Linking Mine Production to Milling and Concentrate using Discrete Event Simulation

Mohammad Tabesh, Ebrahim Azimi, Hooman Askari-Nasab
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Canada

Abstract

Simulation is one of the techniques for studying a system's behaviour, predicting its outputs and anticipating challenges along the way. This is a very powerful technique, especially when uncertainty and time-varying parameters are involved. Numerous simulation studies have been conducted on material processing plants. Simulation and modelling of mineral processing systems focuses on design and optimization of circuits and machine performances. The focus of this project is on simulating the interactions between interior components of a plant using a discrete event approach. An iron ore processing plant, with several comminution and separation stages, is considered for the simulation study. The system involves a continuous process; however, it is modeled as discrete events. One way is to use the batching approach and consider one hour's worth of material fed into the plant (or that of any other time period) as an entity flowing through the model. The model is developed in Arena simulation software. The objective of the study is to develop a simulation model with sufficient details that links the mine production to the final product produced downstream in the presence of uncertainty. The simulation model has shown that the grade and tonnage of the final concentrate and the overall recovery of the plant can be estimated based on a short-term production schedule. The results show that the monthly tonnage of the concentrate produced is the most sensitive output apportioned to different sources of uncertainty in the model input. Various operations and machines are considered and modeled to provide an insight into advantages and shortcomings of such a model.

1. Introduction

The main goal of any mining operation is to maximize profits. The processing plant is the place where the mineral dressing or ore dressing, which is the process of separating commercially valuable minerals from the ore, is completed. Bulk materials have a set of requirements for the product properties, such as minimum metal grade, maximum deleterious material grade and even the tonnage of concentrate needed to be delivered on time. On the other hand, increasing the concentrate metal grade and decreasing deleterious content leads to larger amounts of tailings and lost metal, as well as higher costs. Finding the trade-off, which enables the company to make the highest level of profit and managing the mineral processing plant such that the desired output and costs are achieved, is a complex and challenging activity. Therefore, studying the plant is of great value. Another property of a processing plant is the variety of machines involved in concentrating the product. All of these machines impose uncertainty because of their operational characteristics as well as their failures. The uncertainty in characteristics of the rock delivered to the plant also increases the process uncertainties and makes the decision making more complicated. It is usually

Askari-Nasab, Hooman (2012), Mining Optimization Laboratory (MOL) – Report Four, © MOL, University of Alberta, Edmonton, Canada, Pages 340, ISBN: 978-1-55195-301-4, pp. 206-225.

possible to change the performance parameters of machines to either increase the quantity of the product or the quality. Therefore, gaining an understanding of the possible combinations of machines and choosing the best is another motivation for processing plant simulation.

One of the common techniques for studying a system's behaviour and predicting its outputs and challenges is simulation. This is a very powerful technique, especially when uncertainty and time-varying parameters are involved. There are some fairly comprehensive software packages, such as MODSIM (Mineral Technologies International), USIM PAC (BRGM) and JKSimMet (JKTech), which are currently used to simulate mineral processing plants. These software packages are based on predefined models, which predict a plant's outputs for the specific input data range. The models need to be calibrated on a case-by-case basis. The outputs need verification and validation because of the complex nature of the ore and some unique characteristics at each mine.

This project aims at modeling and simulating the behaviour of an iron ore magnetic separation plant using discrete event simulation. The goal is to build up a framework for simulating processing plants as complicated systems and to gain an understanding of the quality of the output and the effects of uncertainty in input parameters on the output variables. The simulation model is used to enhance the understanding of the stochastic relationship between the quantity and quality of ore delivered to the crusher and the quantity and quality of the final product and tailings produced downstream.

The paper is organized as follows. A brief review of the previous work done on mineral processing simulation is presented in the next section. The third section defines the system of interest for modeling. The proposed approach and the modeling procedure are described in the fourth and fifth sections respectively. The verification process and the output results of the model on synthetic data are presented in sixth section. Various uses of the simulation model, modeling tricks and guidelines on what to expect from a simulation model are provided in section seven. The conclusion and future work are discussed in the final section.

2. Literature review

Several simulation studies have been conducted on mineral processing plants. Simulation and modeling of mineral processing systems focus on the design and optimization of circuits and machine performance (Lynch and Morrison, 1999). Early studies were intended to propose equations representing relations between various parameters of the system. The concepts of modeling and simulation for mineral processing were introduced after the 1960s. Developments in the capabilities of computers in the 1980s helped researchers conduct vast studies on the models and observe deficiencies, through the use of computer programs and simulations (Lynch and Morrison, 1999). These studies can be categorized into two main groups: standalone machine simulations and plant simulations. Most of the simulation studies belong to the first group, in which researchers try to mimic the behaviour of a specific machine based on experiments and computer simulations. The idea behind the second group of studies is to analyze the processing plant as a single system consisting of various machines and to investigate the interactions among components of the system. However, one may only be interested in studying the whole plant as a system and investigating the relationships between inputs, outputs, and operating conditions of the plant instead of a machine by machine study. The focus of this project is on simulating the interactions between interior components of a plant.

Standalone machine studies have been conducted widely on grinding machines, separators, classifiers, etc. Austin et al. (2007) simulate wet ball milling of iron ore using laboratory scale tests. Another study conducted by Wang et al. (2009) investigates the grinding process within vertical roller mills. Pothina et al. propose a model to relate impact parameters to energy consumption in gyratory crushers. Dlamini et al. (2005) simulate the hydrocyclone to obtain physically realistic velocity and pressure profiles. Morrell and Man (1997) use computer simulation as well as existing plant data to design full-scale ball mill circuits. Sosa-Blanco et al. (2000) develop a simulation model for tuning a grinding circuit with the objective of optimizing a flotation plant. Another simulation of a grinding plant is conducted in Duarte et al. (2002), in which the authors use simulation to compare five control strategies in a copper grinding plant. A simulation study on the control parameters of flotation columns can be found in Bergh and Yianatos (1995). For a complete review of models for column flotation, the reader can consult the study by Bouchard et al. (2009).

One of the first simulations of the ore processing plant was done by Ford and King (1984). De Andrade, Lima and Hodouin (2006) performed another simulation study which falls into the second category. The authors of this paper simulate cyanide distribution in a gold leaching circuit. A simulation design which treats the processing plant as a whole and suggests an approach for measuring and managing variations in a mineral processing plant is proposed in Robinson (2003). Fourie (2007) also proposes a modeling approach for studying any metal separation circuit (flotation, magnetic separation or electrostatic separation). Delgadillo et al. (2008) integrate the grinding machines along with the classifiers and magnetic separators and simulate the combination in a magnetite plant.

3. System definition

In this study, a whole processing plant simulation modeling approach is followed. The study focuses on modeling an iron ore magnetic separation plant using Arena discrete event simulation software (Rockwell Automation). A typical iron ore processing plant, with several comminution and separation stages, is considered for simulation. The flow sheet of the process is illustrated in Fig 1.

The plant receives run-of-mine (ROM) as trucks dump loads with specific tonnage, known metal grade, contaminant grade, and rock hardness into the primary crusher (in this case a Gyratory crusher); the crushed materials are carried to the stockpiles through conveyer belts and stackers. The plant's main stockpiles serve as ore feed storage for all process stages. Two similar stockpiles are considered in the simulation to let the trucks dump in one when the other one is feeding the plant and vise versa. Each stockpile is also divided into 3 bins that have their own grades and tonnages so that a better modeling of the stacking and reclaiming operation is performed.

In the next stage, ore is fed to the size reduction section with a known tonnage rate per hour (1000 tonnes/hour). The final output of this section is two streams of ore with restricted particle size distributions (one in the range of 20 to +10 mm and the other in the range of -10 mm) and a tailing stream with particles finer than 3 mm (which have lower magnetic content and higher sulfur and phosphor grades). There are an Auto Genius mill and a secondary crusher in this area.

Ore coming from the size reduction section is fed to the dry low magnetic separator (LMS) and dry high magnetic separator (HMS) in the order depicted in Fig 1. The final outputs of the dry separation section are a mixed concentrate, which is fed to the wet plant after being mixed with water in an intermediate bin, and tail material which is sent to the dry tailings dump.

A closed circuit grinding mill with hydrocyclone is included at the beginning of the wet separation area to grind the material down to -2.5 mm in order to achieve a higher degree of freedom of materials. Afterwards, a wet HMS machine divides material into a higher grade material and a wet tail which is disposed of in the wet tail dam. The final concentrate of the processing line is obtained after meeting one more size reduction stage in a ball mill (minus 1mm) and a wet LMS machine. Both the tail and the final concentrate may need to go through the thickener, the filter, the dryer, and the pumping station before settling in their final points.

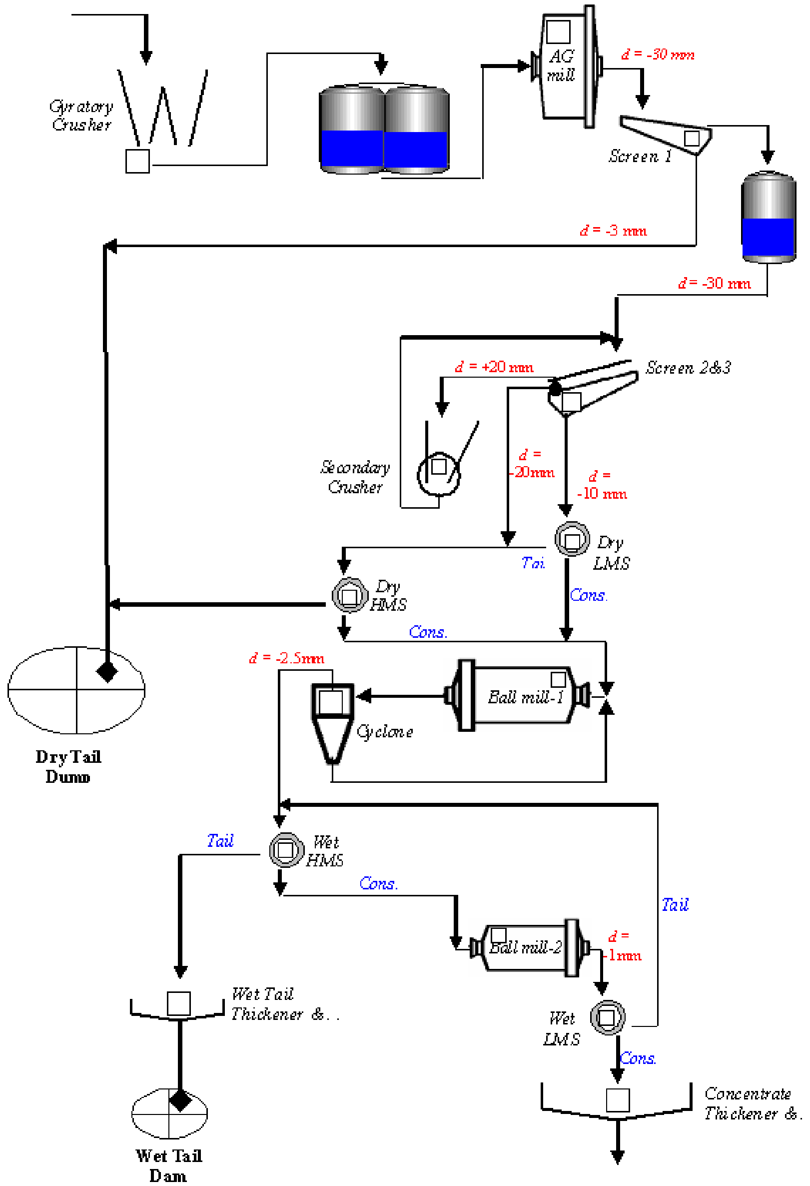

Fig 1.Hypothetical magnetic iron ore separation process flow sheet

The approach of this study is to simulate and trace the material characteristics through the different stages of the processing plant, from the point that material is delivered to the plant from the mine - trucks feeding the Gyratory crusher-to the four exit points of the processes defined above. The main ore feed tonnage, its rock type and its respective three grades (Fe, S and P), can be defined as inputs of the system. The main parameters of importance in output streams of materials are the recoverable tonnage in each of the four system exit points and the magnetic content, sulfur and phosphor grade in each stream as well as machine utilizations.

4. Modeling approach

Among all the machines used in the processing plant, those which have a direct effect on the recoveries and performance of the system are considered to be system modules in the simulation. The other facilities do not affect ore characteristics, but still have an effect on plant operations. Therefore, whenever it is possible, their positive or negative effects (such as failures, capacity restrictions, etc.) are added to the specifications of the corresponding main machine (e.g. conveyer belts).

This system is a continuous process; however, this project seeks to model it as discrete events. One way to do so is to use the batching approach as introduced in Lu et al. (2007), considering a onetime unit worth of material fed into the processing plant (in this case an hour is considered) as an entity flowing through the model. In order to make the simulation more realistic, the production of each plant section is stopped if any of the machines in that division fails, if the bin which feeds the plants gets empty, or if the bin at the end of the plant fills up.

4.1. Continuous to discrete conversion

A magnetic separation plant works in a continuous manner, i.e. material flow on a belt through comminution and separation stages. However, the idea is to use batches, representative of a fixed period of time, as the entities in a discrete simulation model. Each entity carries forward the average characteristics of the material it is representing (grades, particle size distributions and rock hardness) as well as its tonnage.

A continuous processing plant is usually balanced in a way that a smooth flow of material goes through the system. Machines are set up with different rates based on the expected tonnage per hour of material, i.e. their rates and capacities are set based on the portion of input material that is expected to reach the specific machine. In order to mimic the continuous flow of material each entity will stay at each operation based on its tonnage and the balanced capacity of the machine. It is assumed that the machines are balanced when the material from the most dominant rock hardness and average grade is uniformly fed into the plant.

Considering the process flow sheet and parameters of interest, facilities can be categorized into four main groups:

1. Storage bins and piles
2. Comminution machines
3. Classifiers
4. Separators

In the next section, the specifications of each group which are important from the simulation point of view are discussed.

4.2. Storage bins and piles

In all mineral processing plants there is a need to have some storage areas as bins or stockpiles to keep 4-5 days of plant feed. These stockpiles/storage bins are used to store material between different stages of the processing plant in order to avoid unexpected shutdowns of the whole plant. Also, the presence of stockpiles/storage bins assure continuation of material flow in the downstream processes, when for any reason the upstream is shutdown for a short period of time. These storage bins can be considered to be shock absorbers of the processes.

When an entity reaches a storage module its tonnage is added to storage modules tonnage and the entity is disposed. In order to keep track of the material's grades in each bin, the average weighting method is used, i.e. the material is blended in each bin and input batches are not recognizable among the outputs. The material content of the storage is updated every time an entity reaches the storage or when a new entity is created to represent the feed to the next processing stage. The storage grade (as a weighted average) of each species is defined by the following equation:

$$StorageGrade_i = \frac{\left(StorageTonnage \times StorageGrade_i + EntityTonnage \times EntityGrade_i\right)}{\left(StorageTonnage + EntityTonnage\right)} \quad (1)$$

where i can be Fe, S or P. It is also possible to consider limited capacities for each bin, when defining them as tank modules in Arena to avoid the accumulation of material in the plant when the next processing step is out of order because of a fault. On the other hand, if a bin runs out of material, the next part of the plant has to be stopped until a certain level (tonnage) of material accumulates in the bin.

4.3. Comminution machines

Comminution machines play an important role in mineral processing plants. In fact, it is not possible to recover any mineral or metal from ore without comminuting it down to a proper size (reaching the acceptable degree of freedom). Two types of comminution facilities are considered in Fig. 1. First, there are crushers designed to deal with coarse particles of ore. The second group of size reduction facilities considered is mills. Mills usually deal with finer feed size in comparison with crushers, and they also grind the material to much finer particle sizes.

Regardless of all designing and operational conditions, it is important to have an idea about two main parameters of size reduction machines in order to have a correct model in the Arena simulator and to achieve a reality-mimicking model. First, one should consider when and how frequently they are out of order. This can be modeled as the failure schedule in the software. The second important point related to these facilities is the Particle Size Distribution (PSD) of the discharge material. The minerals' degree of freedom, which defines the recovery of metal and grade of the concentrate, is strongly related to the PSD of feed stream to a separator.

The discharge PSD of the materials is affected by various parameters in a size reduction machine. Some of the main affecting parameters are: rock hardness, mineral size and type, dominant comminution mechanism, machine operational condition and ball content, the ratio of ore to ball, and the amount of water in the mill.

Various functions, models, and procedures have been developed to describe the discharge PSD for any specific type of crusher or mill; they can be categorized into two main groups. The first category contains those which are determined based on experiments and correlations of the results to a logically proper model. The second group of models is proposed based on empirical functions. In this study, the discharge PSD of several rock types fed to a special kind of size reduction machine is examined to determine some constant coefficients. None of these methods can predict the exact PSD of the comminution machine; however, they can still obtain a reasonable PSD of the discharge material in each case.

In this study, as no experiment is performed, two famous predicting functions for discharge PSD of size reduction machines are considered: the Gaudin function and the Rosin-Rammler function. The Gaudin function is used for crushers, as in Eq.(2).

$$w = 100\left(\frac{d}{n}\right)^{m} \tag{2}$$

Where w is the weight cumulative percent of the particles with diameter of d or smaller size and n and m are model constants affecting the PSD range. For each machine, different n and m are defined according to the desired particle size.

The Rosin-Rammler function is used for any of the mills discharge PSD as in Eq. (3). a and b are model constants. Considering the desired coarse particle size, different n and m are defined for each machine individually.

$$100 - w = 100 \times \exp\left(-\left(\frac{d}{a}\right)^{b}\right) \tag{3}$$

4.4. Classifiers

Classifiers are used to separate particles based on physical properties such as size, density, and shape. Two types of classifiers, screens and hydrocyclones, are placed in the aforementioned plant flow sheet (Fig 1). Some merely separate or dispose a portion of materials, while others are placed in order to create a close grinding or crushing circuit. There are some advantages to using such a circuit, including lower energy consumption per ton of fragmented ore down to a specific size and lower fine particle (over ground particles) production in comparison with the equivalent open circuit fragmentation. Design quality also affects their industrial (actual) performance to a great extent. Some of the important parameters in the classifier designing procedure are: dry or wet operation, feeding rate, shape and density of particles, proportion of open area (in screens) and slurry feed pressure (hydrocyclones).

From the simulation point of view, one needs to trace particle size range in feed, over flow, and under flow of each classifier. Tonnage and grades of over flow and under flow streams should be traced as well. The mean time between failures (MTBF) and mean time between repairs (MTBR) for the classifiers must be taken into account in the simulation modeling based on the historical data. The MTBF and MTBR should be considered for the classifier itself, and for supplementary instruments such as belt conveyors, pumps, feeders and slurry tanks.

In the simulation model, output tonnages are determined based on feed tonnage and particle size distribution. Also, the PSD of the outputs of classifiers are determined based on the input feed PSD and linear interpolations. It is assumed that the grade of ore in over flow and under flow of the classifier is not the same as the input feed. Therefore, using the R_g concept (to be discussed later) and considering each classifier as a separator of the metal, the metal content of each output stream is determined.

4.5. Separators

Separators play a significant role in mineral processing plants. For any kind of separator, the machine recovery and concentrate stream grade are two of the most important parameters that managers are interested in knowing and controlling. Two types of magnetic separators in both operational conditions (wet and dry) are modeled. High intensity magnetic separators (HMS) and low magnetic separators (LMS) are classified under the category of physical separators. As the category name suggests, such separators deal with inherent physical properties of minerals (magnetic property of iron minerals) more than their chemical properties.

There are many parameters affecting the recovery of magnetic separators. The metal recovery of a magnetic separator (either low or high intensity) can be affected by various parameters such as particle size of material fed to the machine; mineral's degree of freedom; metal carrying (ore) type; magnetic intensity of the machine; physical and operational characteristics of the machine; bed thickness of material fed to machine in dry magnetic separators; and solid content of slurry fed to machine in wet separators. Studying the performance and operational conditions of a separator is beyond the scope of this project and is thoroughly investigated in the literature.

It is necessary, for modeling purposes, to define a function for metal recovery, and a function for determining what weight percentage of the materials should go to concentrate stream or tail stream. Logically, these functions should be defined based on grade, mineral type and particle size distribution of the feed. But since there are no experimental data available, an acceptable constant metal recovery (R_g) and concentration ratio (CR) for each separation machine is defined. At this step of simulation, it is possible to calculate all mass balance related parameters for each machine output stream.

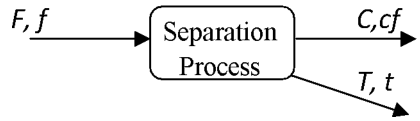

Fig 2.A schematic separator

Considering Fig 2, if *F*, *C* and *T* are defined as feed, concentrate and tail tonnage, and *f*, *c* and *t* as feed, concentrate and tail metal grades respectively, R_g and *CR* can be defined as in Eq. (4) and Eq. (5).

$$R_{g(i)} = \frac{Cc}{Ff} \tag{4}$$

$$CR = \frac{F}{C} \tag{5}$$

i iterates for iron, sulfur or phosphor. Having $R_{g(i)}$ and *CR*, concentrate and tail parameters for all separators can be calculated using Eq. (6) to Eq. (9).

Concentrate tonnage: $C = \frac{F}{CR}$ (6)

Tail tonnage: $T = F - C$ (7)

Concentrate grade of species: $c_i = R_{g(i)} \times CR \times f_i$ (8)

Tail grade of species: $t_i = \frac{F \times \left(1 - R_{g(i)}\right) \times f_i}{T}$ (9)

5. Modeling

The model is developed in Arena simulation software (Rockwell Automation), version 13.90. The plant is separated into 4 divisions which are shown schematically in Fig 3 to Fig 6. Recoveries, processing times, capacities etc. are presented in Table 1 to Table 4.

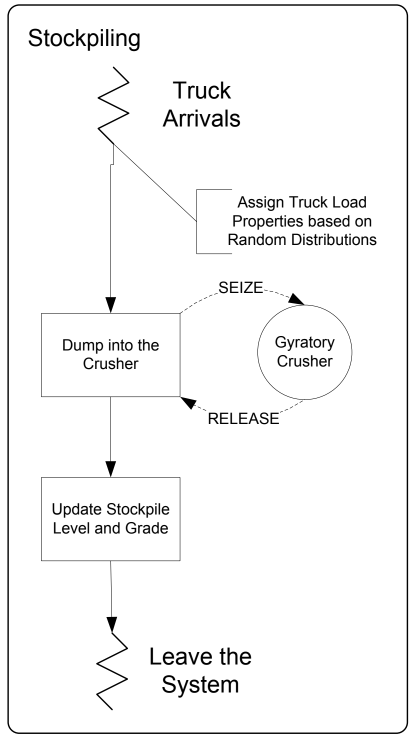

Fig 3.Truck arrival section.

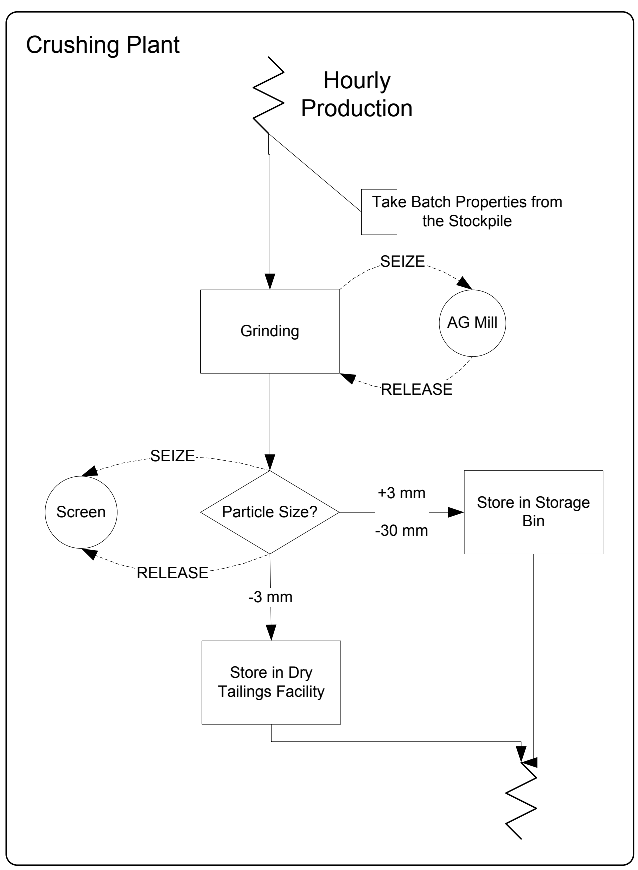

Fig 4.Crushing plant.

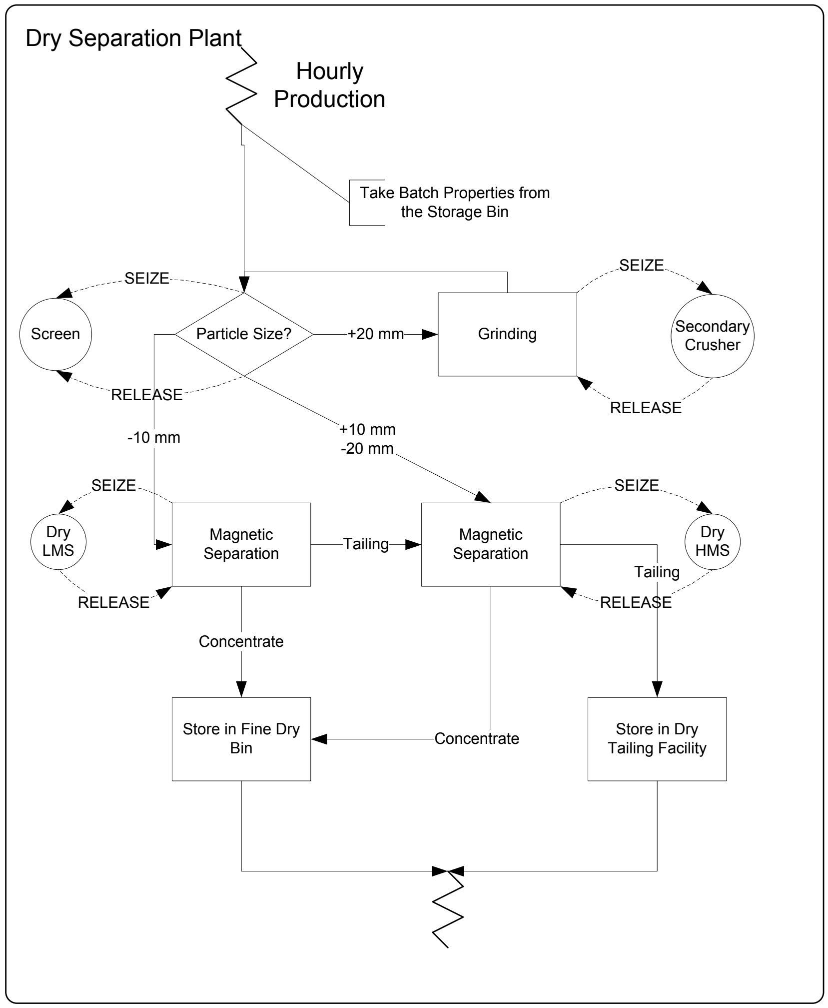

Fig 5.Dry separation plant part 1.

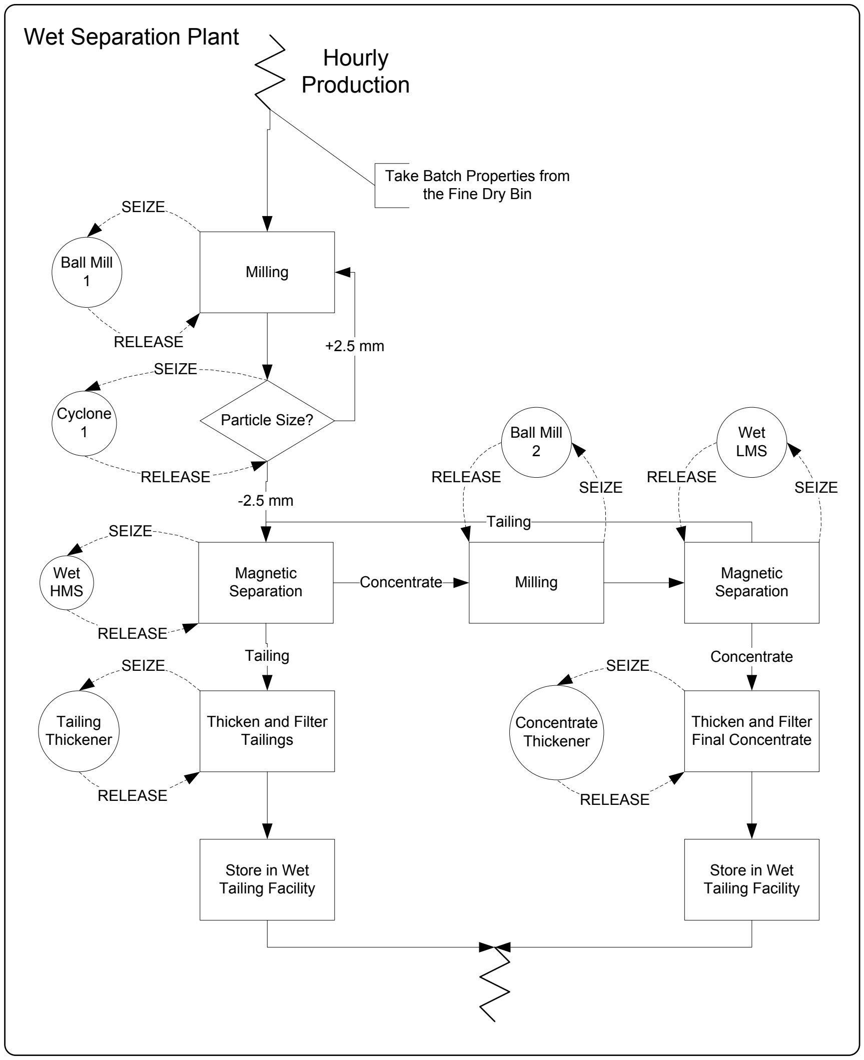

Fig 6.Wet separation plant part 2.

The plant is designed to process 1000 tonnes of ore per hour working in 3 shifts. Therefore, the crushing plant's capacity is set to 1000 tonnes/hour. However, not all the material reaches the next stages of production since some leave the plant as tailings in different stages. Thus, downstream operations would have less material to process per hour. The dry and wet separation plant production rates are determined using the average grade and recoveries and are shown in Table 1. Uncertainty is then added to the production rates by implementing a triangular distribution with 10 tonnes/hour perturbation.

Table 1.Production rates.

Crushing Plant (tonnes/hour)	Dry Plant (tonnes/hour)	Wet Plant (tonnes/hour)
1000	880	735

Failures are also considered based on regular plant maintenance and downtimes and perturbed using exponential random distribution which is commonly used for modeling machine failures. However, fitting distributions on failure and maintenance data is the more accurate approach if historical data is collected. Machine failures considered for the whole model are shown in Table 2.

Table 2.Machine failures.

Resource	Mean Uptime (days)	Mean Downtime (days)
All	355	10
Gyratory Crusher	59	1
SAG Mill	9.6	0.3
SAG Mill 2	175	7
Screen 1	59.6	0.3
Screen 2	9.6	0.3
Crusher	89	1
Dry LMS, Wet LMS	29.8	0.2
Dry HMS, Wet HMS	19.8	0.2
Ball Mill 1	89.6	0.3
Cyclone	29.6	0.3
Ball Mill 2	179.6	0.3

Two sets of operations are responsible for separating ore from waste: classifiers and magnetic separators. Classifiers have two output streams which are determined based on particle size distribution. However, the grade distribution of the output streams would vary since the coarser and finer particles usually have different metal and contaminant contents. Therefore, element recoveries are defined for these separators. On the other hand, magnetic separators operate based on the magnetic content of material and the degree of freedom. This can be modeled using concentration ratios and element recoveries as described in 4.5. The recoveries are perturbed using triangular distribution to take uncertainty into account.

There are two similar stockpiles at the starting point of the operation, one storage bin that holds the crushed material to feed the dry plant, one storage bin that is used for mixing the dry concentrate with water to feed the wet plant and a concentrate bin that holds the final concentrate. The nominal capacities for the stockpiles and bins are presented in Table 4.

Table 3.Bin capacities.

	Stockpiles	Storage Bin 1	Fine Dry Bin	Concentrate Bin
Capacity (tonnes)	12 days of production (300,000)	1 day of production (24,000)	1 shift of production (8,000)	Unlimited

6. Model verification

The developed model is run for a pilot evaluation and verified using 1 month of ROM feed. Since the objective of the study is to track the grades and tonnages of material, a limited amount of rock with constant grades is fed to the plant and the changes in its grades and tonnages are studied. In order to verify the model and make sure that all of the tonnage and metal content of the feed is retrieved at either of the system outputs, the model is run for the whole year but with 1 month of input. The verification results are summarized in Table 5. There are 3 closed circuits in the model in which very small entities keep cycling. Batches representing less than 0.1 tonnes in the 3 circuits are eliminated in order to avoid having an unlimited number of entities and objects. Checking the values in Table 5, 1,296 tonnes of material (0.2% of the input) is not recovered which is due to the previously mentioned modeling approach as well as rounding issues.

Table 4. Model verification results.

	Feed	Stockpile	Screen1 Tailing	D-HMS Tailing	W-HMS Tailing	Final Concentrate
Rock (tonnes)	646,052	45,990	72,704	33,858	66,979	425,225
Magnetic Content (tonnes)	508,010	36,200	9,540	12,397	34,273	413,930

7. Results

The goal of this paper is to build up a framework to find out the opportunities and possibilities of using a discrete event simulation model for studying continuous systems. The use of such a model is not restricted to what is listed here; however, this can show how powerful and useful a processing plant simulation model can be. The upcoming sections can also provide insight into modeling methodologies, performance measures and expectations from a discrete event simulation model.

7.1. Using truck-shovel data

It is common in the mining industry to simulate the truck-shovel operations based on the short-term mine plan in order to evaluate the dispatching systems. However, these models usually assume an always available processing plant with no specific restrictions on receiving and processing material. Linking the truck-shovel simulation model to the processing plant simulation can overcome this problem and result in a better prediction of truck-shovel performance. In addition, having the linkage in place, the input to the plant is more realistic and can produce more reliable measures of plant performance. The big picture can be to adjust the production plan, dispatching system and the plant schedules iteratively, based on other parts of the optimization and simulation models.

Two approaches can be taken to link the truck-shovel simulation model to the processing plant simulation model: integrating both into one model, and creating an offline link between the data from trucks delivery and the plant input data. The second approach is taken in this project by using the simulated truck deliveries from Askari-Nasab et al. (2012) results. Askari-Nasab et al. (2012) form a mathematical model to decide on the fleet size required to satisfy a short-term production plan and simulate the optimized solution through discrete event simulation. In Askari-Nasab et al. (2012), trucks deliver extracted material from an iron ore mine to 6 different destinations which are two waste dumps, two stockpiles and two processes. Arrival time of the trucks at destinations, tonnage of load, and the load properties are recorded as each truck reaches its assigned destination. The best scenario with appropriate fleet size in Askari-Nasab et al. (2012) is used as the input to the plant simulation model. The tonnage and magnetic content grade of input data is shown in Fig 7. It can be seen that there are fluctuations in the delivered tonnage and grade that can affect the performance of the processing plant.

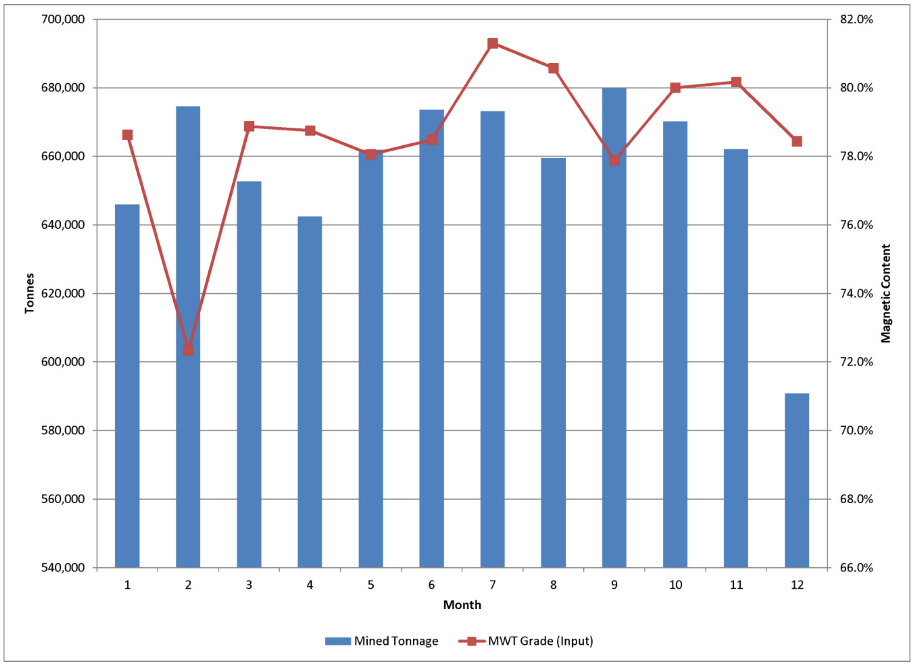

Fig 7.Tonnage and MWT grade of material delivered to processing plant.

The trucks arrive at the processing plant on an average of 3.5 minutes. However, the inter-arrival times vary from 0 minutes to 30 minutes (Fig 8). This can also affect the performance of the processing plant especially the primary crusher and stockpiles at the beginning of the process. This problem is further described in section7.4.

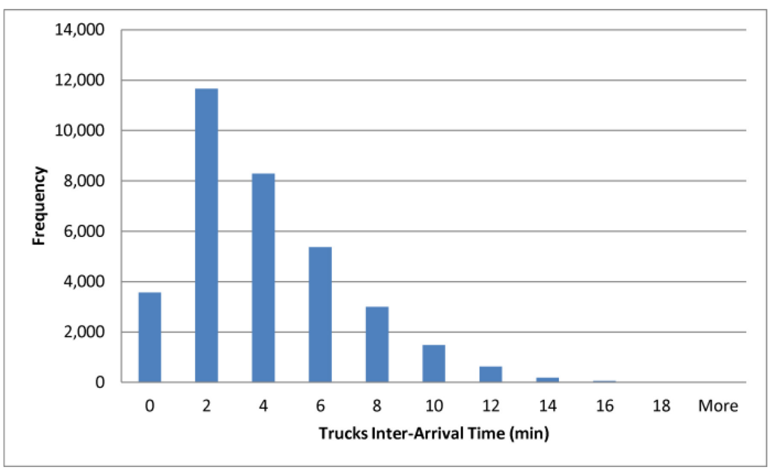

Fig 8. Trucks inter-arrival times.

The goal of this project is to link the production schedule to the truck-shovel dispatching system and finally to the processing plant using simulation modelling. The simulation model assists mine planners to predict the performance of the whole mining operation linked to the quantity and quality of the final concentrate produced. The production schedule could be modified as needed to meet the quality and quantity specifications of concentrate. Incorporating uncertainties in various stages of the production using simulation techniques can minimize the risk of not meeting contract commitments. Accordingly, 20 replications are run to find out the shortcomings of the schedule and to be able to provide appropriate corrections. The expected concentrate tonnage and magnetic content grade are presented in Fig 9 and Fig 10. Fig 9 represents the tonnage of concentrate produced in each month and Fig 10 shows the variations in the concentrate magnetic content grade. The error bars represent one standard deviation from the average values.

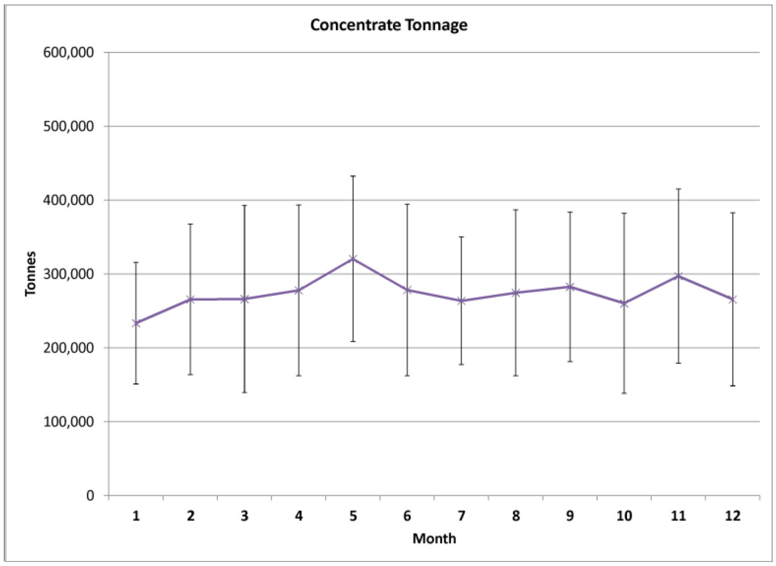

Fig 9. Concentrate tonnage.

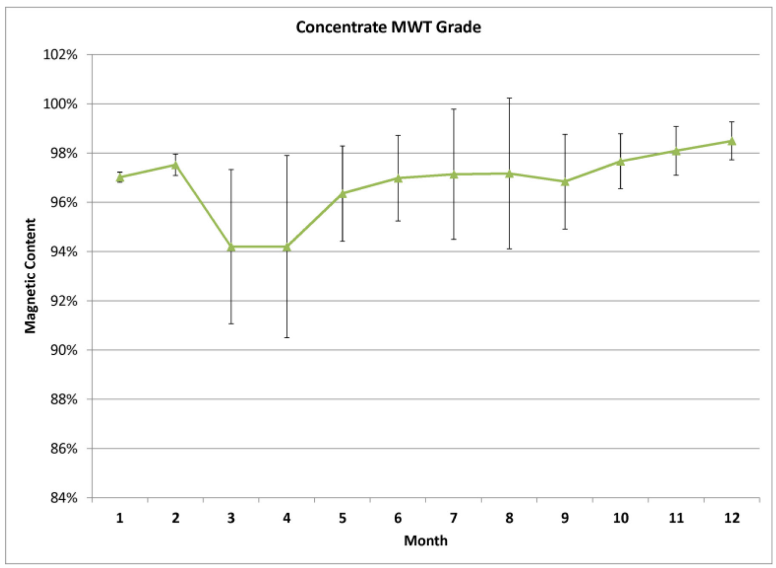

Fig 10. Concentrate magnetic content.

The first interesting conclusion from Fig 9 and Fig 10 is that the MWT grade of the concentrate is not varying too much considering uncertainty. However, the tonnage of concentrate produced is concerning since the plant has to be able to commit to produce specified tonnages of concentrate to sell in each month.

7.2. Balancing the processing line

A continuous processing plant is usually balanced in a way that material flows through the system with minimum jamming and maximum utilization of the machines. This means that the machines are set up to work with a rate when the machine is neither idle nor faced with a large queue in front. However, uncertainty exists and no matter how accurately the balancing is done, it is possible that a machine does not have material to process or is behind schedule and causes jamming of material in the system.

System engineers and designers usually use the expected values for input material characteristics and performance parameters and calculate the expected tonnage of material processed by each machine. However, this approach cannot predict a system's performance in real life when the grade and rock properties of the input material are not as expected or the machines do not perform exactly as their catalogue says. One important use of simulation models is to study a system's performance in presence of uncertainty. In order to achieve this goal, the simulation model is run with a constant MWT grade of 80% and a rock hardness coefficient of 1. It is assumed that the plant is designed based on a bottom magnetite ore zone which forms around 70% of the used deposit. Therefore, a rock hardness factor of 1 is assigned to the bottom magnetite, and hardness factors for the other zones are calculated accordingly. The recoveries are kept as before and the model is run with unlimited feed from the stockpile assuming that the mining operation is working as expected. The processing times are then set in a way that around 90% utilization is achieved for the resources. The balanced capacities of different resources are shown in Table 6. As shown in the table, capacities start from 900 tonnes/hour to achieve 90% utilization for machines working in a 1000 tonnes/hour processing line. However, by having output streams branching out of the main stream less material is processed by later machines.

Table 5. Balanced Resource Capacities.

ID	Resource	Capacity (tonnes/hour)	ID	Resource	Capacity (tonnes/hour)
1	Gyratory Crusher	5,500	8	Ball Mill 1	735
2	SAG Mill	900	9	Cyclone 1	735
3	Screen 1	900	10	Wet HMS	550
4	Screen 2	790	11	Tailing Thickener	37
5	Crusher	35	12	Ball Mill 2	515
6	Dry LMS	485	13	Wet LMS	515
7	Dry HMS	395	14	Concentrate Thickener	295

The next step would be to use the truck-shovel simulation data and check the differences in machine utilizations and queue lengths. Although there is no entity queue in a continuous operation, the queue length can be representative of the tonnage of material waiting to be processed by the machine. Long queues mean that the machine is behind schedule opposed to very short queues which mean there is not enough material to be processed by the machine. The comparison between the utilizations and queue lengths for the two runs with and without variable grade and rock hardness is shown in Table 7. The four magnetic separation machines are considered for comparison since their operation is the main goal of the plant. It can be inferred from Table 7 that the balancing procedure is properly handling the variations in the input material.

Table 6. Balanced utilizations.

Machine	**Synthetic Constant Data**		**Truck-Shovel Data**	
	Utilization (%)	Average Queue Length	Utilization	Average Queue Length
Dry LMS	88.5	0.4	83.9	0.3
Dry HMS	90.2	8.3	86.7	10.0
Wet LMS	85.2	5.4	86.6	5.5
Wet HMS	89.2	13.8	91.0	17.3

7.3. Determining appropriate batch-size

As described in 4.1, the modeling is done by assuming batches of material as entities. However, the question arises regarding how big these batches should be. Chapters 7.1 and 7.2 use 1 hour of production as the batch size. It seems useful to check the model with different batch sizes and study the differences that would occur. Various batch sizes are tried by changing the associated tonnage of entities as well as the intervals of creating entities for different stages of the production. It is obvious that the smaller the batches are the closer to continuous modeling one gets. However, is it necessary to use very small batches to be able to mimic the continuous nature of the system? The answer depends on the modeling, the level of required details and the length of the simulation run.

The same 1 year simulation run with failures and uncertainty is used to study the differences between batch sizes. The results are summarised in Table 8. The first column is the average batch size that enters the crushing plant at the beginning of the separation process. The total number of entities obviously depends on the modeling logic but can be used as a measure to illustrate how big the model gets with small intervals. The fourth column shows the time required to run the model on a dual core 2.4 GHz machine. The fifth column is the overall plant recovery that is calculated based on the magnetic content of the final concentrate divided by the total magnetic content of the input rocks. Although the simulation length is 365 days, a terminating condition is added to make sure that the simulation does not terminate until all the intermediate entities (production batches) leave the system. This can be a way to verify that all the material fed to the plant is recovered and the overall recovery is calculated properly. As mentioned earlier, there are 3 closed circuits in the model and entities representing less than 0.1 tonnes of material are removed from those circuits. The removal of very small entities and rounding errors are the sources of the seventh column.

Table 7. Different batch sizes.

Average Batch Size (tonnes)	Entity Creation Interval	Total Number of Entities	Run Time (s)	Overall Plant Recovery (%)	Lost Material (tonnes)
17	1 min	16.8 M	271	87.6	48,191
167	10 mins	2.7 M	40	88.0	9,117
1,000	1 hour	1.3 M	14	88.1	1,028
8,000	8 hours	0.9 M	7	88.1	87

It could be predicted that models with smaller batch-size need longer time and more computational resources to run. However, the interesting point is that more error is produced with smaller batch sizes. This is due to the fact that smaller batch size results in more entities and thus more operations; each operation has its own error and increasing the number of operations increases the total error. The differences in overall recoveries do not seem to be significant.

7.4. Determining proper stockpile size

Simulation models are usually used to aid the decision making and design processes. A design and operation decision for a processing plant can be the size of the stockpiles and intermediate bins. The decision can be made by simulating various scenarios with different stockpile sizes and comparing some performance measures. Larger stockpiles can hold more material but take longer to get filled up or reclaimed. In contrast, smaller stockpiles do not take a long time to fill up or reclaim but are vulnerable to fluctuations. The size of the stockpile at the processing plant has to be no smaller than one day of production in order to guarantee that there is enough material to feed the plant while there are failures in the crushing system or the truck-shovel mining fleet. On the other hand, physical constraints on stacking and reclaiming equipment may result in long queues of trucks waiting for room at the stockpile to dump their load if the stockpile is very large. Accordingly, two performance measures are defined to compare stockpile sizes: the percentage of time that at least one stockpile is available to receive material (RSA) and the percentage of time that at least one stockpile is able to feed the plant (FSA).

The simulation model with a one-hour batch size is run with different stockpile sizes and the performance measures are presented in Table 9. Putting the data in a chart as in Fig 7 shows how tricky it is to choose stockpile size. Starting from a single day of production a large number of arriving trucks have to wait until a stockpile becomes ready to receive the load. By increasing the stockpile size to 36,000 and 60,000 tonnes, more trucks face a dumping queue. Interestingly, by expanding the stockpile to 72,000 tonnes, the percentage of time that stockpiles are available for dumping (RSA) plunges to around 76%.Upgrading the stockpile to 120,000 and 240,000 tonnes will again decrease the availability of stockpiles. However, the stockpile performance measures hike by raising the stockpile size to 300,000 and 480,000 tonnes. Depending on the physical constraints of the stockpiling area and the capital investments required, either of the stockpile sizes of 72,000, 300,000 and 480,000 tonnes can be chosen.

Table 8. Stockpile size comparison.

Stockpile Size (tonnes)	RSA (%)	FSA (%)
24,000	27.1	36.6
36,000	17.8	20.0
60,000	6.7	6.2
72,000	76.3	64.8
120,000	7.3	6.0
240,000	8.0	5.8
300,000	56.9	69.5
480,000	76.5	79.5

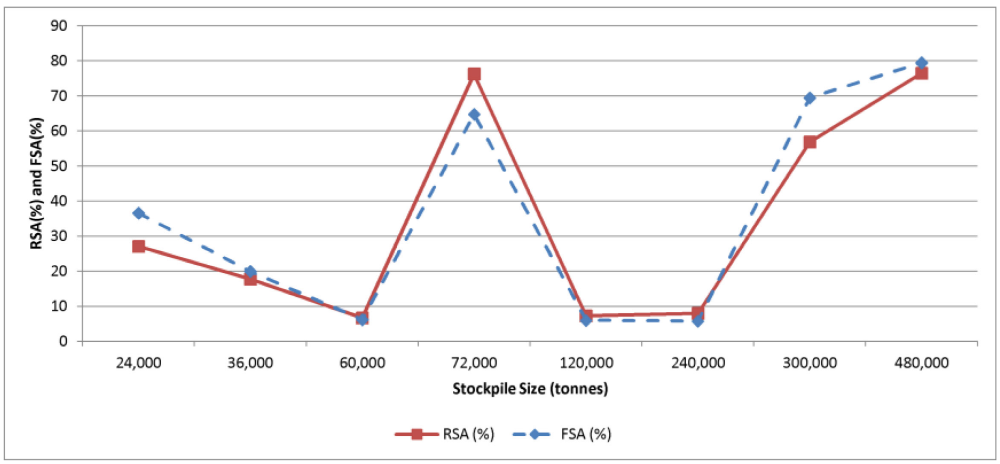

Fig 11. Stockpile size comparison.

8. Conclusions and future work

Simulation models are widely used to study mineral processing plants, circuits and machines. They can be used to predict a system's performance and to study the effects of changes in input parameters and system design. A discrete event simulation model is developed in this paper which mimics the performance of an iron ore magnetic separation plant in presence of uncertainty. The model uses the truck-shovel dispatching data as the input to the plant and predicts the final concentrate's magnetic content grade and tonnage in presence of uncertainty in machines' operating factors and failures. Running multiple replications of the simulation model shows that the concentrate grade does not vary too much with the fluctuations in plant operations and input. The results show that the monthly tonnage of the concentrate produced is the most sensitive output apportioned to failures and scheduled and unscheduled maintenance. It is also shown that various machines and operations of a processing plant can be interpreted into simple processes and modeled using resources, failures and process modules of discrete event simulation software. In addition, it is illustrated how this modeling can be used in making design and planning decisions and in predicting the system's behavior in presence of uncertainty. The modeling procedures and techniques introduced in this paper can be used to develop more accurate models of operating or designed plants.

9. References

[1] Andrade Lima, L. R. P. and Hodouin, D. (2006). Simulation study of the optimal distribution of cyanide in a gold leaching circuit. *Minerals Engineering*, *19* (13), 1319-1327.

[2] Askari-Nasab, H., Torkamani, E., Badiozamani, M. M., and Tabesh, M. (2012). Alignment of Short-Term and Operational Plans Using Discrete Event Simulation, in Proceedings of Society for Mining, Metallurgy & Exploration (SME) Annual Meeting, Seattle, Washington, USA, pp. pp. 1-8.

[3] Austin, L. G., Julianelli, K., de Souza, A. S., and Schneider, C. L. (2007). Simulation of wet ball milling of iron ore at Carajas, Brazil. *International Journal of Mineral Processing, Special Issue To Honor The Late Professor R. Peter King*, *84* (1-4), 157-171.

[4] Bergh, L. G. and Yianatos, J. B. (1995). Dynamic simulation of operating variables in flotation columns. *Minerals Engineering*, *8* (6), 603-613.

[5] Bouchard, J., Desbiens, A., del Villar, R., and Nunez, E. (2009). Column flotation simulation and control: An overview. *Minerals Engineering*, *22* (6), 519-529.

[6] Bureau de Recherches Géologiques et Minières (2012). USIM® PAC [Computer software]. Available at http://www.ozmet.com.au/usimpac.asp.

[7] Delgadillo, J. A., Lopez-Valdivieso, A., and Tello, A. (2008). Optimization of a grinding and classification circuit of a magnetite ore processing plant through computer simulation. *MINERALS & METALLURGICAL PROCESSING*, *25* (4), 223-228.

[8] Dlamini, M. F., Powell, M. S., and Meyer, C. J. (2005). A CFD simulation of a single phase hydrocyclone flow field. *The Journal of The South African Institute of Mining and Metallurgy*, *105* 711-718.

[9] Duarte, M., Castillo, A., Sepúlveda, F., Contreras, A., Giménez, P., and Castelli, L. (2002). Multivariable control of grinding plants: A comparative simulation study. *ISA Transactions*, *41* (1), 57-79.

[10] Ford, M. A. and King, R. P. (1984). The simulation of ore-dressing plants. *International Journal of Mineral Processing*, *12* (4), 285-304.

[11] Fourie, P. J. (2007). Modelling of separation circuits using numerical analysis, in Proceedings of The 6th International Heavy Minerals Conference 'Back to Basics', The Southern African Institute of Mining and Metallurgy,

[12] JKTech Pty Ltd. (2012).JKSimMet® [Computer Software].Available at http://www.jktech.com.au/jksimmet.

[13] Lu, M., Lau, S.-C., and Chan, E. K. Y. (2007). Combined simulation modeling using simplified discrete event simulation approach: a mining case study. in *Proceedings of the 2007 summer computer simulation conference*, San Diego, California, Society for Computer Simulation International, pp. 421-428.

[14] Lynch, A. J. and Morrison, R. D. (1999). Simulation in mineral processing history, present status and possibilities. *The Journal of The South African Institute of Mining and Metallurgy*, 283-288.

[15] Mineral Technologies International Inc. (2010).MODSIM® [Computer Software]. Version:3.6.22, Available at http://www.mineraltech.com/MODSIM.

[16] Morrell, S. and Man, Y. T. (1997). Using modelling and simulation for the design of full scale ball mill circuits. *Minerals Engineering*, *10* (12), 1311-1327.

[17] Robinson, G. K. (2003). Predicting variation in planned mineral processing plants. *Minerals Engineering*, *16* (3), 179-186.

[18] Rockwell Automation, I. Arena Simulation Software. Ver. 13.90.

[19] Sosa-Blanco, C., Hodouin, D., Bazin, C., Lara-Valenzuela, C., and Salazar, J. (2000). Economic optimisation of a flotation plant through grinding circuit tuning. *Minerals Engineering*, *13* (10-11), 999-1018.

[20] Wang, J.-h., Chen, Q.-r., Kuang, Y.-l., Lynch, A., and Zhauo, J.-w. (2009). Grinding process within vertical roller mills: experiment and simulation. *Mining Science and Technology (China)*, *19* (1), 97-101.