Application and integration of a geometallurgical model and integration thereof, with quantitative simulation at Orapa Mine

O. Gilika[1] and P. van der Westhuyzen[2]

[1]Debswana Diamond Company, Botswana
[2]ADP, South Africa

The geometallurgy model has been in operation at Orapa mine since 2022. The model is used as a planning tool for both short and long term planning to identify and manage treatability challenges. The plan is informed by the geomet parameters, taking into consideration a selection of the best ore mix and mixing proportions thereof. This is followed by a reconciliation process at the end of each week and each month.

The geometallurgical model by itself is limited on the level of quantitative analysis. In light of this, Orapa mine has developed a quantitative simulation model in order to bridge this gap. The simulation model will be capable of predicting key process efficiencies (throughput, overall equipment efficiency, power consumption) and allow for strategic planning to minimise the probability of not achieving business objectives. The simulation model has been completed and is expected to be implemented by Q3 2023.

INTRODUCTION

Orapa mine implemented a geometallurgy model in 2022. The model, developed by Grills and Lohrentz (2020) is used as a predictive tool in the tactical planning space and also for medium to long term planning. The model exploits metallurgical response variables (MRVs), particularly ore hardness, smectite clay content and yield to predict possible treatability challenges in the plant and inform the blending strategy to minimise the negative impact on plant throughput. The long-term application of the model will provide input into the five-year and the Resource Development plans. It is also a key input into the stay-in-business and long sustainability projects to inform mine and process designs. The geomet block model by itself has some limitations as it is largely qualitative. In light of this a quantitative simulation model which integrates plant equipment efficiency and MRVs has been developed as an enhancement to quantitatively predict:

- Throughput
- Overall equipment effectiveness
- Power consumption
- Water consumption
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The quantitative simulation model is due to be rolled out in 2023.

Plant throughput at Orapa mine is one of the key business drivers. Up until recently, tonnage optimisation interventions focused mainly on equipment maintenance, operational philosophy, and technology. The Resource Extension Projects of 2007, 2009 and 2014 presented an opportunity to conduct Ore Dressing Studies (ODS) to generate sufficient data to do geometallurgical estimations of the various MRVs. As indicated by Dunham and Vann (2007), geometallurgy aims to identify key parameters, either directly measured or proxies, to allow for estimation of business drivers such as throughput, recovery, and efficiency. The Orapa A/K1 resource comprises of a highly varied lithology, with up to four major rock types namely, South Volcaniclastic Kimberlite Middle (SVK_M), North Pyroclastic Kimberlite (NPK), Basalt Breccia (BBR), Massive Volcaniclastic Kimberlite 2 (MVK2). There are also two other rock types which occur at a relatively lower abundance: the North Pyroclastic Kimberlite with a high dilution of granite gneiss (NPK_GG) and the Massive Volcaniclastic Kimberlite with high dilution of basalt breccia (MVK2_BBR). These rock types have different treatability behaviours in the plant in terms of ore hardness, clay content and generation of yield. These variables have therefore been chosen as the key contributors to treatability challenges leading to non-achievement of plant throughput. The different ore types consist of varying degrees of dilution of basalt and lithic minerals which are a major cause of hardness. The BBR in particular, has very elevated levels of basalt in excess of 90%. Maphane (2014) identified it as the hardest ore type available in the resource. The main consequence of this is that the crushers would struggle to deal with the hard ore, leading to high recirculating load and consequently a reduced intake of fresh feed, which translates to reduced overall throughput. These rock types are also characterised by varying degrees of clay content, particularly the smectite mineral clays. The montmorillonite clay component is typically the most predominant, and the active ingredient in the non-settling slurries due to their dispersive nature (Dunn, 2013). The presence of these clays has also demonstrated that the rock types will have a tendency to generate large quantities of fines, which consequently lead to material buildup and compaction in chutes, and sometimes blockages in material transfer vessels such as pipes.

Yield is another geometallurgical variable that has been identified as a major contributor to treatability challenges at Orapa Mine. Yield is the percentage of the dense media separation (DMS) process concentrate generated from plant feed. Some of the rock types, particularly NPK_GG, NPK and SVK_M have historically shown a tendency to generate excessive yield, eventually causing capacity constraints in the downstream processes. Collectively, these geomet variables are critical for Orapa Mine to keep track of in order to minimise the risk of non-achievement of the tonnage throughput.

TACTICAL PLANNING ASPECTS OF THE GEOMET BLOCK MODEL

Since its implementation, the geomet block model has been extensively used as a tactical planning tool for short interval control. A mine plan is generated on a monthly basis and further broken down into weekly tactical plans at implementation stage. The geomet model is integrated with the geology model, such that a single run of the model will generate a combined output of the geology and geometallurgy variables (Table I).

Table I. Planned monthly tonnages per rock type and geomet model estimated response variables from the monthly planned polygons

Rock Type	MVK2 (725)	SVK_M (725)	SVK_M (710)	SP817 (MVK_BBR)	SP808 (MVK2)	SP802 (BBR)	Total
Total Tonnage	18 049	220 343	278 000	60 000	40 000	79 800	696 192
% in Mix	3%	32%	40%	9%	6%	11%	100%
Yield (%)	0.11	1.21	1.00	0.69	0.23	0.35	
Clay Content (%)	72.77	45.04	69.04	15.78	44.23	35.70	
UCS (MPa)	34.04	15.64	17.34	39.94	45.44	80.66	

Cross sections of the geomet variables are generated to provide a visual outlook of the targeted polygons. Areas of potentially high risk material are easily discernible. This forms the basis for the selection of strategic ore types for the weekly blending plans. It should be noted however that the blending plan serves a dual purpose of managing the treatability risks as well as controlling the grade within plan. This by itself adds some complexity in balancing the blends to achieve both objectives.

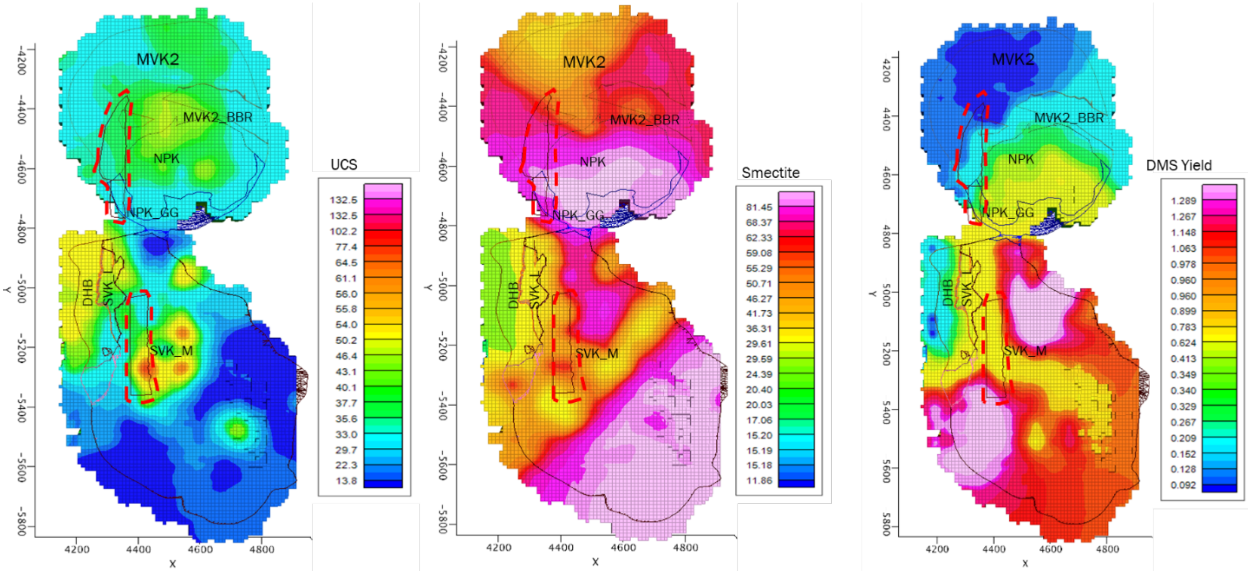

Figure 1. Cross section of the A/K1 resource showing heat maps of the various modelled geomet parameters.

Through an existing blending matrix, the management of the ore treatability risks is normally achieved by employing a blending strategy which works out an optimal blend between two or three different rock types. Usually two to three polygons are planned at one given time to provide adequate flexibility in the blending options. The determination of the blending ratios is informed by the geomet parameters of the planned polygon and also historical performance.

GEOMET MODEL RECONCILIATION PROCESS

The predictive capability of the geomet model is tested through a reconciliation process following the scheduling of the planned material into the plant.

Yield

The modelled yield can be directly plotted against the actual yield measured in the plant and a correlation deduced (Figure 2). A plot of the yield superimposed against the mining mix is crucial as it illustrates the relationship between the geomet parameter and the ore type, thus providing a basis for the validation of the model at the same time. From the graph, although the predicted and actual yield do not follow each other on a point-by-point basis, it is evident that SVK_M and MVK2, as a result of their predominance, have a significant influence on yield variation. SVK_M tends to produce elevated yield while on the contrary, MVK2 gives very low yields. This observation validates the model outcomes, and it is key in identifying MVK2 as a strategic rock type for risk mitigation of excessive yield. The Orapa plant has a tolerance of up to 1% yield. Anything above 1% is considered detrimental to the treatment process. It is also evident that the model generally can either overestimate or under-estimate the yield, particularly where SVK_M is predominant. This is likely due to the factor that while on the ground the SVK_M has been re-classified into two categories (the lithic rich and lithic poor SVK_M), the model itself does not differentiate between the two.

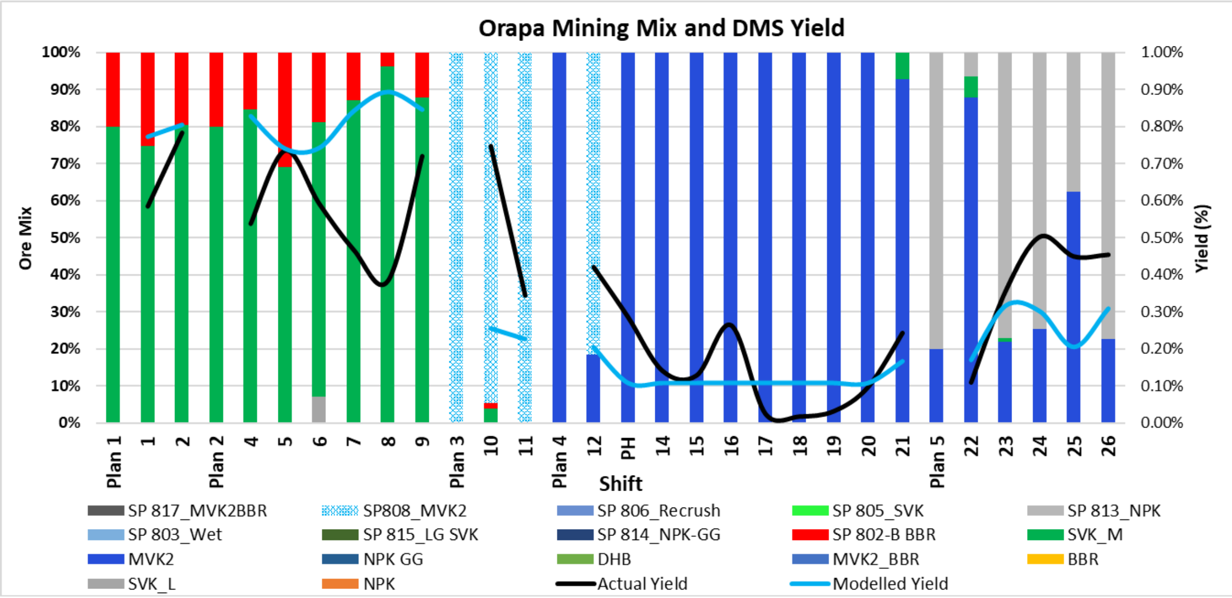

Figure 2. Reconciliation of the modelled yield against actual. Reconciliation is captured on a shift basis as indicated on the x-axis. Changes in the plan are also plotted. Public holidays (PH) are normally indicated on the trends.

Ore Hardness

The geomet hardness model uses the uniaxial compressive strength of the ore type as the input variable. However, the Orapa mine plant is not set up to measure this variable. For this reason, the secondary and high pressure roll crusher (HPRC) power consumption was adopted as a reasonable proxy for ore hardness output variable (Figure 3). This is based on the premise that hard ore will have a relatively higher energy requirement leading to high power consumption. The energy consumption is calculated from the crusher power output and feed tonnage of ore treated through the crusher. From Figure 5, the power consumption consistently trends below the control limits, suggesting an almost idle status of the crusher circuit. Historically, feeding the hardest material (BBR) in excess of 20% in the mix resulted in capacity constraints as a result of high recirculating loads. While the HPRCs display a very stable power consumption, the trends show that the secondary crusher circuit does feel the impact of the presence of BBR in the mix, though not very pronounced as a result of blending interventions. This is likely due to the fact that the HPRCs receive the coarse DMS tailings as feed. At this point a fraction of the basalt content has been purged out of the system through the fines DMS. Apart from the potential capacity constraints at the crushing circuit, the rate of purge of basalt in the process is much slower than the rate of accumulation of the material, further making it necessary to keep the proportions of BBR much lower the mining mix.

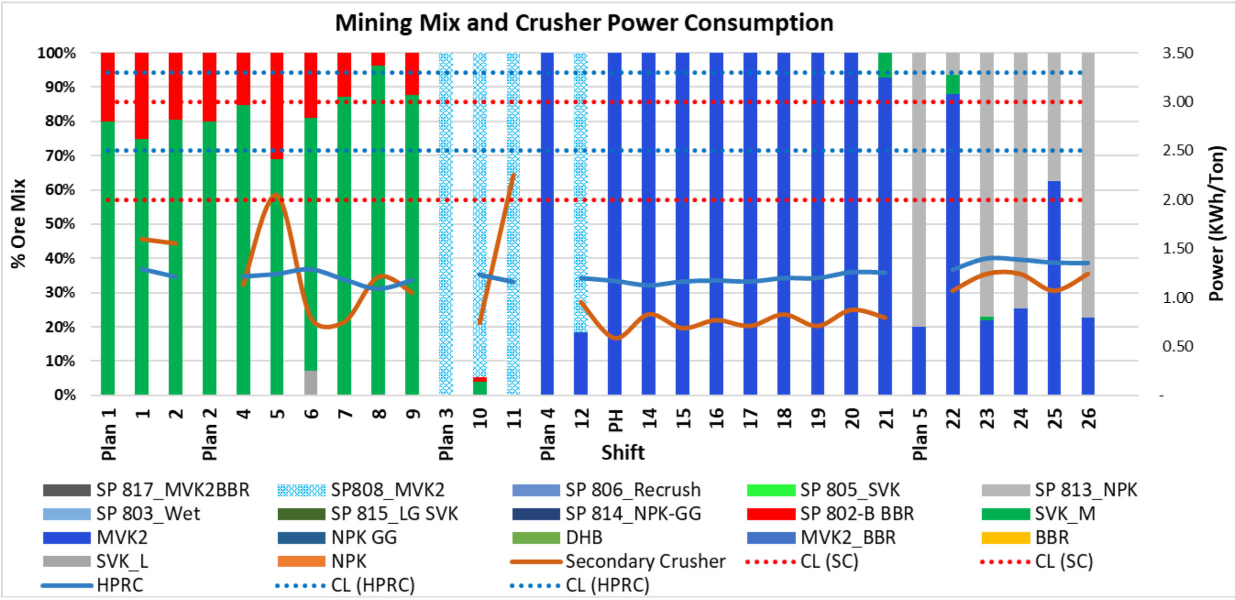

Figure 3. A reconciliation of the crusher power draw against the ore mix.

Smectite Mineral Clays

The smectite clays consist of the montmorillonite clay minerals which is the active constituent in thickened slurries. These minerals create non-settling slurry behaviour due to their exchangeable sodium percentage chemistry. Non-settling slurry makes it difficult to achieve optimum thickener underflow densities and thus plays a major role in the reduced capacity to recover process water for further recirculation in the plant, consequently leading to high intake of fresh water. The slurry behaviour tests conducted on the major facies indicated a wide variability both between the different facies and also within the same facie. Oupa (2014). However, contrary to this expectation, a correlation analysis of ore mix with water consumption at present reflects a good plant response to the impact of clay chemistry on water consumption despite feeding highly clay rich ore types. The water chemistry of Orapa water was conducted alongside the slurry behaviour tests and the results indicate a high salinity (sodium content) in the water. Sodium exchangeable cations are known to create colloidal slurries thereby creating effective settling slurries. The water is therefore naturally conditioned to aid settling in thickeners hence increasing water recovery. The ODS conducted in 2009 also found that Orapa water generally offers natural coagulation of slurry thus aiding settling (Nefadi, 2009). These clayey ores are also synonymous with high fines generation, leading to material build up in chutes and pipe blockages. From the downtime analysis, ore treatability challenges contributed 1% of the total downtime. The total downtime allocated to ore treatability was attributed to material buildup in chutes and blockages as a result of the fines generated. The impact of the clay content therefore is more evident on the transfer equipment than on the water recovery circuit.

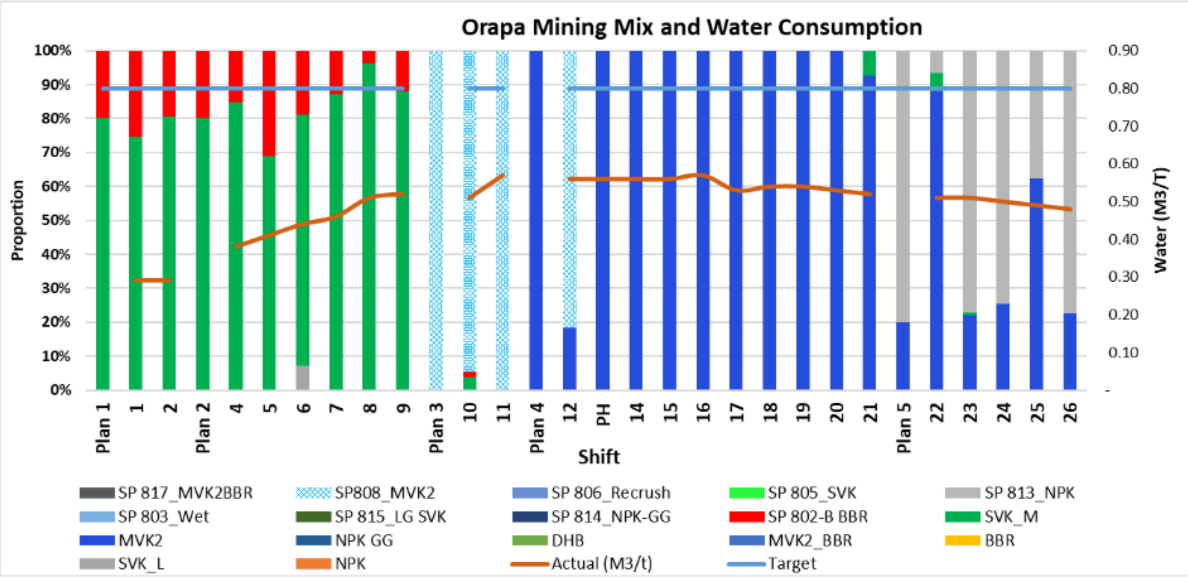

Figure 4. Reconciliation of the water consumption against ore mix.

Table II. Downtime analysis illustrating percentage contribution of ore-related treatability challenges vs other downtime

Downtime Type	Downtime Contribution (%)
Ore Processing	53%
Engineering	39%
Mining	1%
Projects	1%
Treatability	1%
Other	5%

LIMITATIONS OF THE GEOMET BLOCK MODEL

The geomet model has been in use for about 17 months to date. Although the model has demonstrated some benefits in predicting the plant response to various ore mixes, and informing the blending strategy to mitigate the risks, it comes with a few limitations as highlighted below:

- The model provides a qualitative analysis of the ore behaviour and the plant response. It therefore falls short of influencing the decision making around the key lagging indicators for the business such as plant throughput and other process efficiency parameters.
- The model accounts for only ex-pit ores and excludes stockpiles. Although Orapa stockpiles are classified per rock type, the resolution on geomet parameter estimates is lost as a result of varying geometallurgical properties within each ore type. As a result a global average of the variables is applied when feeding stockpiles. Also, over a period of time the stockpile material undergoes weathering which may alter the properties of the material.

It is therefore imperative that enhancement options are explored to increase the predictive capability of the model going forward.

QUANTITATIVE SIMULATION MODEL, DEVELOPMENT ASPECTS AND THE POTENTIAL VALUE ADD

Orapa mine completed a quantitative simulation model as part of the enhancement process of the existing geometallurgical block model. This model presents the opportunity to address some of the limitations presented by the geomet model. The quantitative simulation model mainframe is setup primarily on the basis of the process plant equipment effectiveness. Plant equipment data such as engineering equipment availability and utilisation has been used to model the plant effectiveness as a function of equipment breakdown (unplanned maintenance). The simulation model also utilises the operating model to account for overall plant utilisation which considers planned maintenance hours. The geomet input variables are embedded within the mainframe of the quantitative simulation model to integrate equipment effectiveness, operational philosophy and the ore treatability behaviour. The model offers flexibility to do the following:

- Input multiple ore particle size distributions (PSD). This provides the input variables for the various rock types and customises the simulation model to the geometallurgical requirements.
- Input different ore ratios to mimic the possible ore blending options. The ore ratios will mimic the typical blending ratios under the production environment and these will be weighted according to the geometallurgical input variables.
- Apply a variable standard deviation or a constant to the PSD shifter to accommodate different ore PSD profiles.

In the example illustrated below of a crusher circuit, the simulation model uses the PSD of each ore type as the input variable to predict the possible mass balance that the crusher circuit will generate. The overall mass balance throughout the plant will form the basis for identification of possible bottlenecks at various sections of the plant.

The secondary crusher model is based on the Whiten crusher model (Whiten, 1972) while the high pressure grinding roll crushers are based on the Daniel model (Daniel, 2004). A number of other major plant equipment were also modelled on the basis of their technical specifications. The t_{10} values for the ore properties were included in the crusher model for the modelling of ore hardness.

For the DMS module, the model is set up for a manual data input of the densimetric analysis data. The yield is calculated per sieve fraction and a partition curve generated based on the cut point (D_{50}) and the Ecart Probable (E_p) values which is the gradient of a partition curve which defines the separation efficiency. The DMS parameter is also set on a sliding scale for the D_{50} and E_p. This offers flexibility to do sensitivity analysis on the ore densimetric profile variation.

Calibration of static model

The static model was calibrated, based on actual production data with the discrete facies ore dressing information.

The model comparison is depicted in Figure 6.

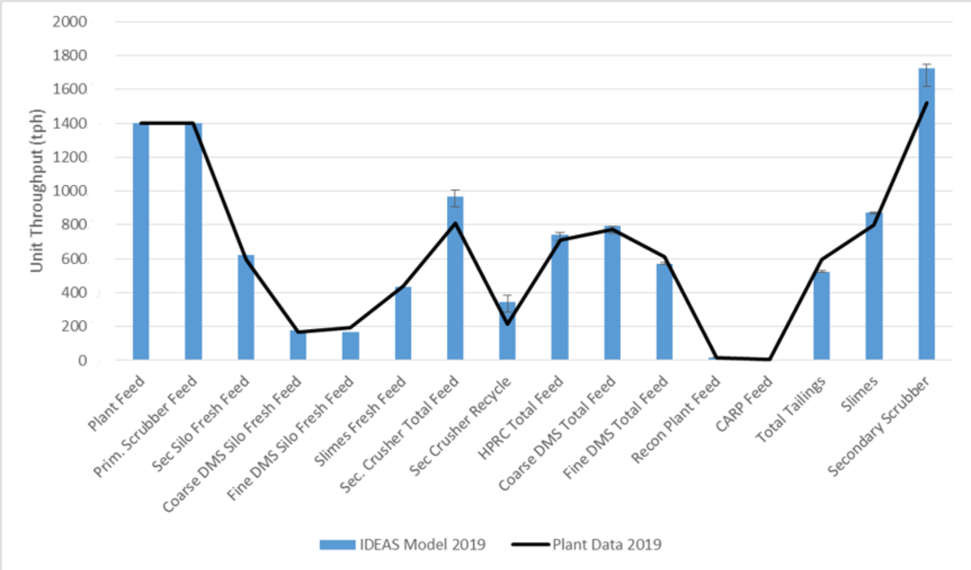

Figure 5. Static model calibration.

The model is within reasonable variance from the production data. The level of uncertainty is as a result of unoptimised process circuits. On completion of the static calibration the dynamic model was compiled and these quantitative input components include the buffer capacity, PSD variation, DMS yield, pumping systems, feed rates to unit processes based on normal distribution (as per production history).

Model inputs (i.e. PSD for discrete facies and ore dressing information) were varied based on the discrete facies treated and blending ratios to the plant, based on the actual facies treated. Firstly, the effect of the discrete facies treated (or a period of time with a discrete facie treated) were modelled based on the ore dressing specific data per facie (ODS data from Orapa Resource Extension Project). The effect of the discrete facies is depicted in Figure 6.

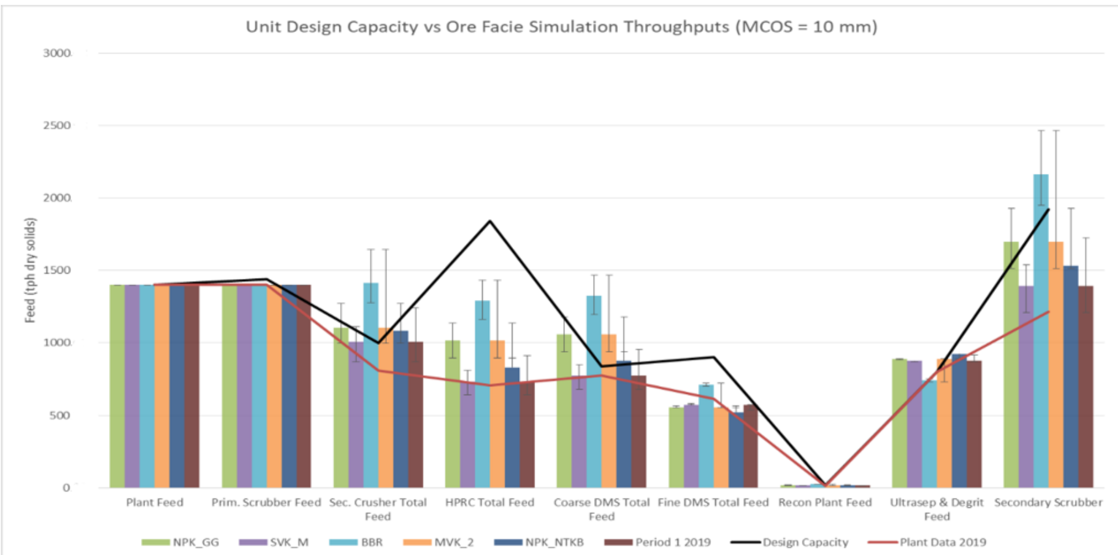

Figure 6. Discrete facie simulation and the effect on design throughput and variability. Error bars denote the level of uncertainty on the predicted throughput for each specific rock type.

The PSD envelope fed to the plant based on the actual production data (and material properties changes with depth), as being part of the quantitative simulation indicated various bottlenecks within the plant as depicted in Figure 7.

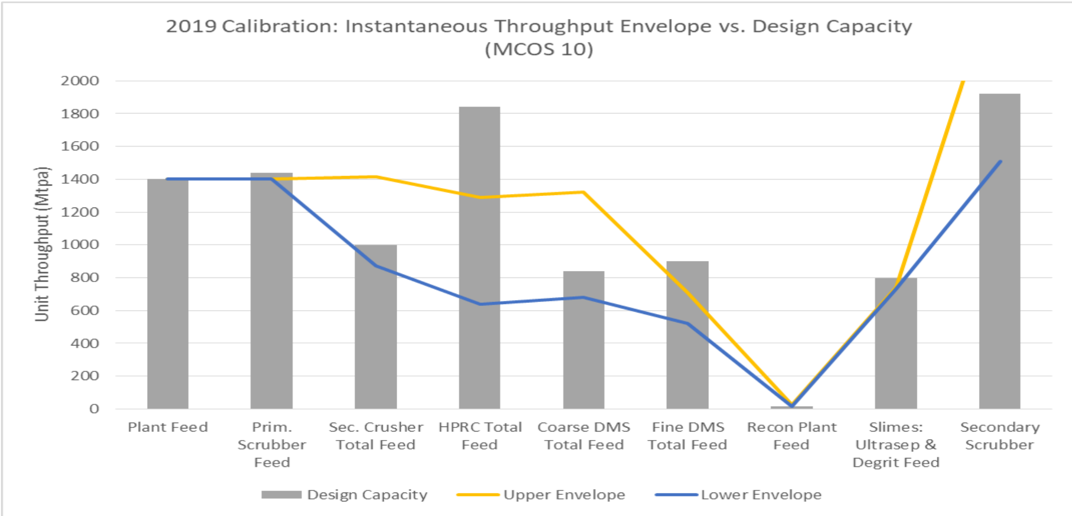

Figure 7. Instantaneous throughput envelope effects.

The plant's overall utilisation and the buffer capacity between unit processes, based on the general arrangement drawings from the plant, formed part of the model and the effect of the overall utilisation and buffer capacity clearly indicate bottlenecks within the process plant and ideally for improvement areas within the unit processes. Within the simulation, the unit process throughput is constrained and either used to determine the throughput or improvement areas (in Figure 8 being the coarse DMS, slimes handling and secondary crushers).

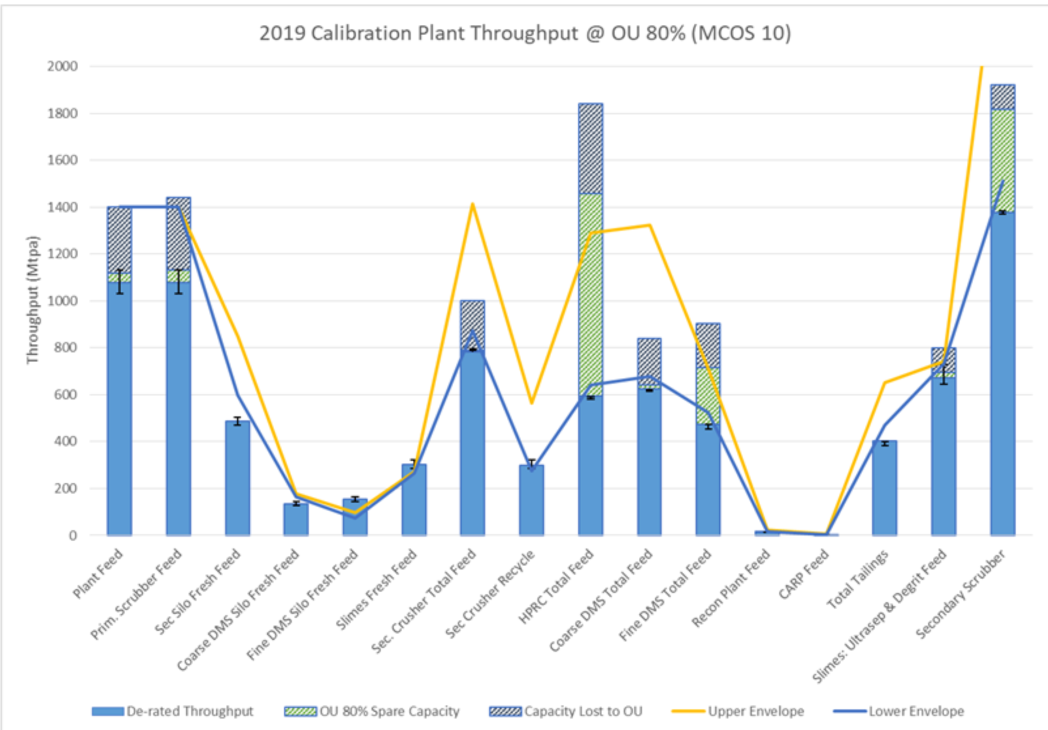

Figure 8. Calibrated plant throughput illustrating overall utilisation (actual vs modelled).

A combination of these geometallurgical input and the plant equipment effectiveness parameters has resulted in a hybrid model with enhanced capability to predict plant throughput, energy consumption and overall equipment effectiveness.

CONCLUSIONS

The geomet model for Orapa mine has set a stage for a paradigm shift as far as mine planning and overall process optimisation is concerned. The block model has demonstrated value in the tactical planning space for short interval control. The ability to predict changes in yield, which is one of the critical geometallurgical variables, has allowed for optimisation of the blending strategy to avert significant downtime, which in the past contributed significantly to non-achievement of throughput. By using crusher power consumption as a proxy for hardness, the geomet model demonstrates a fairly capable process, although this is largely as a result of a well-managed blending strategy which ensures optimum feeding of the very hard BBR material in the mix. While the BBR material has been depleted in the pit, a massive stockpile remains as part of the resource and is going to be instrumental in the future material blending requirements. Opportunities exist to optimise the model through performance reviews and updates. Further enhancement of the model through integration of the geomet inputs into the quantitative simulation model have been initiated and the implementation thereof will determine the potential added value in the model's capability to quantify key business objectives around plant throughput, overall equipment effectiveness and energy consumption. The calibration results of the quantitative simulation model demonstrates the existence of opportunities to identify throughput bottlenecks in the process and develop interventions to de-risk the business.

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Oupa Gilika

Senior Process Engineer
Debswana Diamond Company

Oupa Gilika has more than 20 years of experience in diamond mineral processing, having worked for Debswana Diamond Company since 2000. He has worked in various portfolios including production, process assurance, R&D and projects. He currently specialises in Geometallurgy which embodies the full orebody knowledge for Debswana. He is also involved with Data Analytics initiatives aimed at establishing breakthrough performance through the application and integration of machine learning with Geometallurgy.