

Simulation Modeling of Iron Ore Product Quality for Process and Infrastructure Development

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EXTENDED ABSTRACT

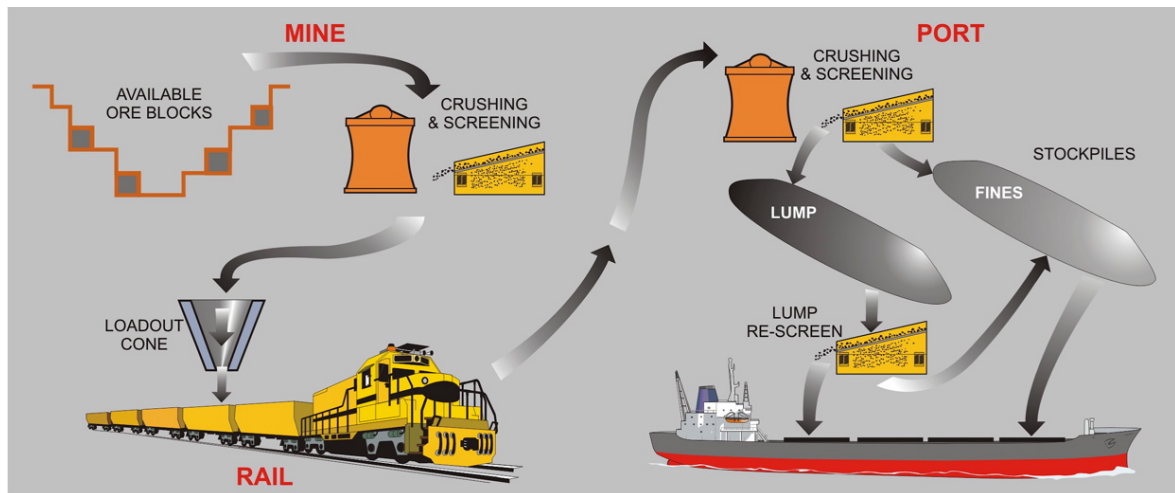


Figure 1: A Typical Iron Ore Production System.

BHP Billiton has several iron ore mining operations in the inland Pilbara region of Australia. Iron ore is mined from open-cut pits, railed several hundred kilometres to two port processing facilities at Port Hedland. Here the ore is processed, blended and the lump product re-screened ready for shipment, mainly to Asia. Customers use the ore as principal feed in steel production. Figure 1 shows a simplified ore flow, although many operational variations exist.

The recent sharp increase in iron ore demand has required a review of capacity. To deliver increased tonnage of ore safely, at minimum cost and acceptable quality, processes need to be upgraded, existing mines and infrastructure expanded, and new mines brought on line.

Expansion assessment requires informed choices involving alternative options of operation and infrastructure development that differ greatly in capital and operating costs. Multiple choices exist between alternative mining practices, ore processing, stockpiling, railing and ship loading operations.

Any expansion option must be assessed to understand the effect on product quality.

Customers assess quality by both cargo grade, and inter-cargo grade variability. As well as iron, several impurities, principally phosphorus, silica, and alumina are important. To gauge the effect of expansion options on shipped product quality, simulation models have been built, enabling mining and handling configurations to be studied, for appropriate time periods.

Since ore production grade shows complex serial and cross correlations, totally synthetic data cannot be constructed. Production was therefore simulated from historic data of geologically similar ore, statistically adjusted to match potential operations.

To help company personnel use the simulation models, they were written as Excel™ workbooks, driven by Visual Basic (VBA) macros, making full use of the provided graphical capabilities.

The simulation models described in this paper have been extensively used to evaluate alternative expansion and development options. The company is using the results from the models to assess the effect on product quality for many processing and equipment options in determining its expansion direction.

1. INTRODUCTION

BHP Billiton Iron Ore produces approximately 110 million tonnes per year of Brockman, Marra Mamba and Pisolite iron ore in two product types; lump (6 to 31mm) and fines (<6mm), from four separate mining areas in the Pilbara.

The worldwide increase in demand for iron ore, and its expected continuance, has led the company to identify opportunities to increase tonnages. BHP Billiton Iron Ore has reviewed the operating principles of its entire value chain as well as conducting investigations into the potential upgrading of existing mines and infrastructure along with the development of new mines.

Assessment of expansion options requires informed choices involving alternative modes of operation and development. These alternatives can differ greatly in expected capital and operating costs. Reviewing the many options that existed is very complex. Resource modeling, infrastructure and capacity modeling along with product grade quality modeling is needed to ensure delivery of the expanded tonnage of ore, safely, at minimum operating and capital cost and at an acceptable quality to the customer.

Simulation modeling was chosen as the appropriate tool for the reviews because of the complex relationships in each alternative. For BHP Billiton Iron Ore, the operating and infrastructure changes to achieve tonnage were studied in one simulation system while the effect on product grade quality was simulated in separate model.

This paper describes the simulations carried out to assess product grade quality. These simulations were based on infrastructure and capacity options identified from the tonnage simulations. They were set up so that the impact of changes to operating practices on product grade quality could also be assessed.

Two particular operating models are referenced in this paper; the Mt Newman Joint Venture, a series of four mines generating a lump and fines product and the Yandi operation with two operating areas where only fines product was studied.

1.1. Production Flow

Figure 1 shows a simplified ore flow. However, many operational variations exist.

At the mine, monthly mine plans take into account the cost efficient use of the resource. Ore blocks are blasted and assigned into floorstocks of

consistent geology and composition using analysis from samples taken during the drilling of the blast holes. Each day, ore for mining is selected from blasted floorstocks taking into account the target grade requirements, the current deviation from target, and cost efficient mine development.

In the case of the Newman area mines, partly processed ore from four mines is railed 400 kilometers to the port where it is crushed, separated into lump and fines products and stacked onto stockpiles typically of 150 kilotonne capacity. The methodology used for stacking ensures optimum blending within a stockpile. Lump product is re-screened before ship loading.

Ore from completed stockpiles is reclaimed and loaded onto ships through multiple ship loading berths and transported to customers. Everett (1996, 2001) discusses methods of iron ore quality control. Kamperman *et al* (2002) describe application of these methods to BHP Billiton's Yandi operation.

1.2. The Cost of Quality

The objective of the production process is to deliver the required ore tonnage safely, at minimum total cost and of an acceptable quality for the customer.

Chemical quality is determined by iron content and the percentage of impurities such as phosphorus, silica and alumina. There are two key product chemical quality criteria: cargo grade and inter-cargo variability. Customers require the product cargo grade to be as close as practical to target composition. In practice tolerances, reflecting process capability, are used to guide quality related decisions, at each stage in the production process.

Any quality decision takes into account the amount of blending of ore that occurs throughout the whole production process. Excessive inter-cargo variation disadvantages customers, potentially affecting price and sales tonnages. This potential cost, containing an element of risk, is extremely hard to evaluate quantitatively.

Blending and rehandling of ore can be a major contributor to operating cost. If carried out for product quality alone, there is a tradeoff between cost and quality. Mining equipment capacity and related production volumes, the methodology of use of this equipment, the amount of blasted ore, the volume of pre-crusher and post-crusher stockpiling are all examples of potential value tradeoffs against product quality.

2. SIMULATION METHODS

BHP Billiton Iron Ore developed alternative production and handling concepts from mine to ship loading as potential expansion options. These changes were evaluated and developed through sophisticated simulations for the study of tonnage movement and to gauge the effect of process interactions and bottlenecks. These models, however, did not assess product quality.

Rather than incorporate product quality into the tonnage simulation model it was decided to set up independent simulation models to explore the quality implications of the expansion options.

2.1. Challenges to Simulating Grade

It was important to understand the effects that operational or equipment changes had on cargo grade variability. Generally two types of grade variability exist in the chemical composition of the ore (Figure 2):

- Long-term variability as measured by trends of monthly or longer duration.
- Short-term variability is generally measured by short period inter-cargo variability around the long-term trend and is little affected by the long-term variability.

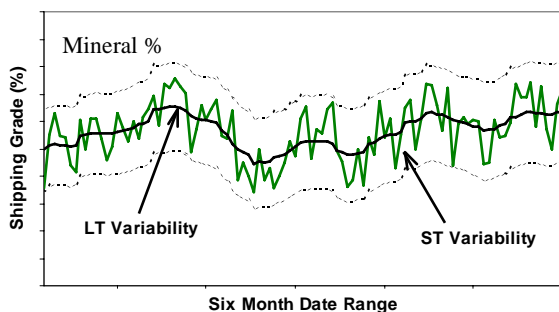


Figure 2: Long-term and short-term variability

Figure 2 shows an example of long-term variability (black line) and the short-term variability around it (green line). Short-term variability was used as the metric to assess and compare simulation results as changes to the operating philosophy and equipment mostly influence short-term variability.

Long-term trends are more controlled by long-term mine planning and marketing decisions which were outside the scope of the simulation models.

2.2. Data Preparation

Early investigations of the historical production data showed evidence of complex serial and cross correlation between the analytes of interest (mainly iron, silica, alumina and phosphorus). These correlations were ascribed to the orderly mining of blast blocks and the daily actions carried out by mine planning staff in response to grade.

As it was not intended to change the mine planning process, it was necessary to maintain the existing serial and cross correlations in the input data for the simulation models. Historic data were used as the basis for generating the required input of future mining production into the simulation models. This decision presented three challenges:

- Historic data contained long-term variation that could mask any incremental improvements identified in the simulations;
- Opening of new mines where no historic data existed; and
- Average grades of historic data did not match the planned grades of the future mining operations.

2.3. Removal of Long Term Variability

The long-term trend was filtered out of the data by taking Fourier transforms of the historic data to yield a frequency spectrum, removing the frequency range that relates to long-term variability, then again applying a Fourier transform to recover the filtered time series.

Figure 3 shows the effect of filtering. The red dots result when the source data (blue dots) are filtered to remove the long-term variability. The smoothed blue and red lines show the filtering has removed the long-term variability, although the scatter of the individual data points is little changed.

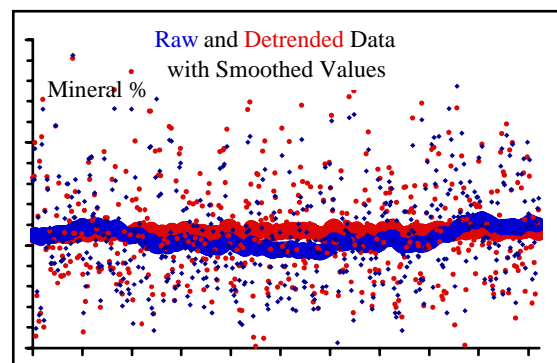


Figure 3: Removing Trends in historic data

2.4. Input Data for Existing Mines

After long-term variation had been filtered out of the historic data, means and standard deviations were adjusted to create synthetic data to match future production. The data preparation model allowed the standard deviation of the data to be reduced, simulating increased effort within the mine to control short-term variability, through such activities as selective mining and precrusher stockpiling.

2.5. Input Data for New Mines

To prepare data for new mines, data were taken from existing mines of similar geology. Long-term trends were removed and synthetic production data created by appropriately adjusting the composition means and standard deviations to match the anticipated mine plans. The changes were based upon long-term plans for the proposed mines and identified similarities in mining and processing operation compared to current operations.

2.6. Process Capability

Once satisfactory input data streams had been created, the models were used to simulate the effects of different processing methods on grade variability. The simulation models were designed to investigate the effects of many process variables, such as changing the number and sizes of stockpiles, and the policies for distributing incoming ore to the available port stockpiles. The key output variable studied was inter-cargo variability, defined as its standard deviation. To ease interpretation, the performance of each simulation run was measured as the "Process Capability" (tolerance divided by twice the standard deviation). For a normal distribution, a unit Process Capability suggests that about 95% of shipments will be inside the tolerance limits.

3. SIMULATION MODELS

For the simulation modeling, the production system was broken down, as much as possible, into sub-systems, with the output of one system providing the input to the next.

3.1. Computer Software

It was decided to develop each simulation model as an Excel™ workbook, controlled by Visual Basic (VBA) macros.

Many excellent computer software packages for simulation modeling exist (for example, Arena, Extend, GPSS and Simul8, and many others). A

useful review of available packages is published biennially in *ORMS Today* (Swain, 2003).

In the authors' experience, a dedicated simulation package requires dedicated specialists to run and interpret the data, and usually has accompanying cost and licensing restrictions. It therefore represents a barrier to practitioners who have to learn a new package if they are to manipulate the models independently. Developing the system in Excel™ allowed hands-on use and exploration of alternative policies and scenarios by company officers with domain knowledge unavailable to the simulation provider. Graphing and analyzing run results was built in, so minimal assistance was required from the simulation provider once the models were built.

For a model developer with a reasonable computer programming background, it is no more difficult to construct a simulation model as a spreadsheet workbook, run by VBA macros, than to do the same task with a dedicated simulation package. Moreover, the spreadsheet's inherent data input and output reporting and graphing capabilities provide fuller facilities than are generally found in a simulation package. The practitioner not only has more ready acceptance and ease of use, but also, being familiar with spreadsheets and their potential, can suggest modifications and extensions of the simulation model. The VBA macro coding is hidden from the practitioner, who can use it by means of inbuilt buttons and menus.

The simulation model comprised three VBA macros. The first macro reads in parameters to set up the simulation. The second macro runs the simulation the required number of time periods. The third macro uses Excel's statistical and graphing power to report the simulation results.

3.2. Spreadsheet Simulation Models

The simulation models were used to study the effects of controllable variables (such as stockpile sizes and stockpiling methods) and uncontrollable variables (such as cargo sizes).

A typical simulation model workbook comprises a number of worksheets, which serve to specify parameters and policy choices, display progress of the simulation, and report and graph the performance summary for any simulation run.

For reproducible results, it was found that the model needed to simulate a year or more of production. The simulation was time-sliced rather than event-driven. The time interval was set to six-hours.

At each time slot, ore was mined and trains loaded, while at the port trains arrive and are unloaded, crushed and stacked to stockpiles. In each interval, ships arrive, commence being loaded from an available stockpile (or wait if none are available) continue being loaded, and depart when full.

As described in Figure 1, the product flow is from mine, to rail, to port, to ship. To assess the product quality, a simulation model was developed around mining and loading trains, with a second model developed for unloading the trains, operation at the port, and loading ships.

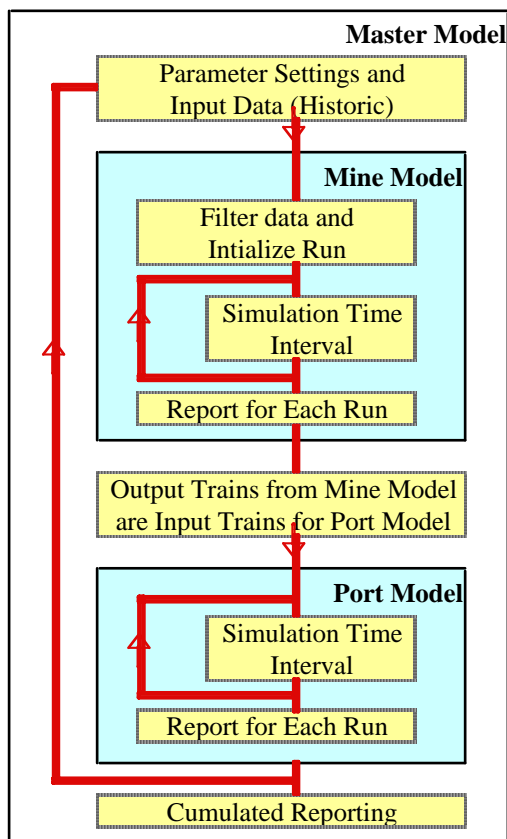


Figure 4: The Simulation Models

During simulation, a macro starts the simulation, setting system parameters and structure in accordance with the specified inputs.

A second macro then loops once each time interval, adjusting the system states in response to the relevant flows and events.

The user can make the model pause and display system states at a specified time interval and range. This function is used to check any unusual events identified in the simulation run.

A third macro takes control at the end of the simulation, preparing graphs and tables to report system performance, as specified by the user.

Typically, simulations are run to explore the effect of steadily changing the values of a particular parameter, or a set of parameters.

Repeated runs can become tedious to set up and record and prone to input error. A “Master” model was developed, with an input sheet list enabling the most common simulation parameters to be changed, and an output sheet reporting the performance criteria of interest for the set of simulation runs. When the Master model is run it repeatedly drives the Mine and Port models, setting the parameters for each run.

Figure 4 is a schematic representation of the simulation models. Red lines show the simulation sequence. The Mine and Port models can each be run individually, or either or both may be run for a sequence of runs, controlled by the Master model.

4. PORT MODEL EXAMPLE

4.1. Model Specification

The Port model workbook contains six worksheets, to simulate and report stacking and reclaiming ore from train to ship.

The “Input Rakes” sheet imports a set of 2,048 train rakes from the “Output Rakes” sheet of the Mine model file. Graphs of cumulative standard deviation against frequency for each analyte, 95% confidence limits and Process Capability were plotted against cargo or single-site stockpile size. The incoming trains are from either of two pits that have a systematically different mean grade, to reflect planned trends in mining in the data preparation worksheets.

Figure 5 shows the “Specify” sheet for Port loading where all of the parameters are set up. Settable parameters are contained in the yellow cells. In the example shown, ore arrives at a rate of 40 million tonnes per year. Every six hours a train arrives. This model is designed to explore the suggested plan of up to four ship berths, with each berth fed from a stockpile of nominated capacity. The stockpiles can be fully Blended in Blended Out (BIBO). Alternatively, it can be built according to the system of First In First Out (FIFO). Stockpile sizes can be independently varied; in the case shown, they are 240kt and 360kt size.

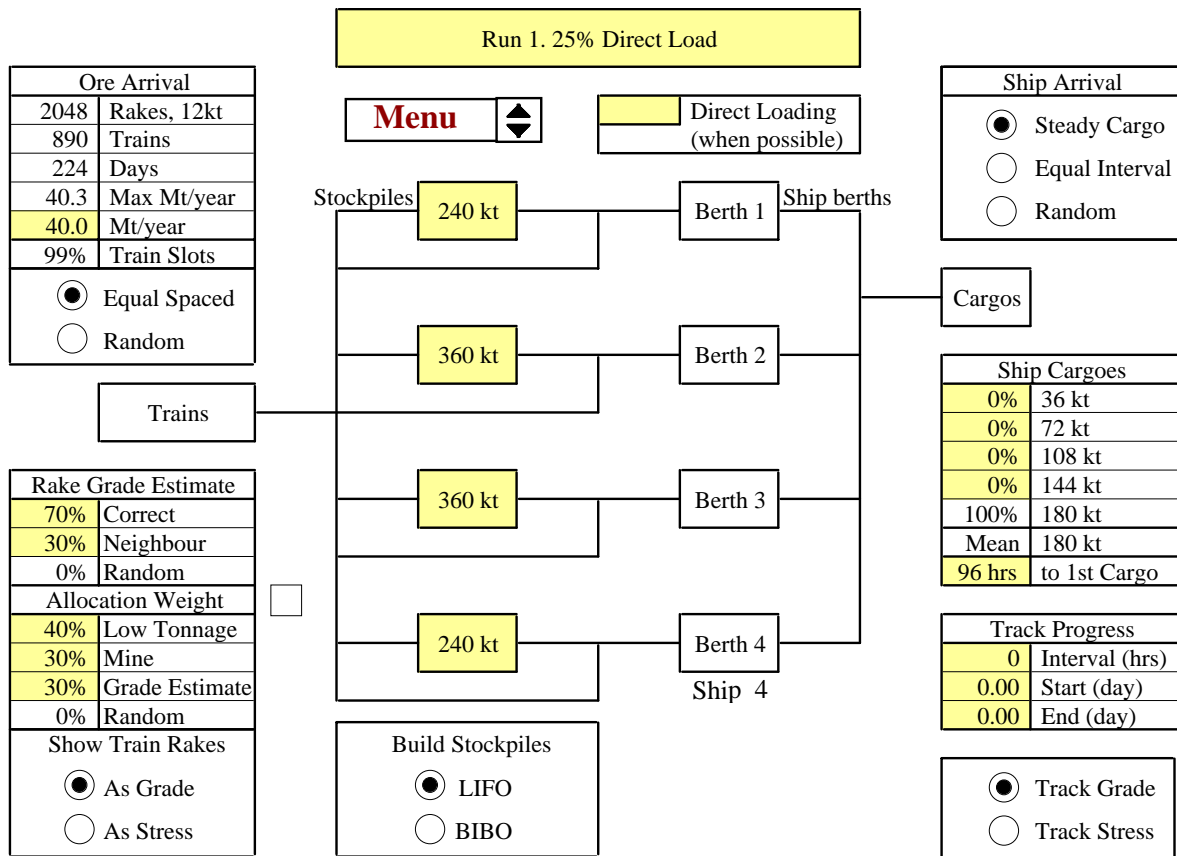


Figure 5: The Port Model “Specify” Worksheet

Trains and ships can arrive equally spaced, or at random. Trains can carry either 24 or 36kt of ore which are generated in the data preparation workbook. Cargo capacities can be from 36kt up to 180kt. Each incoming train can be direct loaded (with settable probability) to a ship, or sent to a stockpile that is not currently being used to load a ship. The destination stockpile choice is based on a weighted composite of four settable options:

- The least full stockpile (taking into account maximum possible).
- The smallest current tonnage stockpile.
- “Intelligent Stacked”, where the match to target of grade is most improved by the incoming train estimated composition.
- At random.

The third option bases the destination decision either on the port grade (not known when deciding the destination), or on an artifact of chosen correlation to the port grade. This last method simulates the unavoidable uncertainty of the train grade before it is sampled at the Port.

A “Progress” worksheet allows the system to be tracked, at set hours intervals (multiple of 6 hours) for a settable time range. This is useful for debugging, and also for better understanding the system behaviour.

4.2. Outputs

The “Cargoes” worksheet reports graphically, for each analyte, the cargo compositions, and how they vary around target. For example, Figure 6 shows that, for Fe, the Process Capability is 1.15 (2% Out of Tolerance).

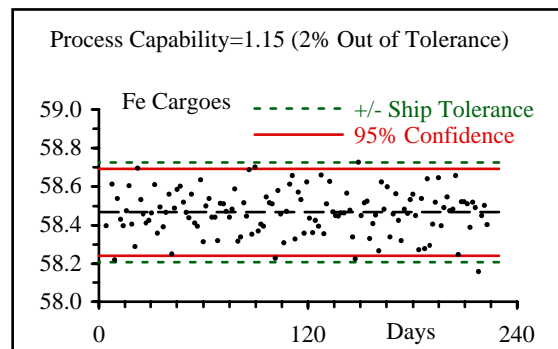


Figure 6: The “Cargoes” Report

The “Audit” worksheet reports the full simulation history, with product flows and stockpile and ship berth states for each time interval. Tonnage aspects of the simulation history are plotted to aid interpretation, and validate the parameter values selected on a particular run are feasible. For example, the tonnage history of a stockpile is graphed in Figure 7.

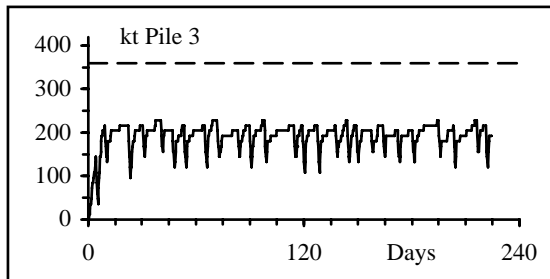


Figure 7: Stockpile History

4.3. Policy Evaluation

Figure 4 showed how the Master model drives repeated runs of the Mine and Port simulation models. To investigate the effect of a policy parameter, its value is changed for successive runs. The Master model then reports summary measures for each run, which can be plotted to aid policy exploration. For example, Figure 8 shows how the Process Capability for one of the analytes relates to the change in Short Term Variability from the Mine while intelligent stacking is taking place at the Port. The simulation was run for several values of the mean grade difference between two source pits (Y1 and Y2).

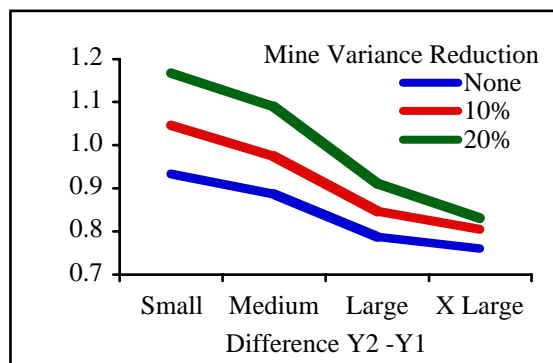


Figure 8: Mine Short Term Variability and Mine Average Grade Separation

4.4. Results

As an example of the results, one simulation run established a scenario that yields shipped ore of acceptable quality at the planned production rate, provided the options below are followed:

- 10% reduction of Mine short-term variability by selective mining or precrusher stockpiling.
- 30% priority to the use of Intelligent Stacking at the Port (as discussed in Section 4.1).
- Increased accuracy of train composition estimates from the mine.

This solution was compared to the installation of a yard with blending stockpiles at the mine and a cost/quality risk analysis carried out. Without the simulation studies, many capacity-related options such as this would have been virtually impossible to evaluate.

5. CONCLUSIONS

The simulation models described provide an invaluable tool to help BHP Billiton Iron Ore examine the effect on product chemical quality of alternative potential development options, to meet the potential capacity expansion required for the rapidly increasing iron ore market.

The particular benefit in using Excel™ based VBA simulation models is that it provides a familiar mode of working for the company personnel, enabling them to efficiently contribute domain knowledge during running of the simulations, without the assistance of the simulation developer. In addition, the use of Excel™ allows easy interrogation of data and generation of reports.

6. ACKNOWLEDGMENTS

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