakdowns; (v) the crushing change over depends on the stockpile level and the rock type being mined; (vi) the whole system consisting of the mining and crushing facilities is analyzed as a single system with the assumption that the crusher can start processing as soon as it is turned on with the same capacity as steady state conditions.

The mining blocks are contained in a user-defined file (BM102.dat) which is read by the read node in the network. The parameters in the user-defined file includes the block tonnages (BlockTonnage, blockP, blockS, and blockMWT), the block grades (pGrade, sGrade, and mwtGrade), the period (Period), fraction of extraction (Fraction), the economic block value (EBV), the rock type (RockType) and the ore value (oreValue). The Visual SLAM network for the read and documentation nodes which represents the mining system is shown with a schematic network diagram in Fig. 2.

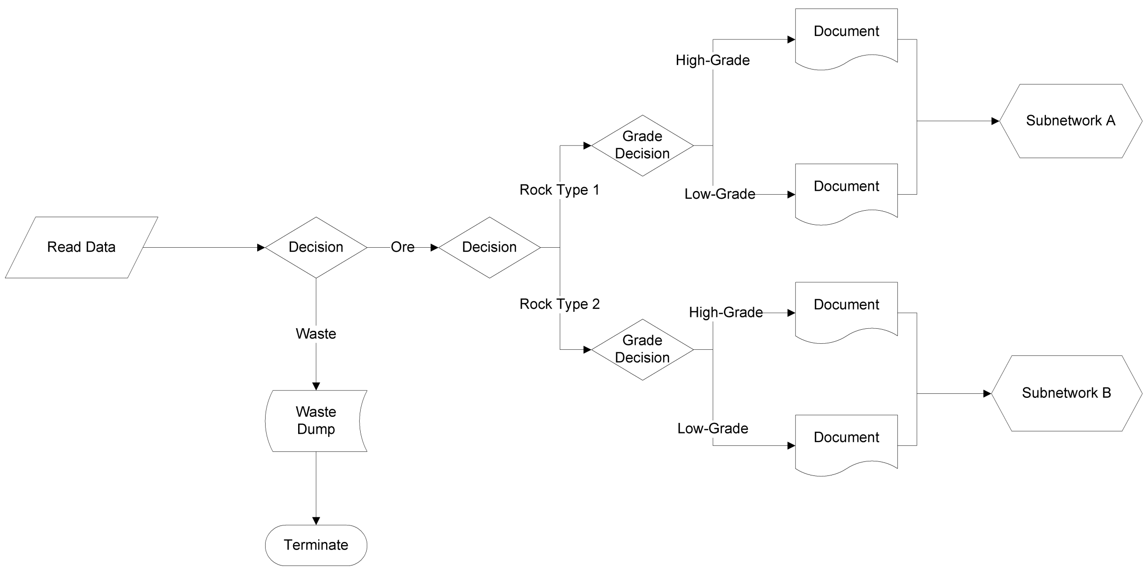

Fig. 2. Schematic network diagram for the read node which represents the mining system and the documentation of the various rock type tonnages and ore grades mined.

The production and processing rates used in the Whittle optimization will be used as the mean production and processing rates in the simulation model. These are further modified systematically to reduce the idling time of the mining operation in the later part of the mine life in line with our objective.

From the read node the daily production from year 1 to 8 is sampled from a normal distribution with a mean of 109,500 tonnes and a standard deviation of 10,000 tonnes from the user defined file, and this is stored by AweSim in the variable, LL[0]. Subsequently, the daily production from year 9 to 14 is sampled from a normal distribution with a mean of 47,000 tonnes and a standard deviation of 10,000 tonnes. When LL[0] becomes zero, the end of the file is reached. The blocks are sent to three different destinations in the network according to their rock types. The waste blocks will go to the waste dump. Rock type one is separated into high-grade and low-grade and the cut-off grade between high-grade and low-grade is 60%. The same rule applies for separating rock type two. The various statistics required from the block model are assigned to entities using Awesim global variables. These statistics are of interest in the simulation and are extracted with collect nodes. The Visual SLAM network for the collect nodes which represents the compilation of various statistics from the mining and crushing system is shown in the schematic network diagram in Fig. 2 and Fig. 3. Collect nodes are used to calculate the average grade of magnetic weight recovery, sulphur, and phosphor. Similarly the ore, sulphur and phosphor tonnages are calculated respectively.

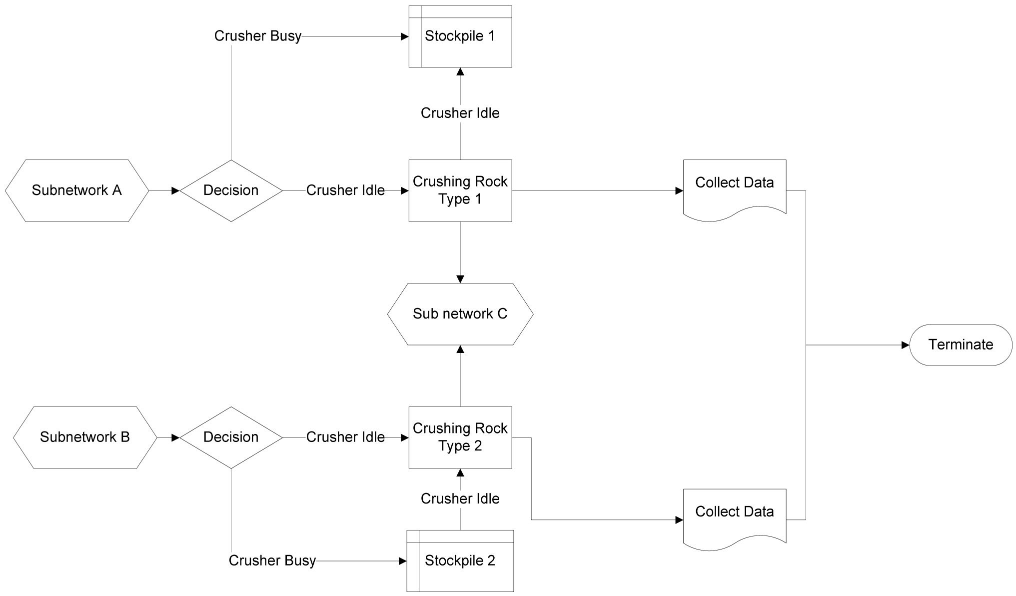

Fig. 3. Schematic network diagram for the crushing and stockpiling system.

The crusher is modeled as two separate resources, however only one of them is in operation at any point in time, so that it will mimic the presence of one crusher in the model. The rock type one material are sent to crusher one and rock type two are sent to crusher two. The crusher breakdowns and changeover time from one rock type to another is sampled from a normal distribution with a mean of 1 day and a standard deviation of 0.5 day. To enforce pre-stripping the crusher is not present in the first two years. From year three to five the crusher can process 22,000 tonnes a day, and any other material that arrives at the crusher during processing, is sent to the appropriate stockpile. The crushing capacity is increased to 33,500 tonnes a day from the sixth year of operation till the end of the mine life. After processing all the material coming directly from the pit to the crusher, the material from the stockpiles will be sent to the crusher for processing.

The change over from one rock type to the other is controlled by the rock type being mined and the stockpile capacities. A sub network is used to monitor the stockpile level and the rock type and once the required capacity is reached, the crushing on the other stockpile is stopped and a changeover is initiated. After the change over, the crusher is turned on again to attend to the stockpile that has reached its required capacity. The crusher will remain with this stockpile until the capacity of the other stockpile initiates another change over. This required stockpile capacity is seven times the daily production target. In cases where both stockpiles are above the required level, a three day excess production capacity of one stockpile over the other is needed to initiate a crusher change. This is to ensure that both stockpiles are fed on a uniform basis as required by the processing plant. This crushing schedule, which is implemented by a sub-network in the model, is utilized until the end of the simulation time. The Visual SLAM network for the crushing system and the stockpile management system are shown with the schematic network diagrams in Fig. 3 and Fig. 4 respectively.

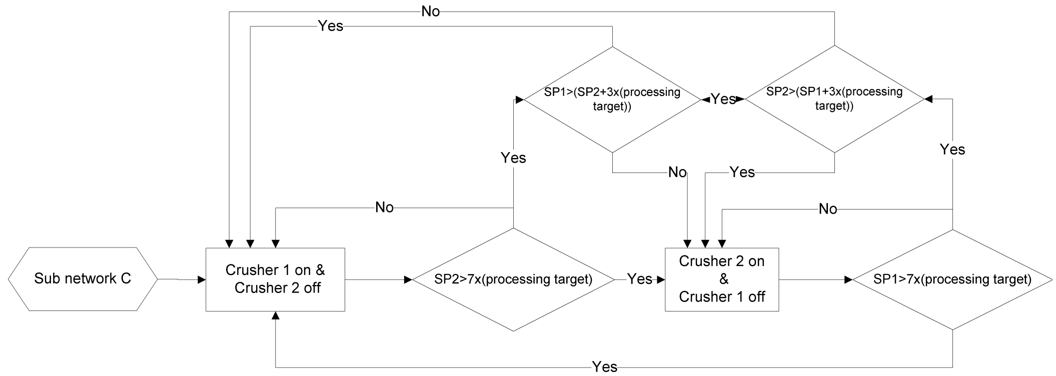

Fig. 4. Schematic network diagram for the stockpile management system.

5. Experimental design

An important aspect in simulation projects is to run the models effectively and try to understand the results in the context of your objective. This involves a careful planning of the simulation experiment to assess the performance of the system with an estimated prescribed set of conditions (Pritsker and O'Reilly 1999; Kelton, 2000).

In this paper, the simulation model was designed with an input mine schedule from Whittle software as per our objective. This contains information such as the block tonnage, grade and rock-type to be mined in each period. A crushing and stockpiling system was introduced with uncertainties to enable the quantification of real operational uncertainties on the mining operation. All simulation functions were tested using simple entity flow tests to determine if they are working properly and as expected.

The choice of the production and crushing rate was based on their corresponding values used in Whittle production scheduling optimization. These were further adjusted systematically based on the objective of minimizing operational idling time. It was decided to combine the crusher changeover time and downtime to reduce the number of variables and nodes that are used in the simulation project. The uncertainties associated with production and crushing rate and crusher changeover and downtime were based on the experience of the researchers. However, for production simulation runs, the statistical distribution for each process need to be calibrated based on the historical data gathered from the site. The general simulation model linking the long-term production schedule to a short-term production schedule under resource availability uncertainty is valid and applicable to different scenarios.

The length of the simulation run was based on the mine life. Once the scheduled blocks in the optimal pit are depleted, the simulation is terminated. For the number of replications, assuming that the sample mean, $\overline{X}_I$ is unbiased and that the sample variance, $Var\left[\overline{X}_I\right]=\sigma_X^2/I$, then the number of replications, I required to obtain a $(1-\alpha)$ confidence that the population mean, μ_X is contained in a prescribed interval can be calculated using standard statistical formulas as demonstrated by Pritsker and O'Reilly (1999). σ_X^2 is the population variance and α is the significance level. In this paper, it was decided to quantify the simulation output uncertainties based on a 95% confidence interval of the input expected values ± 0.5 of their standard deviation. This required 15 runs of the simulation model for each scenario of one production year (Kelton et al., 1998; Pritsker and O'Reilly 1999).

In analyzing the output results, a comparison between the Whittle schedule and the simulated schedule was done. Some specific variables for comparison were the life of mine and the net present value of the mine that has been impacted upon by the uncertainties and the complex operational strategies introduced in the simulated schedule.

6. Results and discussion

6.1. Deterministic schedule from Whittle

In the first stage of the study, the long-term production schedule of the iron ore open pit was developed using Whittle software . The block model contains the estimated magnetic weight recovery (MWT%) of iron ore and the contaminants in the model are phosphor (P%) and sulphur (S%). The blocks in the original geological model represent a volume of rock equal to $25m \times 25m \times 15m$, which were reblocked for simulation. The final pit includes 412.99 million tonnes of rock where 124.09 million tonnes is iron ore with an average magnetic weight recovery grade of 70.3%. Initially a capacity of 109,500 tonnes per day was considered as the upper bound of mining. The objective was to maximize the NPV while providing a constant feed to the mill throughout the mine life. Two years of pre-stripping was considered to open up the mine. The processing capacity gradually ramped up to 33,500 tonnes per day, with year's three to five at 22,000 tonnes per day capacity. There are two rock types (with varying densities) rock type one and rock type two which have been modeled with the code 101 and 102. The two rock types have different stockpiles. Other information such as block tonnage, ore tonnage, economic block value (EBV), magnetic weight recovery, grade of sulphur and grade of phosphor are used as inputs into the simulation model. Fig. 5 illustrates the long-term production schedule modeled by Whittle software . This is the target long-term production goals that we need to meet through the day to day operation. The long-term schedule is not achievable most of the times because the uncertainties of many input factors are not taken into consideration in long-term planning. Fig. 6 illustrates the same schedule with highlighting the portion of ore types one and two in the feed. Fig. 7 shows cross section 600500m looking east of the final pit. The extraction period of each block is labeled based on the Whittle long term schedule.

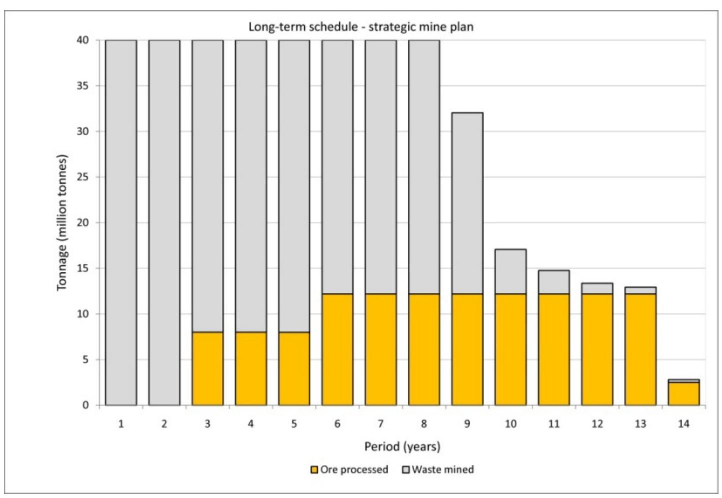

Fig. 5. Long-term production schedule generated based on deterministic input values.

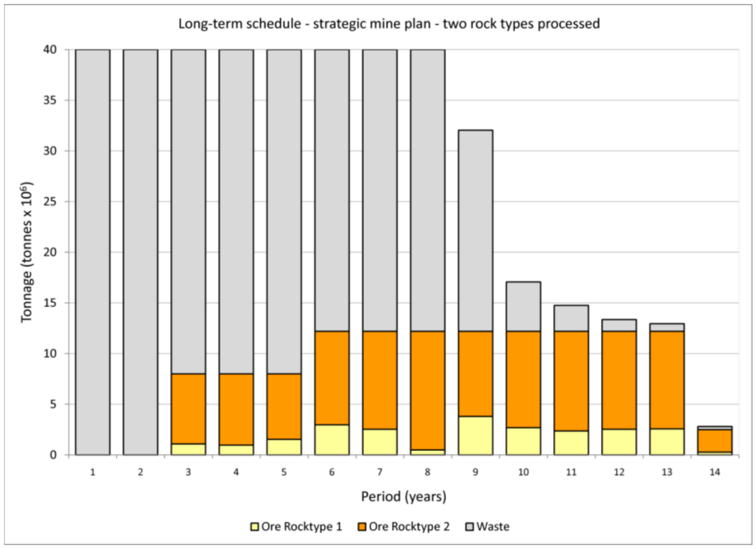

Fig. 6. Long-term production schedule, with the portion of two different ore types in feed.

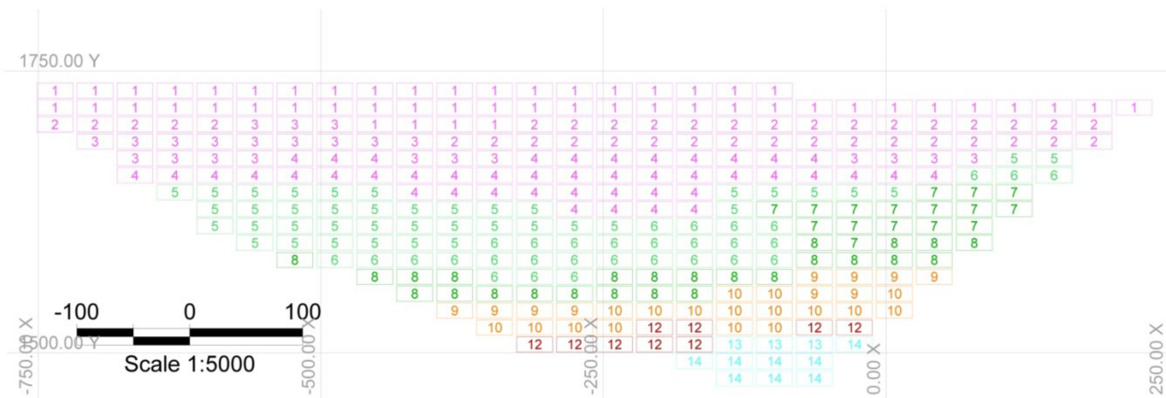

Fig. 7. Cross section 600500m looking east, the extraction period of each block is labeled based on the long term schedule.

6.2. Simulation model results

6.2.1 Tonnage mined and NPV

The long-term schedule presented in Fig. 5 to Fig. 7 is the input into the Visual Slam simulation model to mimic the block extraction sequence with uncertain mining and processing rate and changeover of the crusher. At this stage the stockpiling strategy is simulated as well. The mining rate is set to 109,500±10,000 tonnes per day for the first 8 years and 47,000±10,000 tonnes per day for the remaining years. The crushing rate is 22,000 tonnes per day from year 3 to 5 and 33,500 tonnes for the remaining years. In the first two years only pre-stripping occurred. The stockpile capacities are a minimum of seven times of the daily processing target which is 154,000 tonnes from year 3 to 5 and 234,500 tonnes for the remaining years. Above the minimum stockpile capacity, 3 days excess processing capacity of one stockpile over the other is required as the minimum stockpile capacity. The change over time from rock type one to rock type two is 1±0.5 days and the reverse is true for the other rock type. The simulation was run on annual bases to ascertain the details of what will happen to the mining operation within each production year with our objective of minimizing mining and processing variations.

Fig. 8 illustrates the simulation result of the long-term schedule based on short-term uncertain input variables. The dashed straight line shows the 12 million tonnes per year target set up by the long-term schedule. The amount actually processed after simulation of the mining sequence is shown by the black solid line. Evidently, there is a considerable feed shortfall in years nine and ten. This is due to the unpredicted uncertainties in mining and processing capacities as well as crusher downtimes and ore availability. This shows how the effects of constraints and uncertainties on the mining operation can be quantified. Fig. 9 illustrates the same simulated schedule with high-grade and low-grade material distinguished by rock type. From the simulation, the mine will have an operating life of 14.5 years, which is extended by sixteen months comparing to the long-term schedule. Mining rate will be at an average of 39.6M tonnes of material every period of one year for the first 8 years and then reduced to 15.9M tonnes from year 9 to the end of the mine life. The simulation result is a great assist in choosing the proper truck-shovel fleet to be purchased or the mining capacity that needs to be acquired through contract mining. During the first two periods, only waste material will be available for mining to enable the exposure of ore which will become available in the third period. From this period, the mine will operate at an average stripping ratio of 2.83 till the end of year 10. From year 11, when little waste is left to mine, the stripping ratio reduces to 0.20. The average ore tonnage processed by the crusher from year 3 to 5 is 7.12M tonnes and that from year 6 to the end of the mine life is 10.18M tonnes.

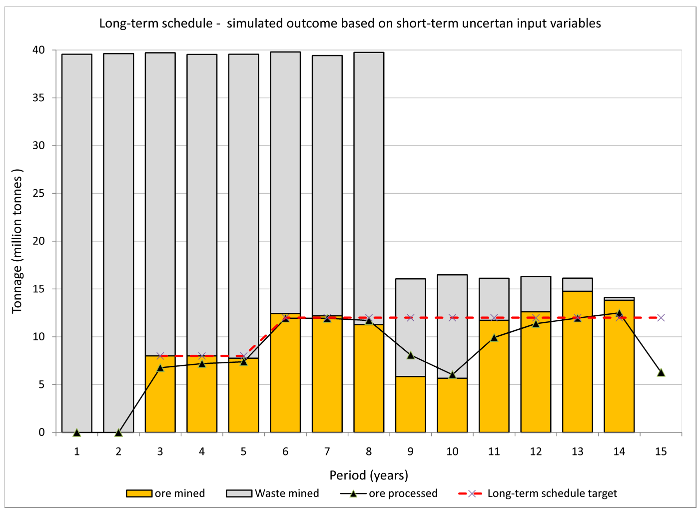

Fig. 8. Long term schedule simulated outcome based on short-term uncertain input variables.

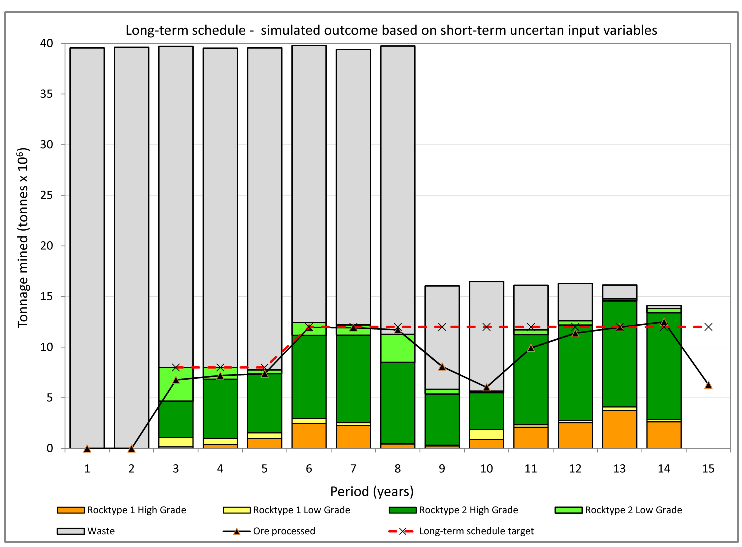

Fig. 9. Simulated long-term schedule with high-grade and low-grade material.

Fig. 10 shows the cumulative progression of the NPV values from one period to another obtained from simulation (dashed line) compared to Whittle results (solid line). This shows a reduction in NPV as a result of the mining and processing rate constraints and uncertainties. The net present value of the operation at a discount rate of 10%, starts from -\$76.23M in period 1 due to the waste being mined and cumulatively decreases to -\$145.64M in period 2. When processing of ore starts from period 3, the NPV increases to \$79.90M and cumulatively increases to \$3175.70M in period 15 when the life of mine is reached. With the operational constraints and uncertainties, the total NPV at the end of the mine life with 10% discount rate is \$3175.70M as compared to \$3251.79M obtained from Whittle with no uncertainty modeling.

Further assessment of mine production uncertainty from the results of the simulation model shows an output mean daily production of 108543 tonnes with a standard deviation of 354 tonnes from year 1 to 8. From year 9 to 14, the mean daily production is 43471 tonnes with a standard deviation of 2399 tonnes. This high standard deviation is as a result of lack of material in year 14 for mining. Excluding year 14, the mean daily production from year 9 to 13 will be 44435 tonnes with a standard deviation of 470 tonnes. These results are consistent with the target set in the experimental design.

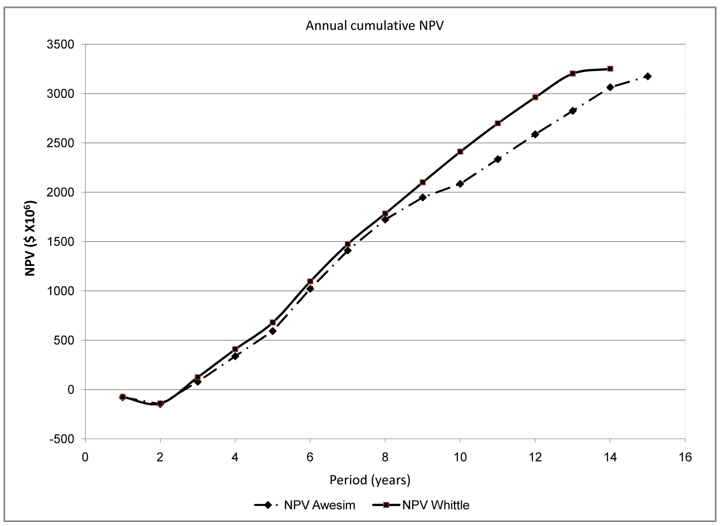

Fig. 10. Cumulative progression of the net present value during the mine life.

6.2.2 Ore tonnage and grade of Fe mined

Fig. 11 and Fig. 12 show the graphical relationship of the different rock types and grades of Fe mined during different periods from simulation and from Whittle respectively. The simulation can provide us the details of the mining operation by rock type and grade on any time scale throughout the mine life as well as the effects of production constraints and uncertainties. The simulation shows that (Fig. 11) with a magnetic weight recovery cut-off of 60% between high grade and low grade for both rock types one and two, the tonnage of ore mined for rock type one high grade starts from 0.16M tonnes at a magnetic weight recovery of 66.2% in period 3 and continues until period 14 when 2.64M tonnes of ore at a magnetic weight recovery of 72.6% is mined. In all a total of 18.86M tonnes of rock type one high grade ore at a magnetic weight recovery of 72.4% was mined as at the end of the fourteenth period. The mining of low grade ore of rock type one also starts in period 3 with a value of 0.93M tonnes at a magnetic weight recovery of 54.1% and continues until period 14 where 0.21M tonnes are mined at a magnetic weight recovery of 49.3%. In all a total of 4.97M tonnes of low grade ore of rock type 1 was mined at a magnetic weight recovery of 49.7%.

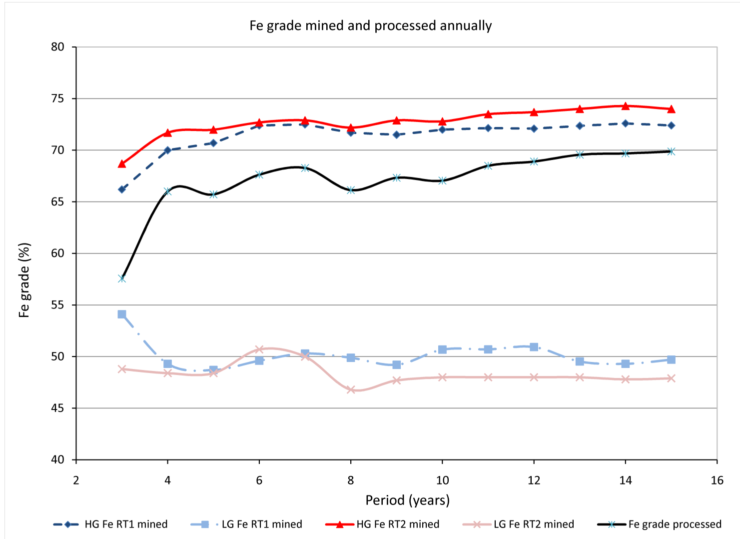

Fig. 11. Graphical relationship of the different rock types and grades of Fe mined and processed from simulation model.

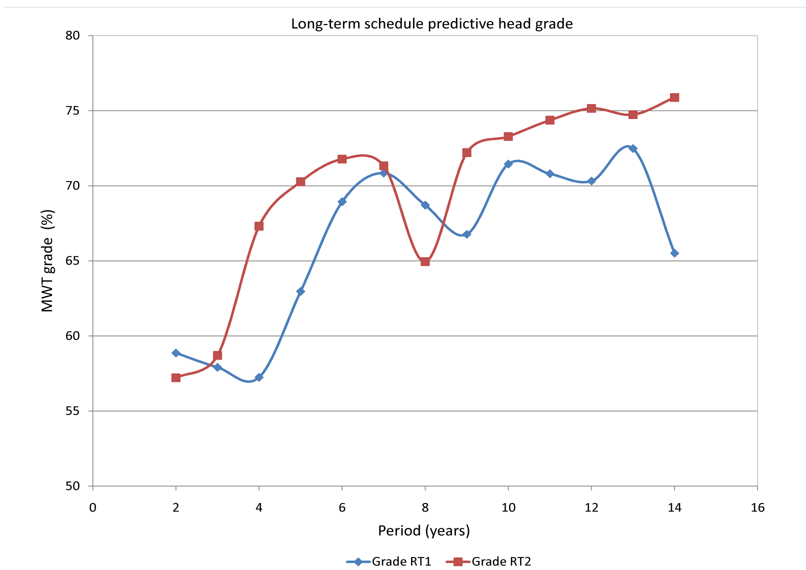

Fig. 12. Graphical relationship of the different rock types and grades of Fe mined from Whittle.

6.2.3 Ore tonnage mined and processed by the crusher directly and from stockpile

The tonnage of ore mined from the pit is either processed directly by the crusher or it is processed from the stockpile by the crusher. The ore is sent to the stockpile depending on whether the crusher is available or it is being utilized. No waiting is allowed at the crusher head, therefore any material that arrives at the crusher when the crusher is busy is sent to the stockpile. Also since the crusher is managing the capacity of the two stockpiles of different rock types, it is available to process one stockpile at a time depending on the stockpile capacity and rock type being mined and hence all material for the other rock type is sent to the stockpile.

Fig. 13 shows the graphical relationship of ore processed directly and processed from the stockpiles. It also shows the cumulative stockpile level changes used to support plant processing throughout the mine life. The total amount of ore of both rock types processed during the mine life is 123.18M tonnes at a magnetic weight recovery of 69.6%. 0.91M tonnes of ore remain at the stockpiles as at the end of the simulation. The tonnage of ore from the pit processed directly by the crusher is 2.57M tonnes in period 3. Crushing continues until period 14 when 9.27M tonnes of material is processed directly, making up a total of 65.00M tonnes of ore throughout the mine life. Similarly, 4.20M tonnes of ore were processed from the stockpile by the crusher in period 3 and processing continued until period 15 when 6.29M tonnes of material were processed. A total of 58.18M tonnes of ore were processed from the stockpile throughout the mine life.

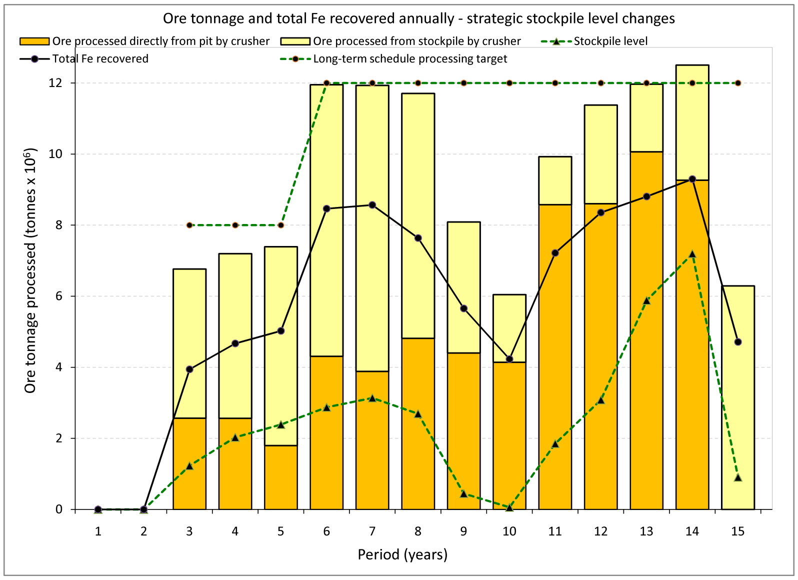

Fig. 13. Graphical relationship of ore tonnage processed directly and from stockpile.

6.2.4 Crusher utilization

During the first two periods the crusher was idle due to the waste being mined. From period 3, crushing of rock type 1 and 2 started with a cumulative crusher utilization of 28%. The cumulative crusher utilization continues to increase steadily as more material becomes readily available for crushing directly from the pit and from the stockpiles. At the end of the mine life in period 15, the cumulative crusher utilization will be 14% for rock type 1 and 62% for rock type 2, totaling 76%. 1±0.5 days are required in setting up the crusher from crushing one rock type to the other as well as crusher downtimes. This together with the crusher idling time during the initial stages of the operation, accounts for the non utilization of the crusher during the mine life and is referred to in this project as the shutdown time. The average crusher utilization excluding the idling time in the initial stages of the operation is 88%. Fig. 14 shows the graphical relationship of the progressive utilization of the crusher during the mine life.

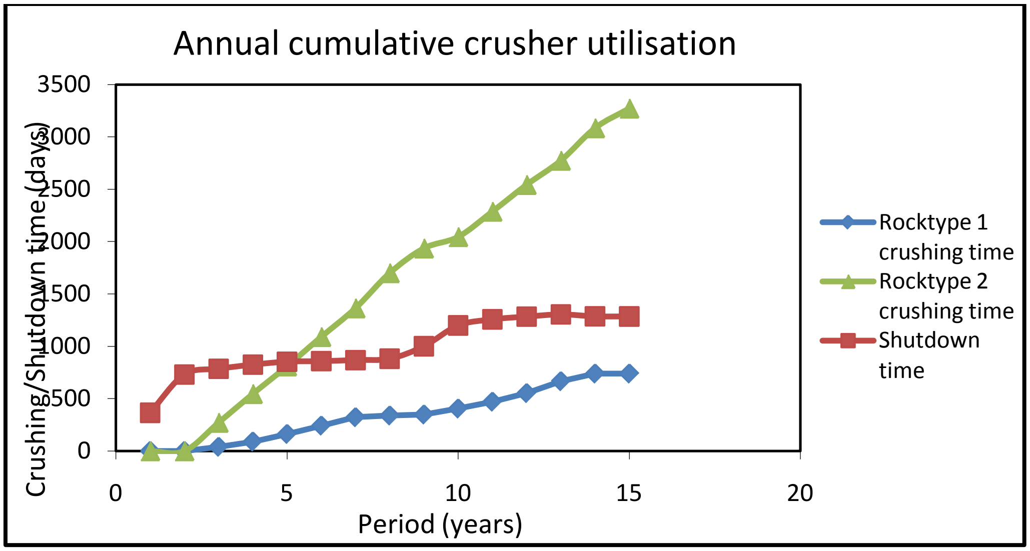

Fig. 14. Graphical relationship of the utilization of the crusher during the mine life.

7. Conclusions

One of the major shortcomings of the current mine planning methods is treatment of stochastic input variables as deterministic parameters, which in turn results in over or underestimation of project value, impractical mine plans, and significant discrepancies between long and short-term predictive models with the actual outcomes. In mining, the relationship between these parameters, decision variables and the physical and economic outcomes are complex and often non- linear. Models that are used for optimization must therefore capture the dynamics of the economic system in question as well as anticipate changes to the relationships between these variables.

We have developed, verified and validated a discrete-event simulation model for open pit production scheduling with the SLAM simulation language. The simulation model proved to bridge the gap between a deterministic long-term yearly plan and a daily dynamic short-term schedule. The simulation model takes into consideration the constraints and uncertainties associated with mining and processing capacities, crusher availability, stockpiling strategy and blending requirements. The results show that discrete-event simulation is a useful tool in minimizing the discrepancies between long and short-term plans.

An iron ore mine case study was carried out by generating the long-term schedule with Whittle software and then simulating the block sequence extraction with the discrete-event simulation. 65.00M tonnes of ore were processed directly by the crusher and 58.18M tonnes of ore were processed from the stockpile throughout the mine life. In all, a total of 123.18M tonnes of ore with a magnetic weight recovery of 69.6% were processed by the crusher with a utilization of 88% while 288.1M tonnes of waste were sent to the waste dump. 0.91M tonnes of ore remain at the stockpiles as at the end of the simulation. With the operational constraints and uncertainties, the total NPV at the end of the mine life with 10% discount rate is $3175.70M as compared to $3251.79M obtained from Whittle with no constraints and uncertainties. The results of the simulation show that for the deposit of 412M tonnes of material, at 95% confidence interval, a duration of 14.5 years is required to mine at a production rate of 109,500±5,000 tonnes per day for the first 8 years and 47,000±5,000 tonnes per day for the remaining years. The ore processing rate was 22,000 tonnes from year 3 to 5 and 33,500 tonnes from year 6 to 14.5. No ore was processed in years 1 and 2. The results show that discrete-event simulation is a powerful tool in assessing different scenarios of long-term mine plans, where multiple elements, multiple processing paths, various blending constraints and complex stockpiling strategies are required.

8. References

[1] Askari-Nasab, H. (2006). Intelligent 3D interactive open pit mine planning and optimization. PhD Thesis, University of Alberta, Edmonton, Canada, Pages 167.

[2] Askari-Nasab, H. and Awuah-Offei, K. (2009). Open pit optimization using discounted economic block value. *Transactions of the Institution of Mining and Metallurgy. Section A, Mining industry*, *118*,(1), 1-12.

[3] Askari-Nasab, H., Frimpong, S., and Awuah-Offei, K. (2005). *Intelligent optimal production scheduling estimator*. Paper presented at 32nd Application of Computers and Operation Research in the Mineral Industry, Tucson, Arizona, USA.

[4] Askari-Nasab, H., Frimpong, S., and Szymanski, J. (2007). Modeling open pit dynamics using discrete simulation. *International Journal of Mining, Reclamation and Environment*, *21*,(1), 35-49.

[5] Askari-Nasab, H., Frimpong, S., and Szymanski, J. (2008). Investigating the continuous time open pit dynamics. *The Journal of the South African Institute of Mining and Metallurgy*, *108*,(2), 61-73.

[6] Askari-Nasab, H. and Szymanski, J. (2007). *Open pit production scheduling using reinforcement learning*. Paper presented at 33rd International Symposium on Computer Application in the Minerals Industry (APCOM), Santiago, Chile.

[7] Banks, J., Carson, J. S., Nelson, B. L., and Nicol, D. M. (2010). *Discrete-event system simulation.* Upper Saddle River, N.J. ; Singapore : Prentice Hall, c2010, 5th ed,

[8] Basu, A. J. and Baafi, E. Y. (1999). Discrete event simulation of mining systems: current practice in Australia. *International Journal of Surface Mining, Reclamation and Environmental*, *13*,(2), 77-78.

[9] Bauer, A. and Calder, P. (1973). *Planning open pit mining operations using simulation*. Paper presented at Application of Computers and Operations Research in the Mineral Industry (APCOM), South African Institute of Mining and Metallurgy, Johannesburg, South Africa. pp. 273-298.

[10] Boland, N., Dumitrescu, I., Froyland, G., and Gleixner, A. M. (2009). LP-based disaggregation approaches to solving the open pit mining production scheduling problem with block processing selectivity. *Computers and Operations Research*, *36*,(4), 1064-1089.

[11] Boland, N., Fricke, C., and Froyland, G. (2007). A strengthened formulation for the open pit mine production scheduling problem. *Optimization Online,* Retrieved Jan. 9, 2009 from: http://www.optimization-online.org/

[12] Caccetta, L. and Hill, S. P. (2003). An application of branch and cut to open pit mine scheduling. *Journal of Global Optimization*, *27*,(2-3), 349-365.

[13] Dagdelen, K. and Kawahata, K. (2007). *Oppurtunities in multi-mine planning through large scale mixed integer linear programming optimization*. Paper presented at 33rd International Symposium on Computer Application in the Minerals Industry (APCOM), Santiago, Chile.

[14] DatamineCorporateLimited (2008). NPV Scheduler. Ver. 4, Beckenham, United Kingdom.

[15] Denby, B. and Schofield, D. (1994). Open-pit design and scheduling by use of genetic algorithms. *Transactions of the IMM Section A*, *103*,(1), A21-A26.

[16] Denby, B., Schofield, D., and Hunter, G. (1996). *Genetic algorithms for open pit scheduling - extension into 3-dimensions*. Paper presented at 5th International Symposium on Mine Planning and Equipment Selection, Sao Paulo, Brazil.

[17] GemcomSoftwareInternational (2008). Whittle strategic mine planning software. Ver. 4.2, Vancouver, B.C.

[18] Gershon, M. (1987). Heuristic approaches for mine planning and production scheduling. *Geotechnical and Geological Engineering*, *5*,(1), 1-13.

[19] Harvey, P. R. (1964). *Analysis of production capabilities*. Paper presented at Application of Computers and Operations Research in the Mineral Industry (APCOM), Colorado School of Mines, Colorado, USA. pp. 713-726.

[20] Kelton, W. D. (2000). *Experimental design for simulation*. Paper presented at Winter Simulation Conference, Orlando, USA.

[21] Kelton, W. D., Sadowski, R. P., and Sadowski, D. A. (1998). *Simulation with Arena.* McGraw-Hill, New York.

[22] Knights, P. F. and Bonates, E. J. L. (1999). Application of discrete mine simulation modeling in South America. *International Journal of Surface Mining, Reclamation and Environmental*, *13*,(2), 69-72.

[23] Konyukh, V., Galiyev, S., and Li, Z. (1999). Mine simulation in Asia. *International Journal of Surface Mining, Reclamation and Environmental*, *13*,(2), 57-67.

[24] Lerchs, H. and Grossmann, I. F. (1965). Optimum design of open-pit mines. *The Canadian Mining and Metallurgical Bulletin, Transactions*, *LXVIII*, 17-24.

[25] Panagiotou, G. N. (1999). Discrete mine system simulation in Europe. *International Journal of Surface Mining, Reclamation and Environmental*, *13*,(2), 43-46.

[26] Pritsker, A. A. B. and O'Reilly , J. J. (1999). *Simulation with Visual SLAM and AweSim.* WILEY, 2nd ed, Pages 852.

[27] Raj, M. G., Vardhan, H., and Rao, Y. V. (2009). Production optimisation using simulation models in mines: a critical review. *International Journal of Operational Research*, *6*,(3), 330-359.

[28] Ramazan, S. and Dimitrakopoulos, R. (2004). Traditional and new MIP models for production scheduling with in-situ grade variability. *International Journal of Surface Mining, Reclamation & Environment*, *18*,(2), 85-98.

[29] Rist, K. (1961). *The solution of a transportation problem by use of a Monte Carlo technique*. Paper presented at Application of Computers and Operations Research in the Mineral Industry (APCOM), Unversity of Arizona, Tucson, Arizona, USA. pp. L2-1 to L2-15.

[30] Steiker, A. B. (1982). *Simulation of an underground haulage systems*. Paper presented at Application of Computers and Operations Research in the Mineral Industry (APCOM), Denver. pp. 599-613.

[31] Sturgul, J. R. and Smith, M. L. (1993). *Using GPSS/H to simulate complex underground mining operations.* Paper presented at 2nd International Symposium on Mine Mechanization and Automation, Lulea, Sweden. pp. 827.

[32] Suglo, R. S., Szymanski, J., Booth, D., and Frimpong, S. (2003). *Simulation analysis of mining models*. Paper presented at IASTED International Conference on Applied Simulation and Modelling(ASM2003), Marbella, Spain. pp. 267-272.

[33] Suglo, R. S., Szymanski, J., and Planeta, S. (2009). Simulaiton of at face slurrying method and continuous miner truck system in an open pit mine. in *Transport*, vol. 1, pp. 2-8.

[34] Sutton, R. S. and Barto, A. G. (1998). *Reinforcement learning : an introduction.* MIT Press, Cambridge, Mass. Pages 322.

[35] Tolwinski, B. and Underwood, R. (1996). A scheduling algorithm for open pit mines. *IMA Journal of Mathematics Applied in Business & Industry*,(7), 247-270.

[36] Turner, R. J. (1999). Simulation in the mining industry of South Africa. *International Journal of Surface Mining, Reclamation and Environmental*, *13*,(2), 47-56.

[37] Vegenas, N. (1999). Application of discrete mine simulation in Canadian mining operations in the nineties. *International Journal of Surface Mining, Reclamation and Environmental*, *13*,(2), 77-78.