Simulation-Assisted Plant Design

A.Lebedev[a*]

[a]*Lebedev Consulting, Bloubergstrand, Cape Town 7441, South Africa*
**Corresponding author: lebedev.consult@gmail.com*

ABSTRACT

Application of dynamic simulation for a base metal processing plant is discussed. The plant receives ore of variable quality from two pits and blending had to be applied to maximise recovery. The plant employs multiple stage crushing, screening, dense media separation, two-stage milling, flotation and further filtration. Stockpiles and bunkers are used in the plant to cater for breakdowns and operating delays, the latter being appropriately incorporated in the model. A detail dynamic simulation model was constructed from the rock face to the filtration plant to assist the plant design, notably with definition of the ore blending method, sizing storage capacity and in-plant conveyors. The plant model was broken down to capital equipment items and various feed types and mass balances were tested to ensure that the production target is met. The dynamic simulation tested the proposed blending method, identified bottlenecks, produced risk profiles for all strategic storage facilities and overall helped minimise the project risks and improve confidence in the plant design.

Keywords: Dynamic simulation, ore grade, blending, capacity, risk profile, throughput, utilisation

1. Introduction

1.1. What Simulation Are We Talking About?

This conference without a doubt will see many papers talking about process simulation, be it comminution, flotation, dense media separation (DMS) etc., going in-depth to the process physics and chemistry, such as for example ore particle breakage.

The simulations this paper discuss go at least one level up and look at the entire plant, attempting to integrate all processes (such as crushing, screening, milling, DMS and flotation) into a system that can be used to predict plant performance given the operating and maintenance schedules, process capacity, feed rates, breakdowns and other delays. This simulation therefore focuses not on the physics or chemistry of each individual process (although this could be incorporated if required) but rather on the ore flow through the plant and the interfaces between all processes, including transfer and storage.

A feature of paramount importance in this type of simulation is time, which is why it is normally referred to as dynamic simulation, modelling a process in time with ups and downs, interruptions etc.

1.2. Dynamic Simulation in Mining and Metallurgy – a Brief History

Dynamic simulation has been applied for various industries including mining and metallurgy since 1961, when the first ever simulation software programme known as GPSS (still being used) was released by IBM (Ståhl, Ingolf 2001 and Sturgul, J. R. 1997a). Since then the range of software tools has expanded dramatically, with 44 packages included in the latest simulation software survey conducted biannually by the Institute for Operations Research and Management Science OR/MS (Anon., 2017). General information on the most popular early simulation software used in mining and metallurgy can be found in a paper by Sturgul (1997b).

Dynamic simulation has been traditionally used for manufacturing (perceived to be the root of simulation), services, transport, logistics & distribution, telecommunications and other typical 'discrete' industries with metallurgy being a relatively small area of dynamic simulation application. For example, in the OR/MS simulation software survey (Anon., 2017) only seven vendors quoted mining/metallurgy as an application area. At the same time mining and metallurgy presents a significant potential for the application of dynamic simulation due to the very nature of its business, as shown by Gentry and O'Neil (1984), to be:

- capital-intensive;
- having long life cycle (up to 30 years);
- containing high risk.

Although mining and metallurgy in the past has been slow in recognition of dynamic simulation, lately there has been a visible growth of simulation studies done. A good indicator is Application of Computers and Operations Research in the Minerals Industry (APCOM), a biennial conference where dynamic simulation presentations have gained a substantial footprint.

1.3. Software Used in The Case Study

While all dynamic simulation software applications handle discrete events, there are a few which are capable of modelling both discrete and continuous processes, the latter found indispensable for most of the typical metallurgical processes. A discrete process is modelled as a flow of units, each representing a fixed quantity of ore, and in order to replicate the rate which is generally variable, an interval between unit arrivals need to be manipulated. In continuous processes ore is modelled as a fluid with natural rates applied to the flows. A comparison of discrete and continuous flow simulations is reported in Lebedev (1998).

Witness™ , developed by Lanner Group is an example of simulation software with both discrete and continuous modelling capabilities (Al-Aomar *et al*., 2015). This software was used for the plant simulation discussed below.

2. Problem Definition and Objective of the Study

2.1. Run of Mine Ore Characteristics

The plant in question processes nickel ore which is characterized by a significant variation of nickel content (also referred to as grade). The importance of taking the variation of key input variables such as metal content in ore into account when simulating mineral processing plants is discussed in detail by Merks (1991). In order to analyse the ore grade and fit distributions for both nickel content and mass of blasted block, the mine supplied data for 68 blocks totaling 1.54Mt. Distributions describing nickel content and mass of blasted blocks appear in Figure 1. Distributions appearing as red lines were used in the model to sample nickel content and mass of blasted rock. Since sampled values from the distribution can exceed over the measured boundaries, sampled values were truncated to the actual minimum and maximum values.

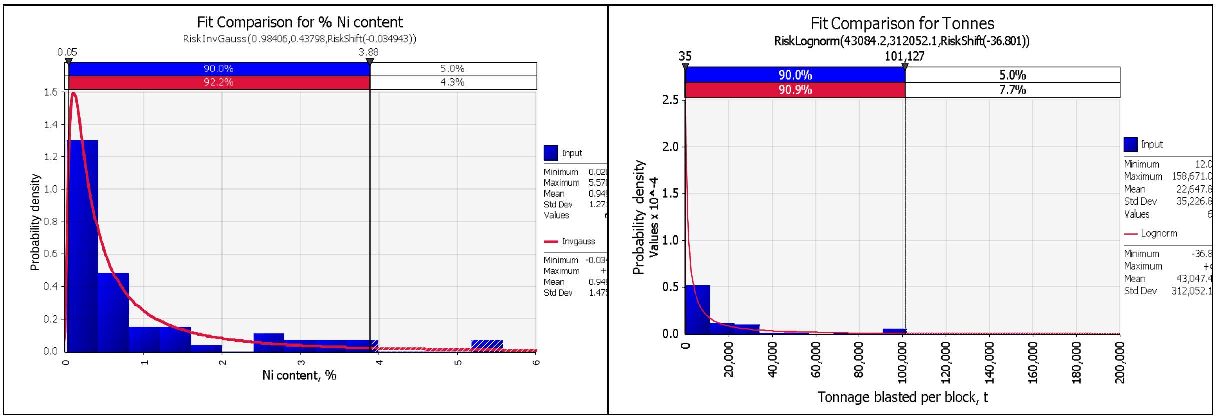


Fig.1. Distributions of nickel content in RoM ore and mass of blasted block.

The overall mass weighted average nickel content is 0.392% (not to be confused with the unweighted mean of 0.9491%). nickel assays vary from 0.02% to 5.57%.

2.2. The Objective

The operating efficiency of processes such as DMS and flotation depend on the metal content in the feed. To maximise the recovery rate the plant required that the deviation of nickel content from the unweighted mean (which in statistical terms refers to a coefficient of variation as per formula 1) did not exceed 10% over a 10-hour period:

$$C_{var} = \frac{\sigma}{\mu} \quad \text{where } \sigma \text{ is standard deviation and } \mu \text{ is the mean} \qquad (1)$$

The company management was also contemplating a brownfield expansion ultimately resulting in an increased plant throughput by the following modifications to the plant:

1) Phase 1 – modifications to the existing plant
   a) An additional primary crusher;
   b) a new secondary crusher;
   c) conversion of the existing secondary and tertiary crushing circuit into a tertiary and quaternary

crushing circuit;

2) Phase 2 - adding a new crushing, screening and DMS plant with tie-in to Milling and Flotation. Due to the variation of the ore quality, three ROM stockpiles were proposed to be established on a ROM pad containing high-, medium- and low-grade ore as specified in Table 1.

Table 1

Parameters of ROM stockpiles.

Stockpile	**Nickel content, %**	**Application**	**Minimum residual content, t**	**Application**
High grade	$Ni > 0.5\%$	Trucks routed to appropriate stockpile according to nickel content	4,000	If content drops to minimum, reclaim from stockpile stopped
Medium grade	$0.2\% < Ni \leq 0.5\%$		10,000	
Low grade	$Ni \leq 0.2\%$		5,000	

The minimum residual content on each of the ROM stockpiles was prescribed by the mine. Feed into the primary crushers thus requires blending to smooth out the variation of nickel content in the plant feed.

The following objectives were therefore defined for this simulation study:

- Size ROM stockpiles and all in-plant storage facilities;
- Develop a blending method for Phase 1 to smooth out variation in the Nickel content into the plant;
- Quantify production throughput for the Phase 2 upgraded plant.

3. Brief Description of the Model

An extensive data gathering exercise and a detailed time and motion study were undertaken on the mine to ensure that the model replicated the real operation as accurately as possible. Most of the variable inputs were consolidated into distributions such as the ones in Figures 1 and 2.

At time zero, the model samples the mass of the first blasted block and nickel content (ore grade) making use of the distributions in Figures 1 and 2.

Provided that the truck hauling shift is active, the first truck approaches the shovel. On arrival to the loading bay, truckload, loading time and time to vacate the loading bay are also statistically sampled from the distributions obtained on site. The truck obtains its load and starts hauling to the ROM pad, travelling at a set speed over a measured distance. On arrival to the ROM pad, the truck is directed to the ROM stockpile according to the ore grade. Having reached the unloading position, truck tipping time is sampled from the appropriate distribution. Once the truck has discharged the load and a delay after tipping has expired, the truck starts travelling back to the shovel.

By iteratively increasing the size of the fleet, three trucks were found sufficient to deliver the ore to the ROM pad. Truck haulage was limited to the actual operating hours with a human break allowed during each shift.

Once the first block has been depleted, the model samples the mass and nickel content of the second block and so on until the simulation run is complete.

Due to the complexity of modelling the rheology of bulk solids, with the agreement of the mine, a simplifying assumption was made that ore behaved as an ideal liquid mixing instantly on a stockpile or in a bin. Weighted averaging was therefore applied to update nickel content in the ROM stockpiles, which although being remote from reality, was seen as a practical approach due to model development time constraints. The objective was to limit the variance of the metal content within $\pm$10% over a shift duration, assuming that shift on shift the mean content can change. The same approach was applied throughout the plant up to the milling circuit.

It should be noted however that if an accurate mathematical model describing the mixing of ore particles and quantifying the metal content for example in a form of a 3D distribution was available, it could have been incorporated into the model with relative ease.

On the ROM pad, a wheel loader and two trucks were allowed for to re-handle ore from the stockpiles into the primary crushers. In order to constrain the variance of nickel content within the given range, a sequence of reclaiming ore from different ROM stockpiles was established, whereby X truckloads were reclaimed from low-grade stockpile, Y truckloads from medium grade stockpile and Z from the high-grade stockpile. Depending on the current nickel content downstream, notably in the secondary crusher feed bin, the X, Y and Z numbers could be adjusted to either increase or decrease the metal content in the mix.

Sufficient statistics were gathered during the site visit to allow definition of timings intervals for all elementary procedures such as truck loading time, actual truckloads, truck speeds in the pit, on the ramp and on surface, as well as tipping time etc. Distributions were fitted for all these variables which were statistically sampled for each truck trip making the simulation model representative of the actual data observed in the plant.

The model incorporated operating and maintenance schedules and where possible, staggered maintenance shutdowns were applied. For example, in the DMS plant where four or five cyclone modules were tested, planned shutdowns were staggered to maintain one module per day in order to minimise the plant maintenance department requirements.

Raw logs of the downtime events in the plant were obtained which resulted not only in the calculation of Mean Time to Repair (MTTR) and Mean Time Between Failures (MTBF), but also in fitting of distributions of breakdown durations and intervals between failures for further use in the model. Examples of such distributions for the primary crushers appear in Figure 2

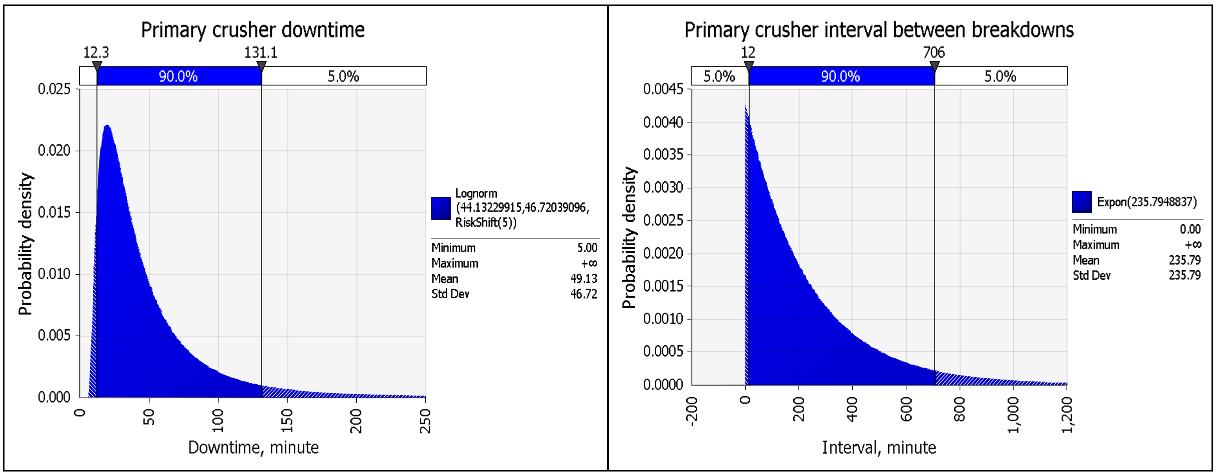


Fig.2. Distributions describing duration of, and interval between, primary crusher breakdowns

Unlike planned maintenance which always started and ended in scheduled time, breakdowns were floating and occurred in random time and lasted a variable duration.

The model incorporated the plant mass applicable to the screens and the DMS modules as well as all the feed rates. Actual feed rates were also retrieved from SCADA system and distributions were fitted. Figure 3 shows an example for the apron feeder beneath the primary crusher rock box.

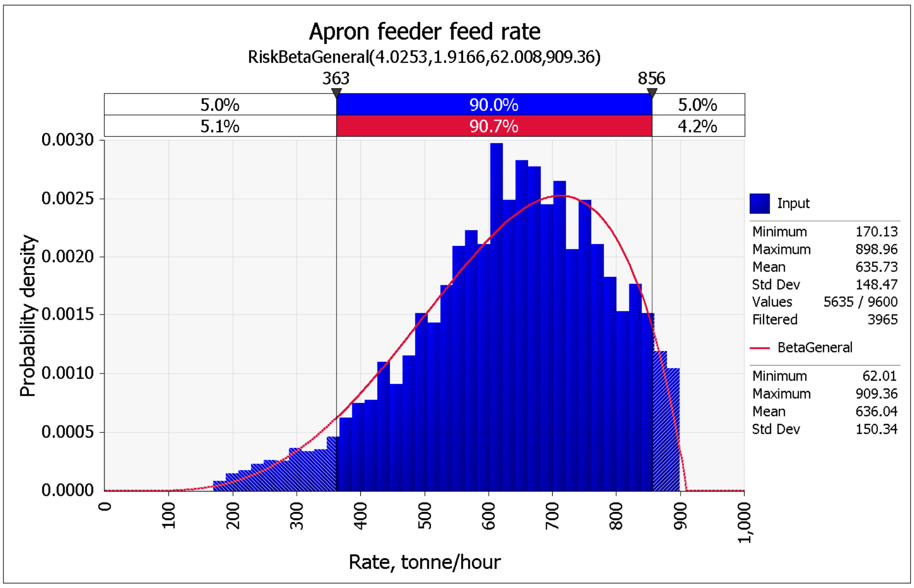


Fig.3. Distribution of apron feeder feed rate from primary crusher rock box

The model minimizes the use of constant values, instead, all variables are sampled from distributions fit to real data, making the simulation well representative of the actual operations.

All simulation experiments were executed to cover a full year of real-time operation (365 calendar days or 8760 hours equivalent to 525,600 minutes). The simulation time increment was set to 1.0 minute.

The screenshot of the dynamic simulation model (without the mine, i.e. the shovel in the pit and haul roads to the ROM pad) appears in Figure 4.

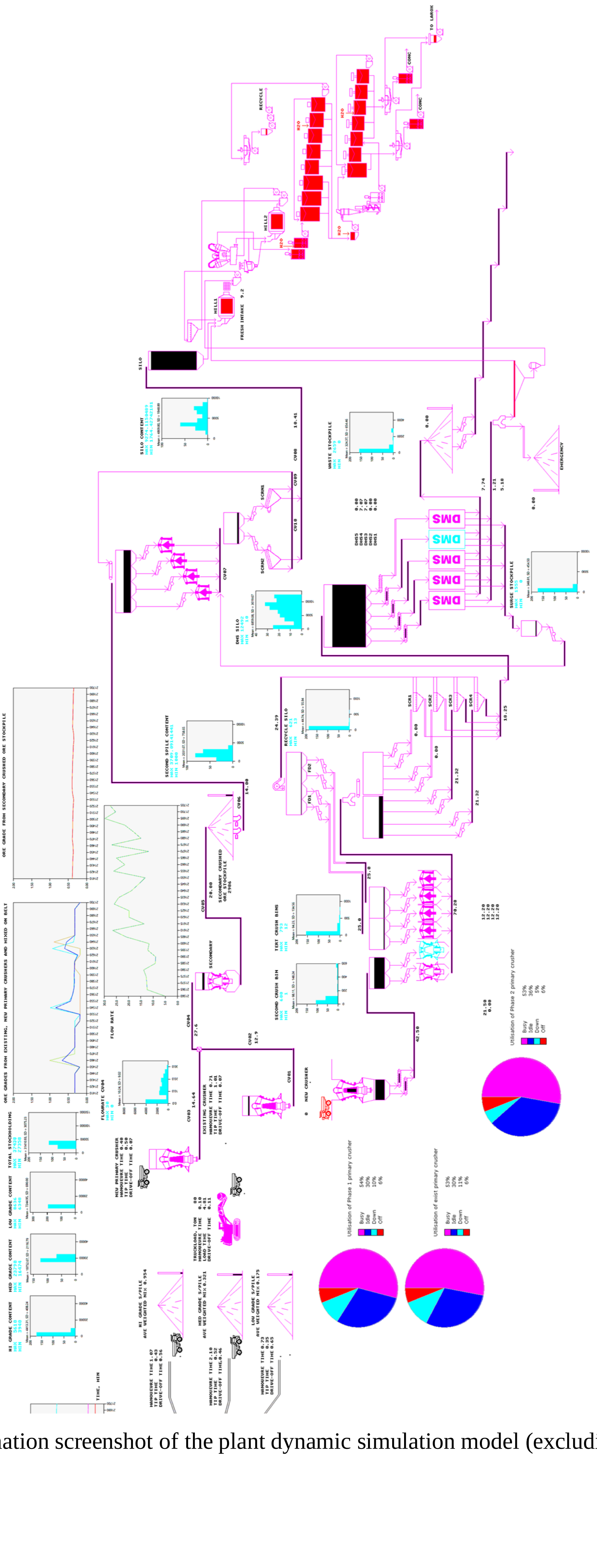


Fig.4. Animation screenshot of the plant dynamic simulation model (excluding the pit).

4. Discussion of Simulation Results

4.1. Production and Grade Control

The ROM target was set at 12Mtpa. This was achieved in the model by running multiple iterations and adjusting equipment and storage capacities.

The model recorded the weighted average nickel content in all plant key points such as feed bins and stockpiles and an example of such content after the primary crushers over a day is shown in Figure 5.

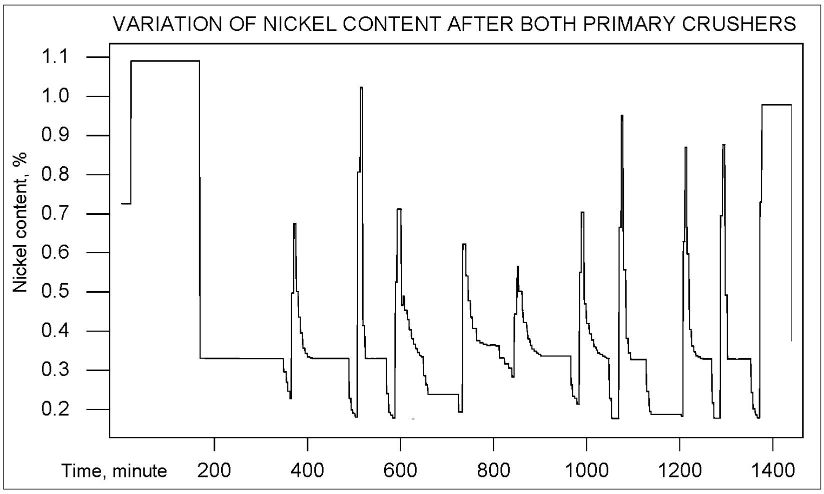


Fig.5. Sample of weighted average nickel content after two primary crushers.

A histogram of the same variable over the full year run appears in Figure 6.

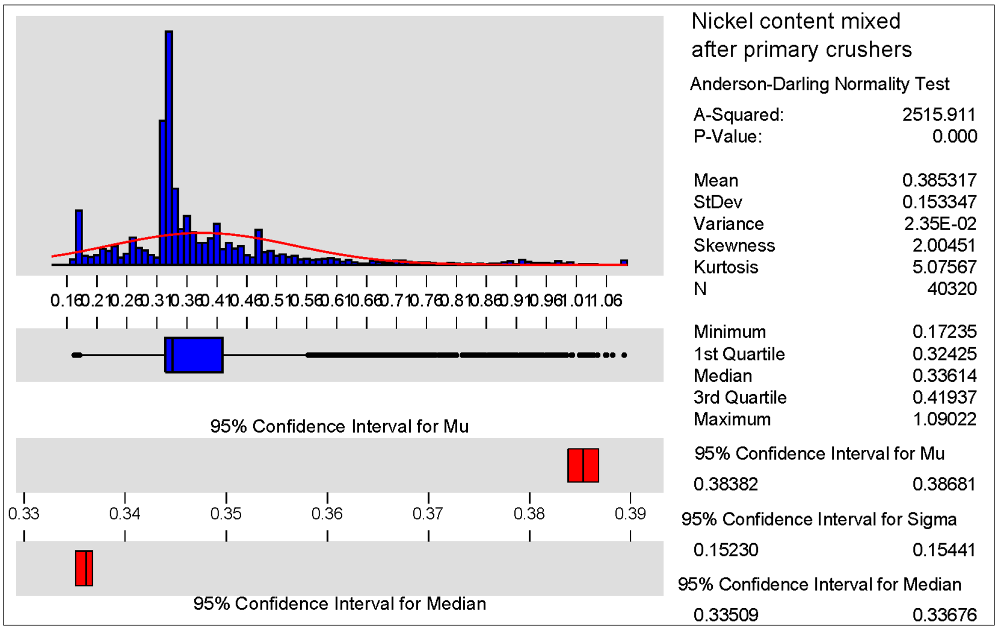


Fig.6. Weighted average nickel content after two primary crushers over a year.

While the standard deviation of nickel content is substantially lower than in the ROM ore (from 1.21 as shown in Figure 1 to 0.153 in Figure 6), the actual variation is still wide from 0.17% to 1.09% nickel content.

Figure 7 summarises the achieved nickel content variance in the plant.

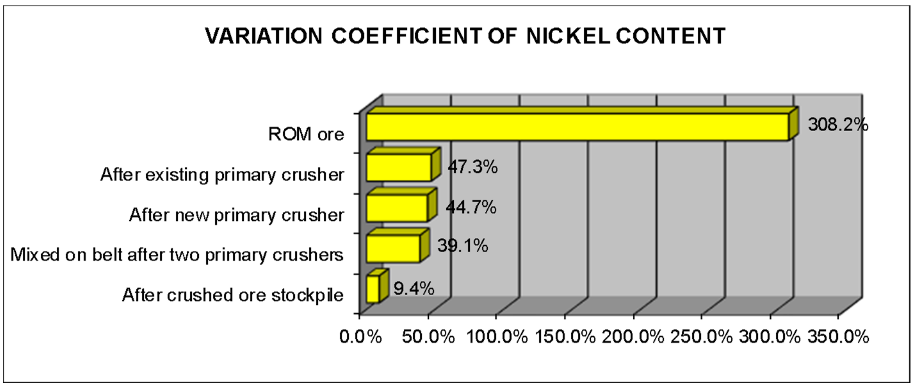
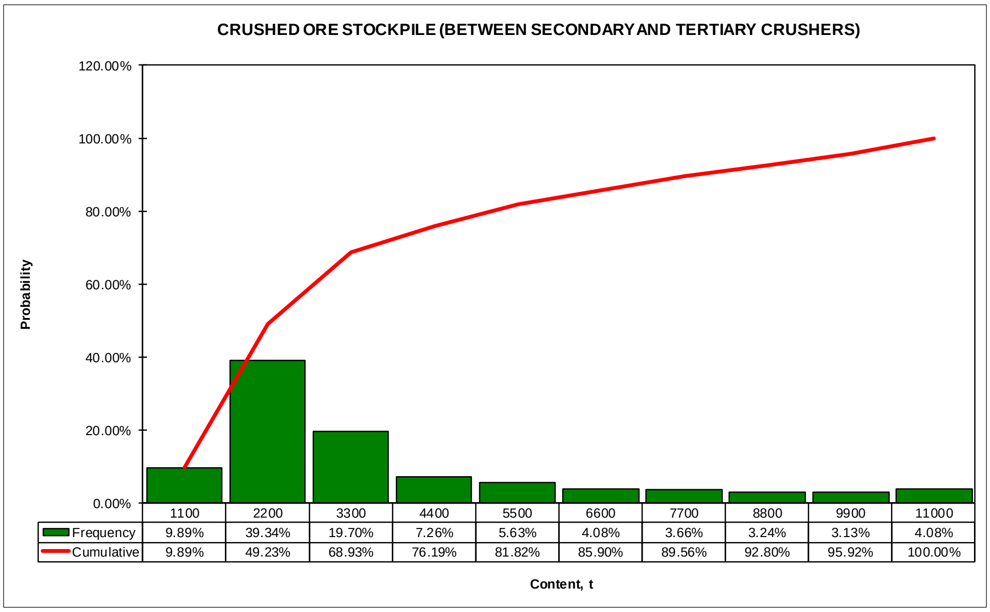


Fig.7. Variation coefficient of nickel content in the plant

As a result of blending and multiple points of ore mixing the coefficient of variation reduces from 308% in the ROM feed to under 10% mill feed.

4.2. Approach to Storage Requirements

One of the objectives of this study was to quantify storage requirements in the plant starting from the ROM stockpiles and up to the mill feed silo. A concept of risk profiles was applied to quantify the storage capacity versus risk of overflowing and running empty, an example of such risk profile for the crushed ore stockpile (between secondary and tertiary crushers) appearing in Figure 8.



	1100	2200	3300	4400	5500	6600	7700	8800	9900	11000
Frequency	9.89%	39.34%	19.70%	7.26%	5.63%	4.08%	3.66%	3.24%	3.13%	4.08%
Cumulative	9.89%	49.23%	68.93%	76.19%	81.82%	85.90%	89.56%	92.80%	95.92%	100.00%

Fig.8. Risk profile of the crushed ore stockpile

The stockpile was sized at 11,000t live capacity which was divided into 10 virtual ‘bins’ which appear in Figure 8 in the X axis, with each ‘bin’ covering content a range of content from 0t to 1100t, from 1100t to 2200t and so on with the last one covering content from 9900t to 11000t. Each hour the model recorded the current content of the stockpile and placed an observation into the corresponding ‘bin’. For example, if the crusher ore content was 1500t, the observation will be added to the second 'bin'. Green bars therefore reflect the number of observations in each 'bin' and hence the observations were taken with a constant interval, the bars also reflect the proportion of time the stockpile was holding ore in each of the 'bins'. The red line shows the cumulative probability and of the stockpile content, which is used to quantify the risk of the stockpile running full (about 4% of time) or empty (about 10% of time). Ideally this stockpile needs to be made larger as both values present operational challenges, potentially 'starving' the downstream plant for 10% of the time and stopping the upstream plant some 4% of the time due to interlocks in the plant.

Similar risk profiles were obtained for all other storage facilities including the ROM stockpiles.

4.3. Plant Performance

Apart from storage requirements the model was also used to measure the plant performance which was quantified in terms of time durations of equipment status such as:

- 'Busy' time when equipment was performing the intended duty.
- 'Idle' time when equipment was available but was not performing the duty either due to absence of feed or downstream plant blockage
- 'Down' time when equipment was either broken down or had an operating delay such as oversize rock stuck in a crusher.
- 'Off' time, when equipment was shut down for planned maintenance.

An example of such a performance chart appears in Figure 9.

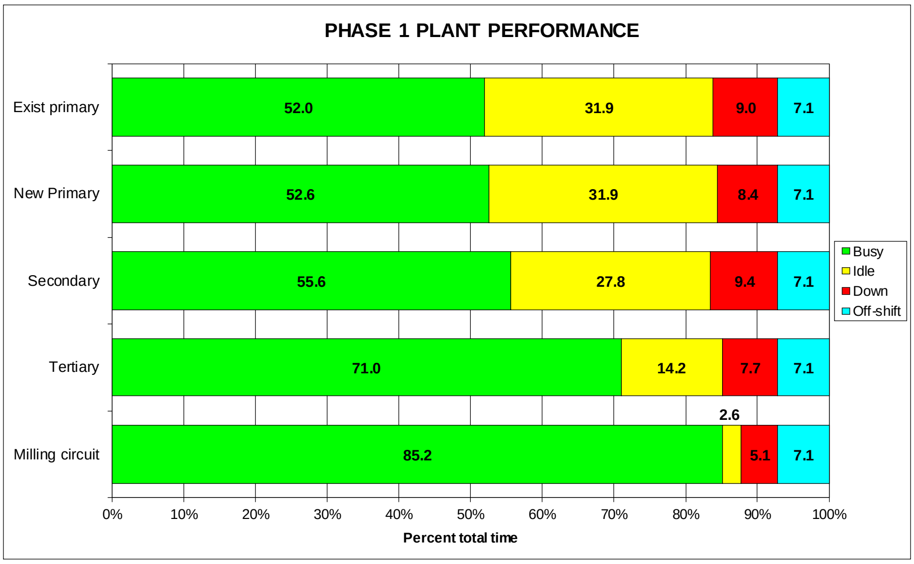


Fig.9. Risk profile of the crushed ore stockpile

5. Conclusions

Dynamic simulation was found to be a useful tool for the plant design, allowing integration of plant processing and storage capacity as well as time. In this study the model was used to develop an ore blending method to achieve the required grade envelope to feed the mills, check all stockpiles and bins and identify the plant bottlenecks, which were identified as the milling circuit in Phase 1 and the DMS plant in Phase 2. The model confirmed that the proposed plant brownfield expansions could reach the production targets. It suggested corrections to equipment selection specifically in the crushing and screening circuit and assisted in sizing the ROM pad. It significantly increased overall confidence in the design.

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