Developing an Advanced Throughput Forecast Model for Minera Los Pelambres

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Abstract

Minera Los Pelambres (MLP) is a copper mine in north-central Chile. The comminution circuit consists of two primary crushers and three parallel grinding lines each with an SABC configuration (semi-autogenous grinding [SAG] mill with pebble crusher then ball mill), treating a total of 175,000 tonnes per day (t/d). MLP built an empirical throughput model using their comprehensive drill-core database. The main parameters were SAG feed size (80% passing [F_{80}]), ore breakage and comminution parameters (Axb and BWi), and feed blend proportions. The model achieved good accuracy, with mean relative errors of 3.5% and 3.2% on a monthly and annual basis, respectively. However, MLP aimed to further enhance the accuracy and eliminate the need for frequent recalibration to deal with changes in ore characteristics and operating conditions.

Hatch was engaged to review the current model, ore characterisation, blast fragmentation, and plant operation and develop a new power-based throughput forecast model. This semi-mechanistic model provides better prediction of the SAG mill feed size based on rock characteristics and blast fragmentation modelling, and accounts for coarse (F_{80}) and fines (−10 millimetre [mm] material) in the feed. Thus, the new model achieves lower relative errors—3.0% and 1.4% on a monthly and annual basis, respectively. The new model is more reliable for future changes in ore characteristics, eliminating the need for frequent recalibration, and improving long-term accuracy.

Keywords

Throughput modelling, SAG mill, power-based modelling, drill and blast modelling, ore hardness, fines content

Introduction

The throughput of comminution circuits is typically influenced by the feed size, ore characteristics (rock structure and strength or hardness) and their variability, circuit configuration, comminution equipment power utilization, operating conditions, and required product size. Accurate models to estimate throughput are necessary for production planning in the short and long terms (life-of-mine planning).

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Power-based modelling is widely adopted for comminution circuit modelling and design and can also be used for throughput forecasting when the future ore properties are known. Morrell's modelling method (Morrell, 2004a, 2004b, 2009) and SMC tests have been widely and successfully adopted in the industry, and Farmer et al. (2021) and Brennan et al. (2022) describe recent Hatch examples of their application. The specific comminution energy for each geometallurgical domain that will be mined in the future is calculated, then averaged according to the proportion of each domain in the feed over a certain time.

Deviations between the actual and estimated circuit throughput using the MLP empirical model had previously been explained by operating factors such as downstream process limitations, water restrictions, low stockpile levels, SAG mill relining, and so on. Their effect cannot be accurately estimated by any model and are generally filtered out. Once the production data have been filtered, the other major factor affecting the MLP empirical model's accuracy was the difference between the estimated feed size F_{80} used in the model and the F_{80} measured by image analysis on the SAG feed conveyor belts. The F_{80} model required frequent adjustments (recalibration), and therefore an alternative SAG F_{80} model has been proposed, one that accounts for rock properties and primary crusher settings.

Another critical parameter impacting SAG mill throughput is the content of fines (% −10 mm) in the SAG mill feed. This is strongly influenced by ore properties and the drill and blast operations, and is not typically included in power-based modelling, which is based on feed size F_{80} only. However, Hatch developed a method to estimate the feed fines content and incorporate this in the proposed power-based throughput model.

This paper summarizes the development and validation of an improved power-based throughput forecast model for MLP. MLP has a comprehensive database of hardness and breakage parameters, which is an important basis for accurate throughput forecasting, and this is described along with the MLP geometallurgical domain definitions. The standard power-based modelling method for SAG milling circuits is presented. Additionally, the method Hatch developed to account for the fines content (% −10 mm) in the SAG feed is also described (in addition to the SAG F_{80} size parameter typically used in power-based models). The method to estimate the SAG feed fines as a function of blasting powder factors and ore properties is also explained. Finally, the proposed throughput forecast model prediction errors were compared with those of the historical MLP empirical model.

Method

Power-based modelling is a common approach to throughput forecasting. The principle of power-based modelling of comminution circuit throughput is to estimate the comminution circuit's specific energy as a function of ore properties (specifically hardness), and feed and product sizes. One example of power-based method is the Morrell Power-based method (Morrell, 2004a, 2004b, 2009). In the Morrell method, hardness is represented by the comminution indices drop weight index (DWi), Mia, Mih, and Mic as measures of hardness applicable in autogenous grinding (AG) and SAG mills, high-pressure grinding rolls, and crushers, and the Bond ball mill work index (BWi) as a measure of resistance to breakage at finer size fractions in ball milling circuits. The circuit feed and product sizes are incorporated using the 80% passing values (F_{80} and P_{80}). Throughput is then calculated from the specific energy, assuming a typical power draw for the SAG mills and ball mills. This approach requires an estimation of the SAG mill specific energy, which can be used to determine if the circuit is SAG mill- or ball mill-limited (Brennan et al., 2022).

Historically, the MLP circuit has been mainly SAG mill-constrained, and therefore the SAG mill specific energy can be used directly for throughput estimation, rather than the total (SAG + ball mill) specific energy. MLP provided historical operating data relating to ball mill power draws demonstrating that the ball mills have unutilized available power, confirming that the SAG mill was constrained and SAG specific energy can be used for total circuit throughput. The SAG specific-energy calculation is detailed later in the paper.

The main required inputs for accurate throughput forecasting using power-based modelling are comprehensive ore characterisation in terms of hardness and a reliable estimate of feed size (and changes in feed size with ore characteristics).

GEOMETALLURGICAL DOMAIN DEFINITION AND ORE HARDNESS DATABASE

MLP has an excellent and comprehensive characterization method to define different domains in the pit in terms of geotechnical classification and also to categorise the ore in metallurgical units. This includes extensive testwork conducted historically, which served as the basis for the ore hardness classification and structural conditions for the different lithologies present.

Five main lithologies are present in the MLP ore body, with some sub-groups. These are diorite (DIQ), porphyry, (PA, PB, PD), breccias (BH), andesites (AND), and porphyry–quartz–feldspar (PQF). These lithologies are intersected with the five mineral zones, namely leaching-total (LXT), leach-partial (LXP), secondary zone (SEC), primary with anhydrite (PRI), and primary with no anhydrite (PRI S/ANH). The intersections resulted in six geometallurgical M units (M1, M2, M3, M4, M7, and M8), as shown in Table 1.

Table 1—Matrix of geometallurgical M unit definitions

<table>
<tr><th colspan="2" rowspan="2">Geometallurgical M Unit</th><th colspan="7">Lithologies</th></tr>
<tr><th>DIQ</th><th>PA</th><th>PB</th><th>PD</th><th>BH</th><th>PQF</th><th>AND</th></tr>
<tr><td rowspan="5">Mineral Zones</td><td>LXT</td><td colspan="4" rowspan="3">M1</td><td rowspan="3">M2</td><td rowspan="5">M7</td><td rowspan="5">M8</td></tr>
<tr><td>LXP</td></tr>
<tr><td>SEC</td></tr>
<tr><td>PRI</td><td colspan="5">M3</td></tr>
<tr><td>A</td><td colspan="5">M4</td></tr>
</table>

Very detailed drill core breakage testing database was available at MLP, including SAG Mill Comminution (SMC Test), BWi, SAG Power Index (SPI), and point load test. There were 2,264 SMC tests in the database which provided a very good resolution of the hardness within the ore body. The distribution of the number of tests for each geometallurgical M unit and their drop weight index (DWi) are shown in Table 2. The distribution of DWi within each M Unit is shown in Figure 1.

Historically, the MLP block model was programmed to provide the Axb breakage index as the hardness parameter of the M units of a given production volume, which was then directly used in the throughput model. The JKTech (JK) Axb breakage index is determined by either drop weight testing or SMC testing and is an indicator of ore resistance to impact breakage. The A and b parameters are typically used in the JK SAG mill model, while the Axb breakage index is a designation of the ore hardness; note that a lower Axb indicates harder ore and higher Axb value indicates softer ore. This is contrary to all other hardness parameters which increase with increasing ore hardness.

The Axb breakage index is not an additive hardness parameter and therefore cannot be averaged directly to determine the hardness of a particular blend of ores (i.e., cannot be used directly in throughput forecasting). However, the Axb breakage index can be corrected for specific ore densities into a DWi, which has units of kilowatt hours per cubic metre (kWh/m^3). The DWi is directly proportional to hardness (higher DWi are harder, and lower DWi are softer), and can be averaged, and thus can be used to determine ore hardness for an ore blend using a weighted average. For this reason and based on Hatch's experience with power-based modelling, the DWi is preferred for SAG throughput modelling rather than the Axb breakage index.

Table 2—Summary of geometallurgical test database per M units

M Unit	**DWi (kWh/m^3)**	**Number of SMC Tests**	**Specific Gravity (t/m^3)**	**Axb (Calculated from Average DWi)**
M1	5.66	1,132	2.55	45.0
M2	5.16	91	2.52	48.7
M3	7.73	119	2.62	33.8
M4	7.81	712	2.64	33.8
M7	8.97	27	2.58	28.8
M8	8.42	183	2.63	31.2

Historically The M units were grouped into soft and hard categories based on testwork and the MLP block model:

- M1, M2, and M8 were reported as soft units
- M3, M4, and M7 were reported as hard units.

The M8 unit was originally considered to be soft; however, this was mostly driven by the in situ structural rock characteristics (more fractured). The DWi value distribution within each of the M Units shown in Figure 1 revealed that the M8 unit should be classified as hard according to rock hardness. Due to the range of hardness and structure properties, the M8 unit (which represents the andesite lithology) has been divided into two units, based on the evidence of differences in rock structure. The two units, namely M8 primary (M8p) and M8 secondary (M8s), represent more- and less-competent rock, respectively, driven by the rock structure.

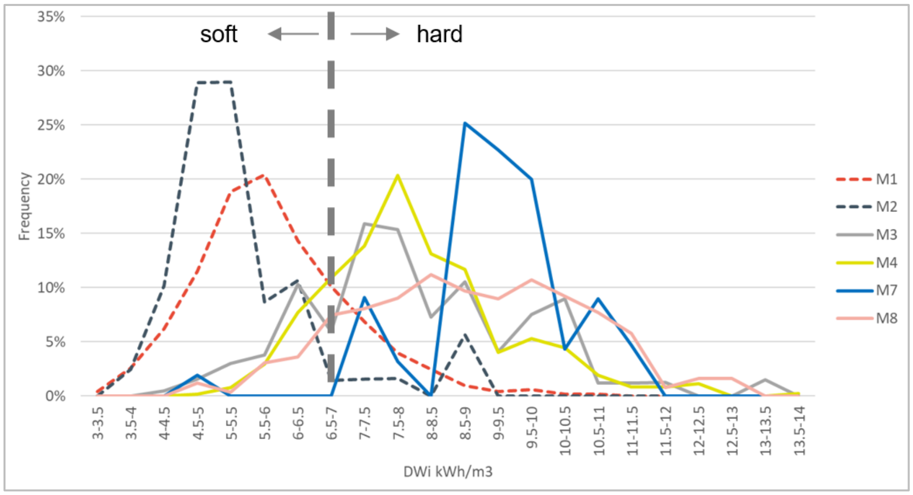

Figure 1—Distribution of DWi values for each M unit (drill core testing)

The MLP drill core testing database is very large and is a world-class example of detailed geometallurgical mapping of ore hardness for block modelling. MLP previously estimated the error associated with the hardness parameters, as a function of sample density. Previously published simulations (Caceres et al., 2015) demonstrated that the accuracy of the hardness parameter values populated in the block model is very good, with approximately one sample for every million tons in the block model. Simulations were conducted to assess the error in the hardness parameter estimation for each production volume (monthly, annually). On an annual basis, the hardness parameter estimation error was ±1.7 % for the hard domain, and ±2.5 % for the soft domain. On a monthly basis, the error for the hard domain was ±3.4 %, and for the soft domain was ±4.9 %.

In the present study, the hardness parameters generated by the block model were used to validate the model against historical data and to predict the hardness parameters of future ore blends in the life-of-mine (LOM) plan.

MODELLING FEED SIZE

The SAG mill specific energy and throughput are strongly influenced by ore hardness and feed size, as already recognized and accounted for in the previous MLP empirical throughput model.

One of the main challenges for throughput forecasting is to predict the SAG mill feed F_{80} size of future blends. The input parameter "SAG F_{80}" was previously estimated based on regression analysis of the F_{80} measured by the online image-analysis system, as explained below. The regression coefficients had to be updated after some time to reflect the changes in ore characteristics which influence run-of mine (ROM) fragmentation and thus SAG feed size.

The SAG feed size F_{80} is measured online by WipFrag image analysis system that is installed on SAG mill feed conveyors. The accuracy and reliability have been assessed and the WipFrag F_{80} was used with confidence by the operation. In the MLP SAG F_{80} model, a single value of F_{80} is assigned to each M Unit and the overall F_{80} is calculated based on the proportion of each M Unit (weighted average F_{80} as shown in Equation 1). The F_{80} value for each M Unit was determined by regression of the WipFrag data:

$$\mathrm{F80} = (\%\mathrm{M1} \times F80_{M1} + \%\mathrm{M2} \times F80_{M2} + \%\mathrm{M3} \times F80_{M3} + \%\mathrm{M4} \times F80_{M4} + \%\mathrm{M7} \times F80_{M7} + \%\mathrm{M8} \times F80_{M8}) \qquad (1)$$

Over the last three years of operation, two different versions of the SAG F_{80} model were developed based on regression of plant data. The performance of the two models is compared with actual WipFrag F_{80} data in Figure 2. The F_{80} Model v1 was more accurate for the older data because it was regressed in 2019. The F_{80} Model v2 seemed to predict the recent F_{80} data quite well, because of the regression that was performed in 2021, but it was not reliable for the older data.

This demonstrates that the SAG F_{80} regression models required continual updating and refitting regression coefficients due to changes in ore characteristics. The need to continually update the F_{80} model is time consuming and also limits the model's predictive capabilities over the longer term, particularly over the LOM.

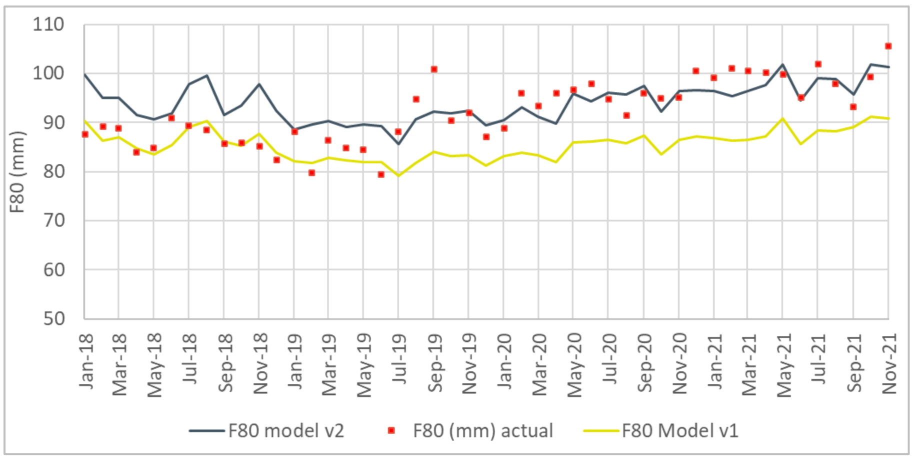

Figure 2—SAG F_{80} image analysis measurements compared with previous SAG F_{80} regression models

Hatch proposed a different approach to predicting the SAG F_{80} to provide increased accuracy over the long term and eliminate the need for frequently adjusting the model parameters. Hatch proposed a mechanistic approach for the F_{80} model based on ore properties and the crusher gap:

$$\mathrm{F80} = \mathrm{OSS}^{\mathrm{K}} + \sum_{\mathrm{j}} \left(\mathrm{kj} * \mathrm{DWi_j} + \mathrm{fj} * \mathrm{RQD}\right) * \%\mathrm{blend_j} \quad (2)$$

where *K, kj, fj* are constants (13 in total) that are specific to MLP and fitted to the F_{80} data during model calibration.

The index *j* represents the seven M units.

RQD is rock quality designation, which is a measure of the in situ rock structure which influences blast fragmentation, and in particular the coarse end of the fragmentation size distribution.

The principle of the equation for SAG F_{80} is that the SAG feed size is influenced by the primary crusher gap, as expected, but is also influenced by ROM fragmentation. The rock structure, rock strength, and drill and blast design influence the ROM fragmentation, thus also influencing the SAG feed size. Therefore, the proposed SAG F_{80} model includes the following input parameters: rock quality designation (RQD) for rock structure, DWi for rock hardness parameter, and open-side setting (OSS) for crusher gap. The input parameters for each M unit are then compounded into a weighted average of the hardness and structure information and added to the contribution of the primary crusher OSS.

The proposed new SAG F_{80} model showed good accuracy over the entire period based on monthly averages, as shown in Figure 3. This indicates that the ore strength and structure (DWi and RQD) are significant contributors to the SAG feed F_{80}. The OSS parameter in the F_{80} model had a relatively low significance compared to the others (DWi, RQD, and blend proportion). This was explained because the average OSS of both primary crushers was relatively constant throughout the period analyzed.

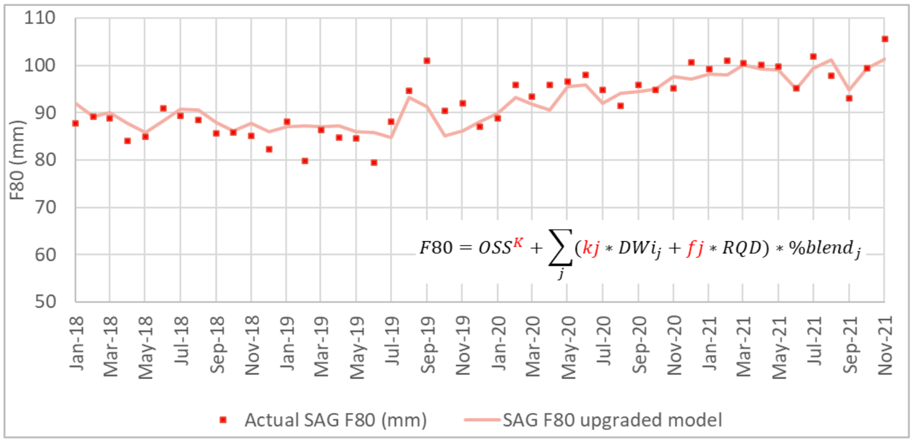

Figure 3—Actual monthly SAG F_{80} from online measurement compared with predictions of the SAG F_{80} model proposed by Hatch

Effect of Fines (% −10 mm)

Throughput forecast models typically do not consider the impact of fines (generally defined as the percentage of −10 mm in the feed). Power-based models rely on SAG F_{80} alone as a measure of SAG feed-size distribution, which is the parameter used in the Morrell power-based equation for feed size. This method is robust, has been proven, and is convenient for model reconciliation because the variations in SAG F_{80} can be measured relatively well by online image-analysis systems. However, the amount of fines in the SAG feed is also known to have a significant affect on throughput and SAG specific energies (Kanchibotla et al., 1999; Valery et al., 2001, 2007, 2019a). This is generally not included in throughput models because image analysis systems have a limited ability to measure fines, but its inclusion should improve the accuracy of throughput forecast models.

To address this, Hatch used blast fragmentation modelling to estimate the ROM fines content based on ore properties (structure and strength) and blast design. The fines in the SAG feed are mostly generated during blasting and are strongly influenced by in situ ore characteristics, in particular rock strength. The blast fragmentation modelling provides a mechanistic calculation of fines from blasting to plant feed, instead of relying on online fragmentation measurements. It was proposed to incorporate an additional factor (% passing 10 mm) into the SAG specific-energy calculation used in the throughput forecast model to account for varying fines content, with the objective of improving the model accuracy. The proposed SAG specific-energy model is:

$$\text{SAG specific energy (kWh/t)} = \text{Q} \times \text{DWi}^{\alpha} \times (\text{F80 Hatch})^{\beta} \times \frac{1}{(\%\text{−10mm})^{\delta}} \quad (3)$$

Where *Q*, *α*, *β*, and *δ* are constants that are specific to MLP and fitted to the production data during model calibration, as explained in the discussion section.

Modelling the Fines in the SAG Feed

The Hatch blast fragmentation model is a tool that simulates ROM fragmentation-size distribution based on the ore characteristics (hardness and structure), the drill and blast design parameters, and explosives properties. This drill and blast fragmentation model has been used in previous mine-to-mill projects with the objective of improving ROM fragmentation and increasing comminution throughput (Evangelista et al., 2021; Hill et al., 2022; Valery et al., 2018, 2019a, 2019b). The model calibration requires accurate measurement of the resulting fragmentation. Blast fragmentation was measured using SPLIT Desktop image analysis of photos collected at trucks dumping ROM ore to the primary crushers. Image-analysis systems used for measuring ROM fragmentation cannot accurately measure fines content (such as %passing 10 mm), as this material is often below the surface and is too small to be accurately delineated by the image-analysis software. To overcome this, the fines content is calibrated by sieving material from a primary crusher-product belt cut sample, as described in the previously published mine-to-mill projects. Figure 4 shows the ROM size-distribution envelope obtained with image analysis of the material coming for a specific polygon that was used to calibrate the blast fragmentation model. The SAG feed size (i.e., primary crusher product) distribution was also compared to confirm the ROM, and the amount of fines was consistent with the material feeding the plant at that time.

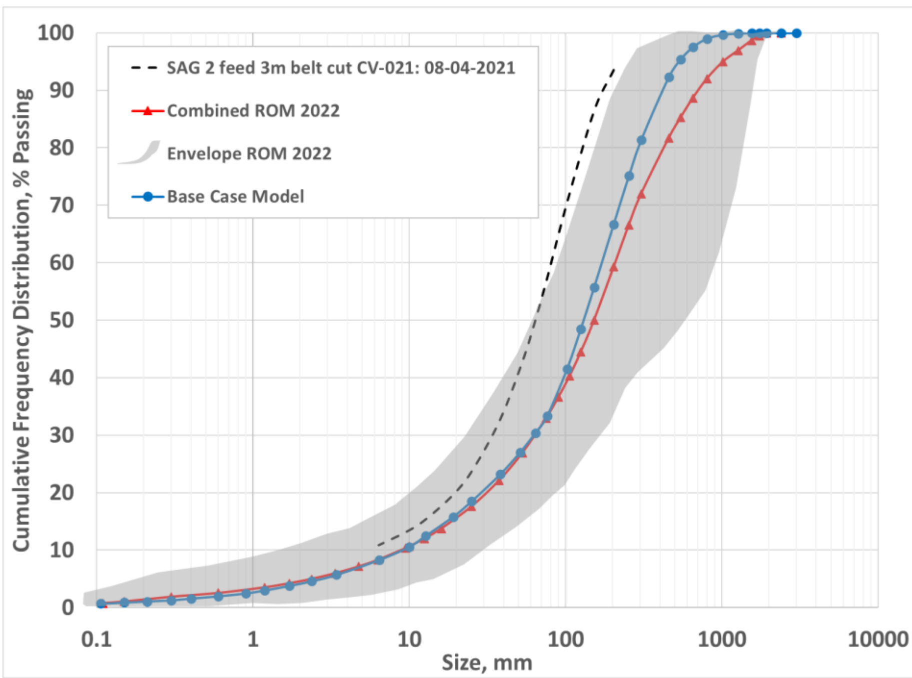

Figure 4—Calibration of the Los Pelambres drill and blast fragmentation model

While the blast fragmentation model can predict the entire ROM size distribution, it was used in the present study to determine the relationships between fines content (% −10 mm) in the ROM and the blast intensity and ore characteristics. The fines content was then incorporated into the throughput forecast model. This section explores the method of using the Hatch blast fragmentation model to determine a simple relationship between blast intensity, ore hardness, and fines generated for each M Unit.

Firstly, simulations were conducted at varied blast energy (powder factor PF) for the different M units. The simulations covered the current range of blast intensities used for each M unit (Table 3). The blast designs were varied in the model to produce the required range of powder factors, while also ensuring the blast designs were practical for implementation in each case.

Table 3—Blast intensity (powder factor) range for each M unit

	Powder Factor (kg/t)		
M(X)	**Minimum**	**Typical**	**Maximum**
M1	0.215	0.272	0.355
M2	0.215	0.272	0.355
M3	0.196	0.351	0.546
M4	0.196	0.546	0.631
M7	0.196	0.546	0.631
M8	0.205	0.446	0.546

The results from the blast fragmentation simulations were used to generate correlations between the fines (% −10 mm) and blast intensity (powder factor) for each hardness class. For this purpose, the hardness classes are specified based on unconfined compressive strength (UCS), which is an appropriate strength measurement for the compression breakage that occurs during blasting. The resulting correlations for M1, as an example unit, are summarised in Figure 5 and Figure 6.

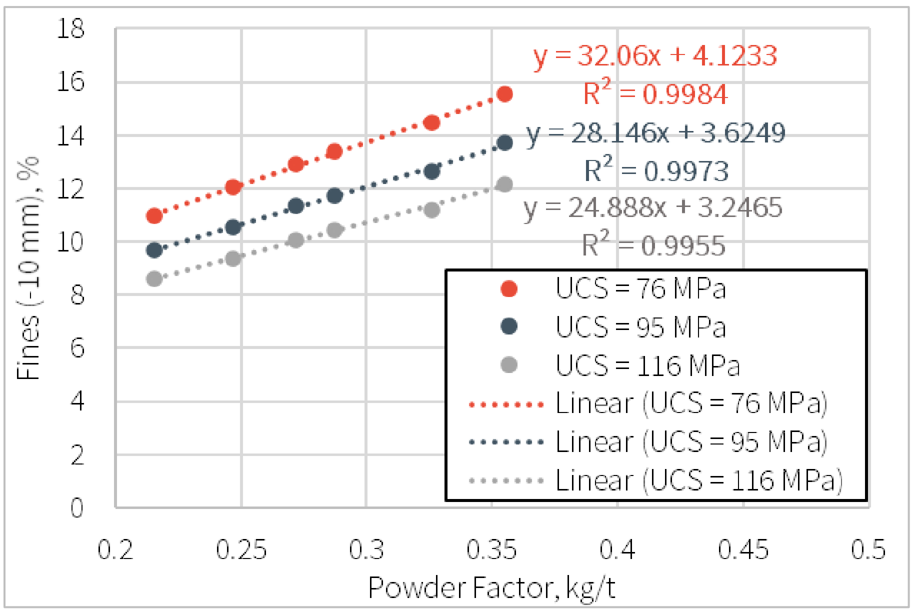

Figure 5—Relationship between powder factor and fines for M1 unit (constant hardness)

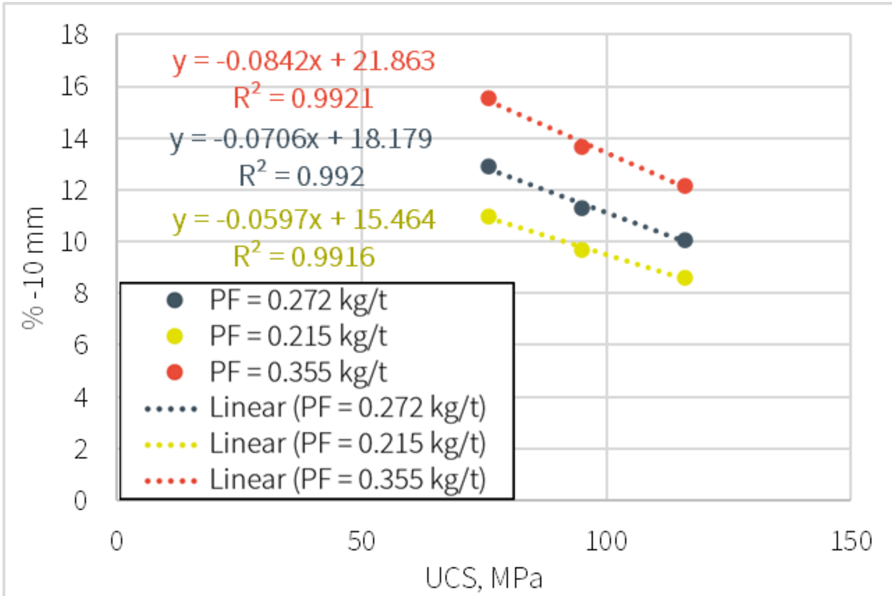

Figure 6—Relationship between hardness (UCS) and fines for M1 unit (constant power factor)

Blast simulations were performed and correlations generated for each of the M units, as per the examples shown for M1 above. For each M unit, the average relationships for powder factor and hardness are combined into an overall relationship to estimate the −10 mm fines content for that M unit using the following equation structure:

$$-10\text{ mm Fines (\% in ROM)} = A * (PF) - B * (\text{hardness}) + C \tag{4}$$

Where *PF* is the powder factor, and hardness is either UCS or DWi hardness values.

The Hatch blast fragmentation model generally uses UCS for ore strength input parameters, but to align with the throughput forecast model inputs, these equations have been expressed in terms of DWi. The equations have been transformed based on the mean UCS value and mean DWi value for each M class.

The range of hardness for units M3 and M4 were similar; therefore, a single equation was used for these two units (their combined annotation is M34). The M8 unit is further separated into two sub-units, M8p and M8s, due to the difference in structure, as discussed before. However, as structure mostly influences the coarse end of the fragmentation-size distribution, this did not have a significant impact on fines generation during blasting. Therefore, a single equation can be used to estimate blasting fines for the M8 units.

The resulting equations, in terms of DWi, are:

$$\text{M1 Fines Content (\%)} = 28.365 * (PF) - 1.6231 * DWi^{0.789} + 10.5 \tag{5a}$$

$$\text{M2 Fines Content (\%)} = 28.938 * (PF) - 1.6352 * DWi^{0.789} + 10.4 \tag{5b}$$

$$\text{M34 Fines Content (\%)} = 21.927 * (PF) - 1.3091 * DWi^{0.789} + 10.25 \tag{5c}$$

$$\text{M7 Fines Content (\%)} = 21.123 * (PF) - 1.2409 * DWi^{0.789} + 10.3 \tag{5d}$$

$$\text{M8s or M8p Fines Content (\%)} = 21.142 * (PF) - 1.4952 * DWi^{0.789} + 12.5 \tag{5e}$$

The fines content (% −10 mm) estimated from these relationships for each of the M units using the typical powder factor (Table 3) are shown in Figure 7. These results correspond well with the measured SAG feed-size distribution from the available belt cut survey MLP performed. The estimated % −10 mm content for the M1, M8 and M7 units processed during this survey are 12%, 14%, and 14.5%, respectively. The belt cut sizing reported about 13% −10 mm in the SAG feed for the feed blend of M1 (52%), M8 (36%) and M7 (12%), and a powder factor of the surveyed polygons around 0.33 kg/t.

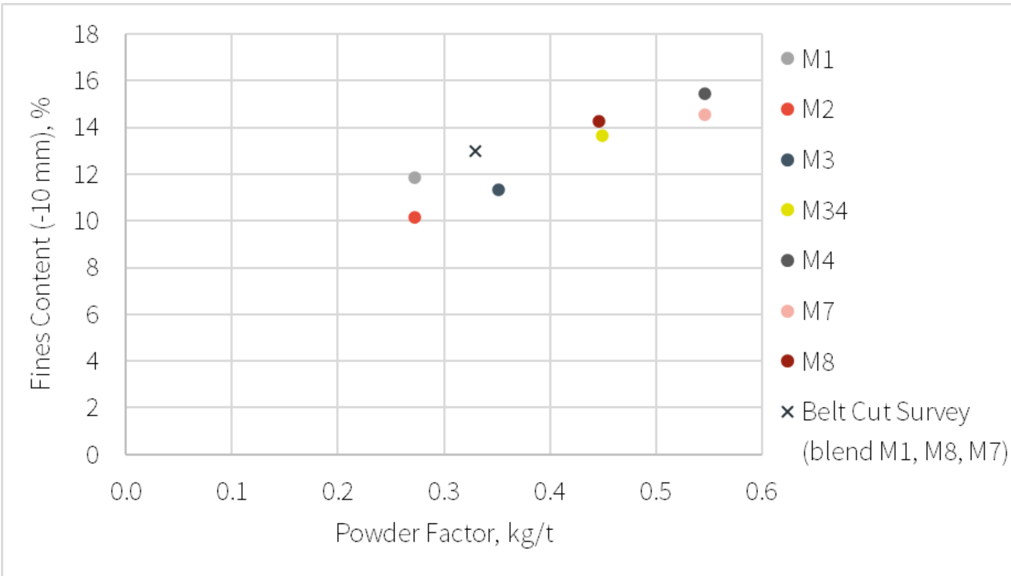

Figure 7—Fines content for each M class with typical powder factor

The primary crusher mostly acts on the large rocks, affecting the coarse end of the size distribution, and does not contribute significantly to the proportion of fines in the SAG feed. The fines are mostly generated during blasting. However, a small amount of −10 mm can still be produced in the primary crusher, and this was added to the calculated amount of −10 mm in the ROM. The primary crusher's effect on the amount of −10 mm material in the SAG feed was determined using a JKSimMet primary crusher model that was calibrated during previous plant surveys in 2014. Even though the actual amount generated in primary crushing is difficult to practically measure and model—as it depends on the ore properties (softer ore tends to generate more fines in primary crushing)—the small amount of fines generated by primary crushing within the JKSimMet model was in the range that was previously observed and measured during previous mine-to-mill audits performed by the Hatch team. An equation was developed to add the fines generated in primary crushing:

$$\% - 10 \text{ mm SAG feed} = 0.6569 * (\% - 10 \text{ mm ROM}) + 9.7116 \tag{6}$$

NEW POWER-BASED THROUGHPUT MODEL STRUCTURE

The throughput forecast modelling approach Hatch used is a power-based model. The total specific-energy model (SAG and ball mill) aligned well with the actual total specific energy for the MLP circuit. However, a model based on SAG mill specific energy only provided better model accuracy, as the grinding circuit is SAG mill limited. Therefore, the SAG mill specific energy calculation is the basis for the power-based model developed for MLP.

The SAG mill specific energy and SAG throughput are strongly influenced by ore hardness and feed size (as recognized and accounted for in the previous empirical throughput model MLP developed. Therefore, ensuring an accurate throughput forecast model requires high-quality input parameters for hardness and feed size. As discussed above, it was proposed to improve the estimate of feed size to provide better model accuracy. This was achieved by both improving the SAG F_{80} model's accuracy (by using a semi-mechanistic model rather than regressions of past performance) and incorporating an estimate of the amount of fines (−10 mm) as this strongly influences SAG mill throughput. Therefore, Hatch proposed a specific-energy model incorporating both SAG feed F_{80} and % −10 mm.

In terms of hardness, MLP has an extensive and world-class database, which is fundamental to accurate throughput forecasting. The MLP throughput forecast model Hatch developed uses DWi as the measure for hardness, as this is additive, and can be used to determine hardness of the scheduled feed blends based on a weighted average.

To incorporate all the factors discussed above, the throughput forecast model carries out a series of calculations as follows:

1. Estimate the weighted average hardness DWi from feed blend proportions:

$$\text{Average DWi} = \sum_{\text{j}} \text{DWi}_{\text{j}} \times \ \%\,\text{M blend} \tag{7}$$

2. Estimate the SAG F_{80} for each M Unit. The SAG F_{80} is estimated using the ore properties (DWi, RQD) and crusher gap using Equation 2.
3. Estimate the % −10 mm in SAG feed:
    a. Correlations established from drill and blast modelling (Equations 5a to 5e) are used to calculate the % −10 mm in ROM for each M unit.
    b. Calculate the % −10 mm in the SAG feed for each M unit, using Equation 6. This accounts for fines produced during primary crushing.
    c. Estimate the % −10 mm for the feed blend based on proportions of M units (weighted average)
4. Estimate the SAG mill specific energy (kWh/t) based on Equation 3.
5. Calculate the average throughput of all three grinding lines based on the predicted SAG Specific Energy and available power:

$$\text{t/h} = \frac{\text{SAG Power (kW)}}{\text{Specific Energy(kWh/t)}} \tag{8}$$

6. Calculate the yearly capacity from usability (availability x utilization) rate U:

$$\text{Feed to Mill (Mtpa)} = \text{t/h} \times 8760 \times \text{U} \tag{9}$$

The calculation steps are shown diagrammatically in Figure 8. To calibrate the throughput model for the MLP operation the fitted parameters were determined using mine and plant data, as detailed in the discussion section.

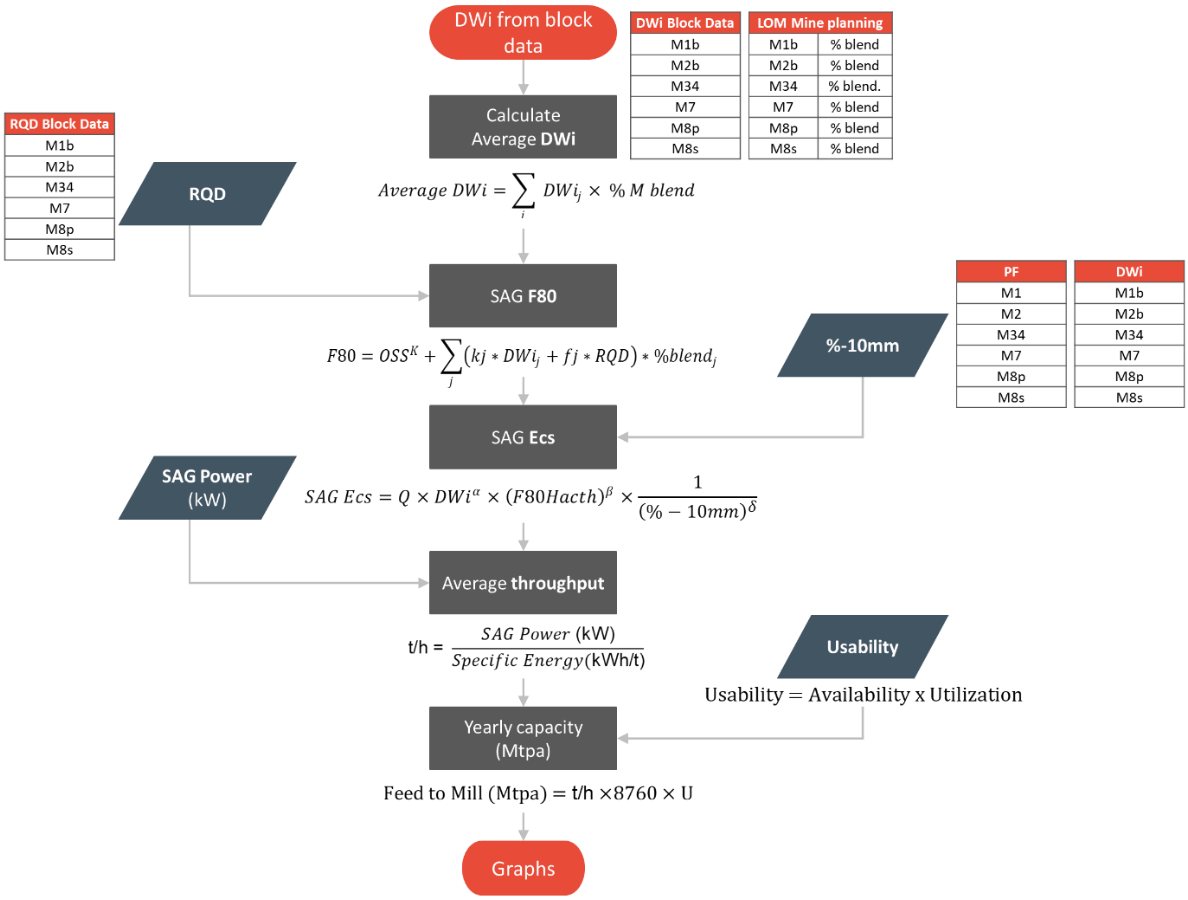

Figure 8—Concept diagram of the Hatch F_{80} and throughput model calculation steps

Discussion

The updated power-based throughput model was calibrated based on three years of historical data. Daily data were provided from 1 January 2018 to 30 November 2021. After filtering to remove any unusual downstream or upstream constraints of the comminution circuit that would not represent typical operations, 748 days (data points) were remaining which were used for model calibration. The model parameters of the SAG mill specific-energy equation (Equation 3) were calibrated using regression analysis of the daily data (748 data points).

HISTORICAL DATA USED FOR MODEL CALIBRATION

The monthly variation in throughput, feed blend, feed F_{80}, mill power, DWi (obtained from the block model), and powder factor are illustrated in Figure 9 to Figure 12. Monthly data are shown here for greater visual clarity; however, the daily data were used for model calibration. The calibrated model, with fitted parameters, was then used to predict throughput on a weekly, monthly, and yearly basis, and compared against the actual data. The model error was also estimated for the different times scales.

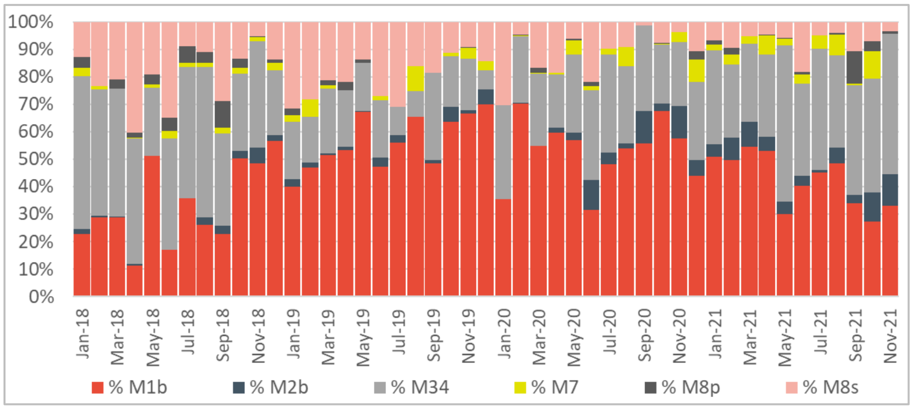

Figure 9—Monthly average blend proportion of the M units

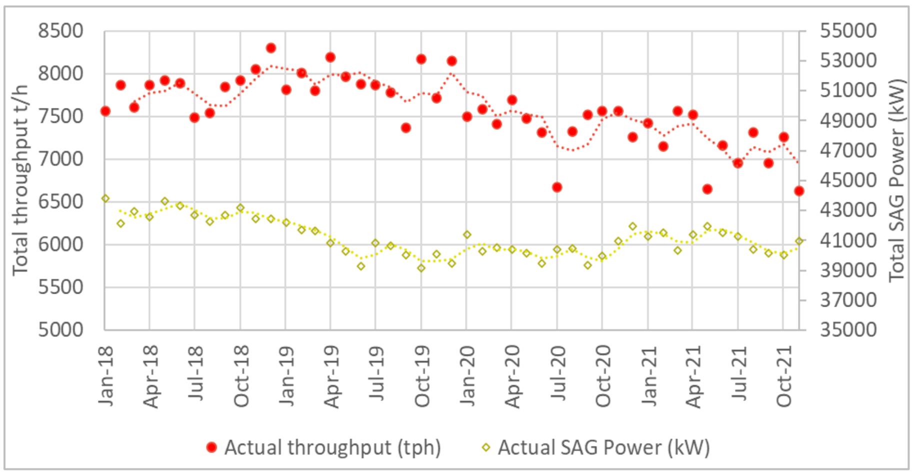

Figure 10—Monthly average throughput and SAG mill power (dotted lines are 3-month moving averages)

SAG throughput decreased since 2018 and 2019, despite maintaining a similar range of power draw (as shown in Figure 10). At the same time, the F_{80} had been coarsening quite consistently, which may explain the reduction in throughput. The coarser SAG feed size was also consistent with the trend of ROM P_{80} MLP supplied, as well as with SAG feed-size distribution from 2021 belt cuts.

The variation in M unit DWi hardness is shown in Figure 11; these values have been converted from the Axb breakage index generated by the block model. The hardness of the softer domains, such as M1 and M2, decreased over the period analyzed, but at the same time, the RQD value increased, meaning the ore became coarser and blockier. Rock mass structure (RQD values) strongly influences coarse fragmentation from blasting; thus, the increased RQD counteracts the reduction in hardness for these domains. The harder domains increased in hardness in the most recent months of the period, which would decrease throughput.

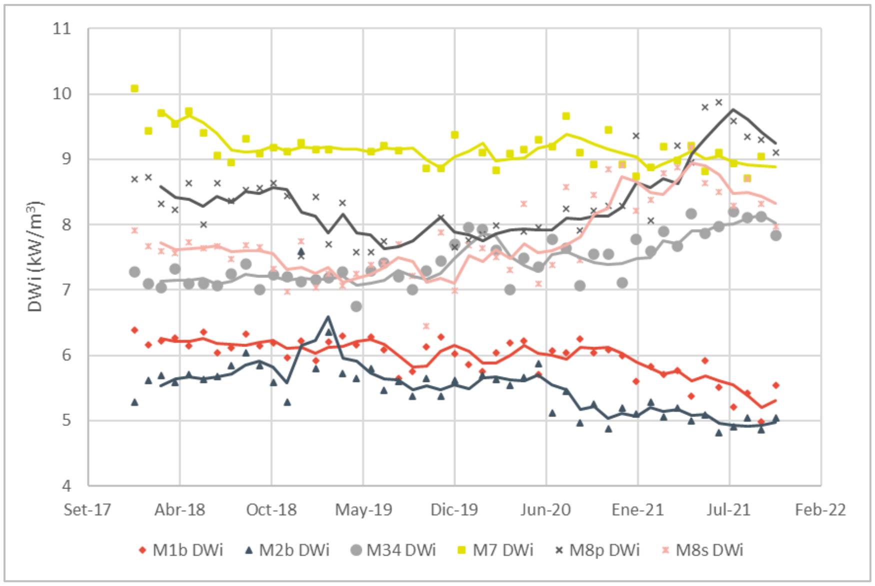

Figure 11—Monthly DWi values from block model (lines are 3-month moving averages)

Given the coarsened ROM particle-size distribution and reduced plant throughput, MLP has been increasing the powder factors over the years (Figure 12). Blast fragmentation is strongly influenced by the properties of the rock mass (structure and strength) and, as indicated previously, the high RQD in most of the ores is likely affecting fragmentation. Having observed that RQD (rock structure) affects particle-size distribution at MLP in addition to the inherent rock hardness, this factor was included within the model calibration. In particular, as structure mostly influences the coarse end of the size distribution, RQD was incorporated in the SAG F_{80} model, as previously explained in the method section. The new SAG F_{80} model was calibrated based on the plant data in a similar manner to the SAG specific-energy equation—that is, using regression analysis. However, unlike the previous SAG F_{80} model, this will not need recalibration for future ore types, as the ore characteristics (DWi and RQD) are incorporated in the new version of the SAG F_{80} model.

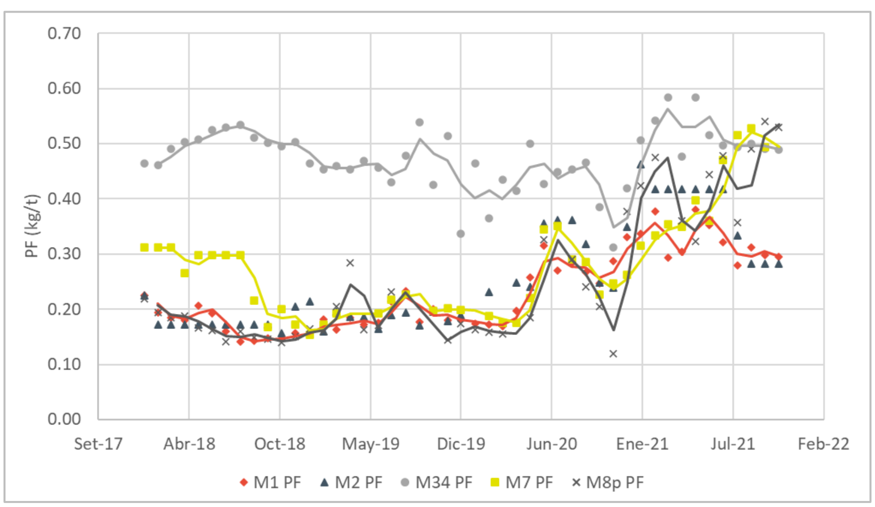

Figure 12—Monthly average of powder factor (PF) by M unit (lines are 3-month moving averages)

MODEL VALIDATION AND ERROR ESTIMATION

The calibrated power-based throughput model, with fitted parameters, was reconciled against actual plant throughput. The model was calibrated using regression against daily data (748 data points). The calibrated model was then used to estimate throughput on a weekly, monthly, and yearly basis and compared against plant data. The Hatch throughput model results are compared against actual data on a monthly and yearly basis in Figure 13 and Figure 14, respectively. The mean relative error was calculated for each time basis, and compared to the previous MLP empirical throughput model (Table 4). The comparison of models in Table 4 also includes the previous MLP empirical model using the new SAG F_{80} model proposed by Hatch, rather than the F_{80} model MLP developed previously (i.e., the weighted average of fixed F_{80} values for each M unit).

The accuracy of the previous MLP empirical throughput forecast model was already very good, in part due to the excellent ore characterization data and classification. The accuracy of the previous MLP empirical model is improved by using the new SAG F_{80} model (see the second row of Table 4). The new power-based throughput forecast model achieved a similar accuracy on a daily basis but improved accuracy on weekly and monthly bases (see the third row of Table 4). In particular, the accuracy over the long term is greatly improved (1.4% mean relative error on yearly basis compared to 3.2% for the previous model). This is one of the highest accuracies in throughput forecast modelling compared to many operations globally and is a great benefit for long-term strategic and LOM planning and optimization.

Some of the improvement in model accuracy, particularly over the long term, is contributed to by the model for SAG F_{80}, which factors in the feed ore characteristics and is therefore more responsive to ore changes. This also eliminates the need to frequently recalibrate the F_{80} regression model. The inclusion of fines content (% −10 mm) in the SAG feed also contributed to the improved model accuracy. This considers the impact of both ore characteristics and drill and blast conditions on the proportion of fines in the feed, which has an impact on SAG mill throughput.

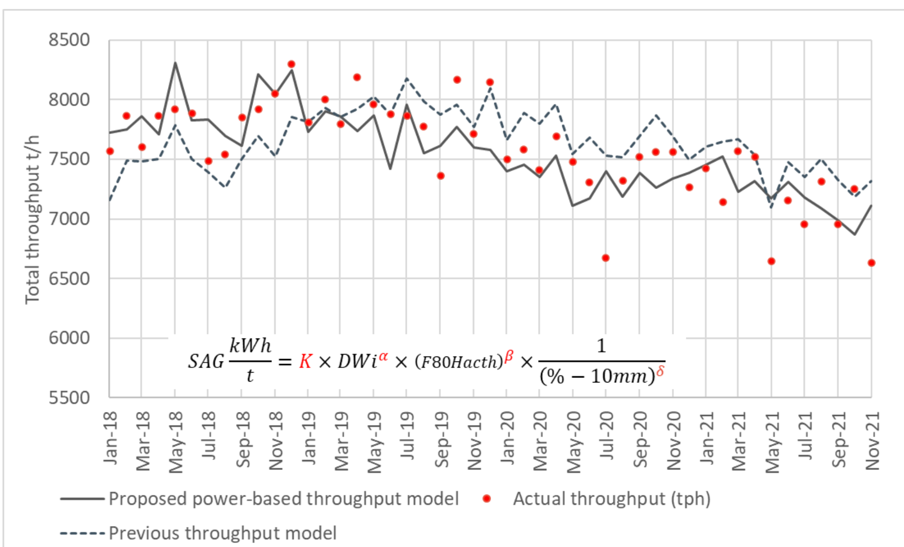

Figure 13—Proposed power-based throughput model validation—monthly basis

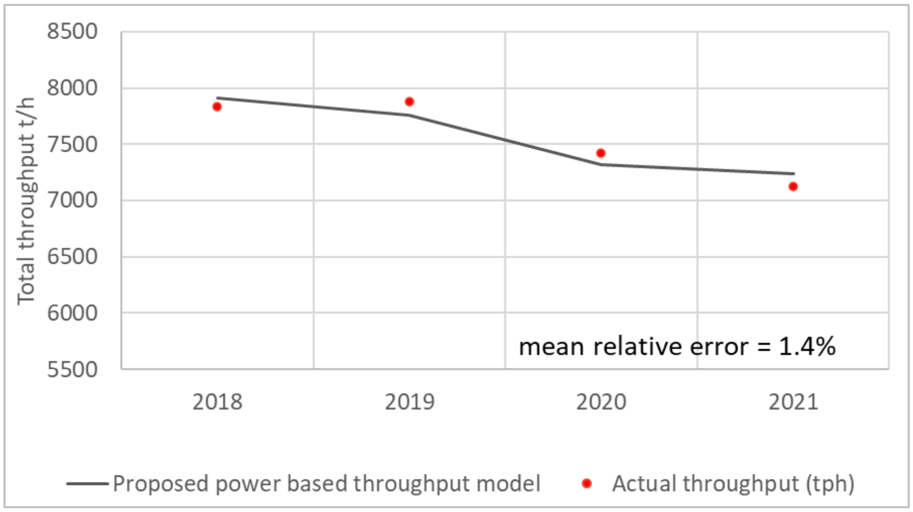

Figure 14—Proposed power-based throughput model validation—yearly basis

Table 4—Model prediction error at different time scales

Model	Mean Relative Error (% t/h)			
	Daily	**Weekly**	**Monthly**	**Yearly**
MLP Empirical Throughput Model with MLP F_{80} Model	6.0%	5.0%	3.5%	3.2%
MLP Empirical Throughput Model with Hatch F_{80} Model	5.7%	4.8%	3.2%	2.8%
Updated Power-Based Throughput Model with Hatch F_{80} Model	6.2%	4.5%	3.0%	1.4%

Conclusion

The empirical throughput model previously developed at MLP was good overall, leveraging the comprehensive geometallurgical mapping of the hardness within the ore body. However, it had limitations, particularly related to the accuracy of predicting SAG feed size. The SAG feed F_{80} was sensitive to changes in ore characteristics, and the previous empirical SAG F_{80} model required continual adjustment of the regression parameters, thus limiting accuracy and predictive abilities for the long term. Hatch has developed an updated model that addresses these limitations. The throughput forecast model Hatch developed is power-based and includes a semi-mechanistic model for SAG F_{80} which accounts for changes in ore characteristics. It also incorporates the fines content (% passing 10 mm) in the estimation of feed size, as this has a significant impact on SAG mill throughput. The resulting throughput forecast model has improved accuracy, particularly when forecasting over the long term. Thus, the new model is of great benefit for long-term strategic and LOM planning and optimization.

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