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Key Performance Indicators for Electricity Conservation in Open Pit Mining

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Abstract: In mining operation, blasts are used to fracture the in-situ rock mass and prepare it for excavation, crushing and grinding. The High-energy blasting, which uses increased amount of explosive material per tonne of rock, is considered to be one of most effective ways to reduce the consumption of energy in the milling process, resulting production saving as well as reduction in dust (PM5) and tailing. In this article, the main focus is to investigate the electrical intensity of the five grinding lines in the mill, as they accounted for the majority of site electricity consumption, in relations to other operational procedures, in particular the high-energy blasting. Several regression models were established, the data points were fitted within 10% of the actual values, and the majority within 5%. The models provide management better ways to predict and target electrical consumption and environmental impact.

Keywords: Key Performance Indicator (KPI), Energy Conservation, Electricity Intensity, Open-Pit Mining, High-Energy Blasting, Powder Factor

1. Introduction

In the open-pit mining industry, blasts are used to fracture the in-situ rock mass and prepare it for excavation, crushing and grinding. High-energy blasting uses increased amount of explosive material per tonne of rock to increase fragmentation and reduce particle size. Reduced particle sizes require less time in the grinding process to be reduced to the necessary size for processing resulting in an increased rate of throughput and a decrease in the energy consumption of production. The High-energy blasting is considered to be one of most effective ways to reduce the consumption of energy in the milling process, resulting production saving as well as reduction in dust (PM5) and tailing. Highland Valley Copper (HVC) is an operation within the Teck Copper Business Unit that produces copper and molybdenum concentrates. To better understand its energy performance, the investigation focuses on developing a set of Key Performance Indicators (KPIs) suitable to the needs and priorities of HVC in supporting decision making of efficient operations, and providing benchmarks and monitor tools for energy conservation.

Key Performance Indicator (KPI) is a crucial tool to measure one's progress towards pre-defined objectives. KPIs have been widely used by organizations to measure financial or operational performance, as well as sustainability, conservation, environment, and health or safety issues from times to times [1, 2, 4, 5, 6, 8, 9, 12].

The primary focus of the study was on the electrical intensity of the five grinding lines in the mill as they accounted for the majority of site electricity consumption. A relationship between electrical intensity and mill throughput was initially established. It was then determined that the previous throughput model used in planning was inadequate to accurately account for recent adoption of blasting technique, high energy blasting.

In order to produce a more accurate model of mill throughput, several key variables were used: the rock hardness, the powder factor used in blasting, the percentage of high energy, and trim & buffer (wall control) blasting. A series of models focus on the viability of using powder factor, hardness, blasting rates as independent variables with weekly or daily data. A polynomial model for throughput using weekly data for the hardness, high energy blasting rate, and trim & buffer blasting rate was found to perform best. In this model, all data points from the model were within 10% of the actual values, and the majority within 5%. The model performed considerably better than the previous prediction and has also been shown to work with relative accuracy for 2012 data where no high energy blasting was carried out.

While the use of the model in the prediction and targeting of electrical consumption are clear, it will also be of use in many other areas. The more understanding of throughput provided by the model has many uses such as more accurate planning, the identification of energy savings through blasting practices, and as a performance indicator in itself. This work can be taken further and used as the basis for developing more comprehensive models such as one including recovery rate of mill operation.

Blasting as an important mine-to-mill strategy was investigated in relation with other processes by several researchers. For example, Rorke [10] considered the blasting to improve the free flow to loader and to increase loading rate. Burger *et al*. [3] considered the correlation of blasting and mill throughput. Valery, Jankovic and Sonmez [11] used Process Integration and Optimization methodology to increase mine efficiency and mill throughput by considering rock characterization and blasting patterns.

2. Model Development

HVC is committed to the efficient use of energy and the reduction of greenhouse gas emissions. Central to the HVC Energy Policy is the inclusion of energy efficiency and GHG considerations into its process designs and operating decisions. Currently, HVC uses a collection of complex spreadsheets to monitor the site's energy consumption and produce energy-specific targets. The fundamental challenge behind this study was to determine how to extract energy-related information that is informative, concise, and useful to a wide range of users at the mine.

Operations at HVC follow a standard process of drilling, blasting, excavation, hauling, crushing, conveying, grinding, flotation, and molybdenum leaching. The Mill itself is comprised of 5 grinding lines, with three Semi-Autogenous (SAG) mills (A, B and C) and two Autogenous (AG) mills (D and E). Just over half of all energy consumed on site is electrical, with much of the remainder being diesel; however, electrical consumption is tracked at a much higher resolution. As more than half of all electrical consumption is in the grinding process, the study primarily focuses on the effect of different blasting techniques to the throughput of the five grinding lines in the mill.

Key Variables

In order to understand the electrical performance of the grinding process, several key variables were identified. An important factor in selecting these variables was that data related to the variables was tracked and recorded on a regular basis and are therefore readily available.

- *Electrical Intensity:* The electrical intensity refers to the electrical consumption in the grinding lines per dry metric tonne of ore milled (kWh/DMT).
- *Hardness:* When blast holes are drilled, the drills record a 'drilling resistance' indicator (the "Aquilla" or "Leica" number) which reflects relative variations in rock strength, and is consequently used as an indicator of the hardness of the material to be blasted.
- *Mill Throughput Rate:* Throughput rate is measured by tonnes of ore processed in mill per operating hour (often referred as mill TPOH). For individual lines, such as A-line throughput, this is simply the total tonnes through A-line in a given time period divided by the total operating hours within that same period.
- *Powder Factor:* The powder factor is simply the kilograms of explosive used per tonne of rock blasted. There are three categories of rock hardness, and three different blast designs alongside a standard production blast design, there is also one for high energy blasting and trim and buffer blasting (T&B), corresponding to higher and lower powder factors. The principal behind high energy blasting is that using a greater powder factor results in greater fragmentation of the rock, reducing the amount of work that the mill has to do, and thus increasing throughput. T&B blasting is used for wall control where a lower powder factor is necessary to avoid destabilizing or damaging the pit walls.
- *Blasting Rates:* Blasting rates are used to quantify the amount of high energy and T&B blasting performed. The blasting rate is a percentage of the total rock blasted that was done using each of the blast patterns. Only high energy and T&B blasting rates are used as the production blasting rate is naturally included as the remainder.

3. Data Analysis

The electricity intensity is affected by mill throughput rate. Higher throughput usually means softer ore and the ore requires less electricity to be ground, and results a lower electricity intensity. At first, we build a model to determine whether A-line is suitable to be a representative of other four lines. The model reveals that all five lines are significantly related and each line can be represented by A-line equivalence with an appropriate weight.

At HVC, the ore from different pits gets mixed before they reach the stockpile. The ore are intentionally blended so that it is roughly uniformly mixed going into different lines, which justifies the strong correlation between different lines.

3.1. Model for Electricity Intensity

Monthly data for A-line electricity intensity (kWh/DMT) and A-line throughput is available. So in this model, we use the A-line electricity intensity as the dependent variable and A-line throughput as the independent variable. The plot of the data is given in Figure 1, where the line is the fitted linear regression. The linear model seems fitted fairly well. After deleting one outlier, the summary of the model is given in Table 1.

The *R*-squared represents the percentage of the variation of the dependent variable, which is close to 0.5, that indicates that the model fits very well. The $Pr(>|t|)$ is the *P*-value (i.e., the probability that the corresponding independent variable is 0). So a small *P*-value means the independent variable has a significant impact on the dependent variable, and usually the threshold is 0.05. Here the *P*-value for Throughput is much smaller than 0.05 indicating that the throughput has a very significant effect on the electricity intensity. We can also see the estimated coefficient for Throughput is negative. So when the throughput increases, the electricity intensity decreases, which is in line with our expectation.

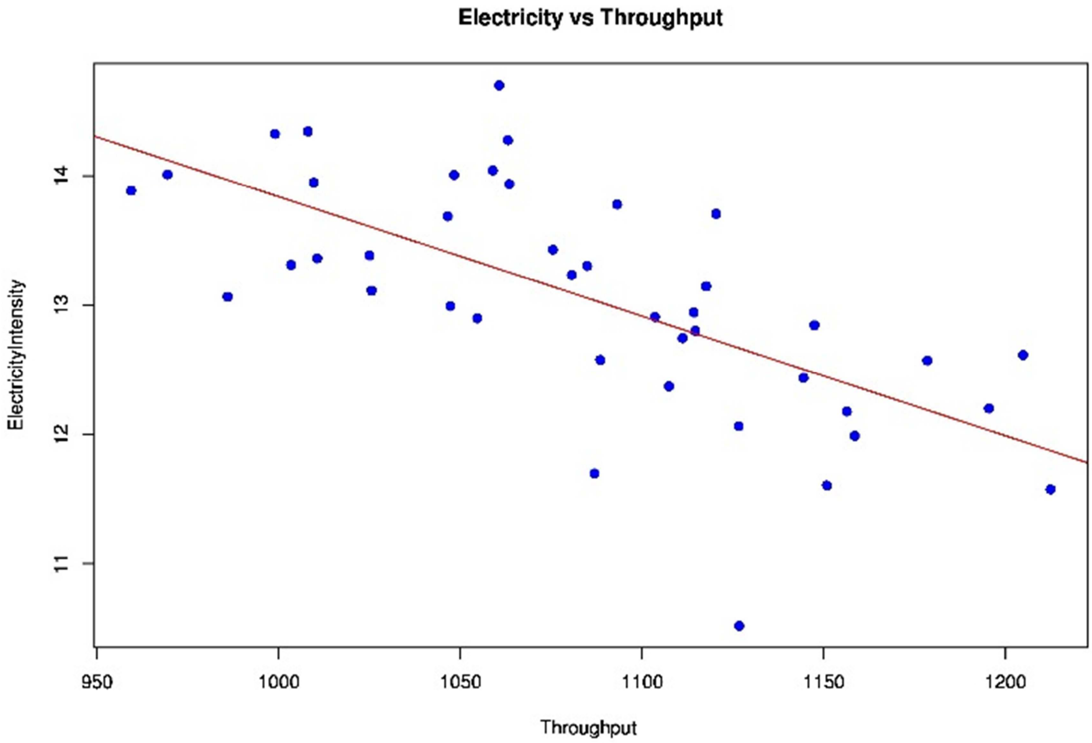

Figure 1. *Linear regression of mill throughput and electricity intensity.*

Table 1. *Summary of electricity intensity model (Electricity Intensity ~ Throughput).*

Residuals:				
Min	1Q	Median	3Q	Max
-2.14711	-0.40336	0.02349	0.38944	1.42350
Coefficients:				
	Estimate Std.	Error	t value	Pr(>|t|)
(Intercept)	23.061887	1.779022	12.963	6.61e-16 ***
ALineTPOH	-0.009225	0.001638	-5.632	1.56e-06 ***

Signif. codes:	0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1			
Residual standard error: 0.6707 on 40 degrees of freedom				
Multiple R-squared: 0.4423, Adjusted R-squared: 0.4283				
F-statistic: 31.72 on 1 and 40 DF, p-value: 1.555e-06				

3.2. Models for Mill Throughput Rate

We found the strong relation between the electricity intensity and the throughput in the mill. Next we attempt to find the key input metrics that affects the throughput, so that we could link the electricity intensity with these key input metrics. There have been several studies done by other researchers (e.g., [3], [11]) to determine key inputs. It was indicated that hardness and blasting have impact on mill throughput rate.

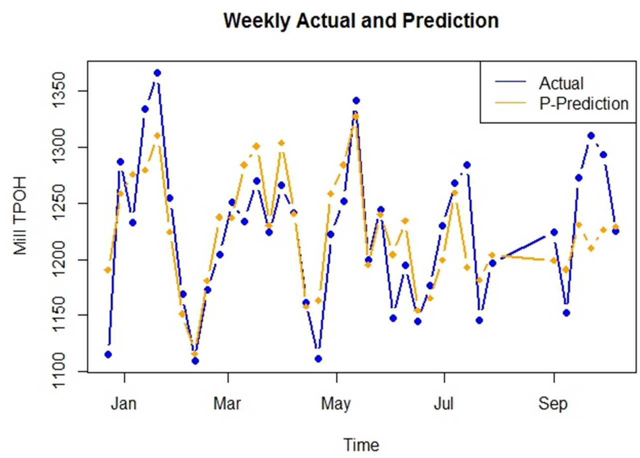

Figure 2. *Weekly actual throughput versus prediction.*

Consulting with the geologists at HVC leads us to other mining techniques which have the potential impact to throughput: high energy blasting, and trim and buffer (T&B). High energy blasting rate and T&B rate are the percentages of ore blasted in high energy blasting design and ore blasted in T&B design, respectively. These two metrics are recorded when the ore get removed from the ground. It has less time delay before the ore reaches the mill, generally less than 12 hours. Meanwhile, these two rates link to powder factor because of different powder factor are used in each blasting design. The high energy blasting, which results greater fragmentation of the rock and therefore reduce the energy in grinding, is a new practice introduced recently. We build a model by choosing the calculated throughput as the dependent variable, hardness, high energy blasting rate and T&B rate as the independent variables. The testing shows that the model has a much better R-square value, and all independent variables are significant. The estimated coefficient for high energy blasting rate is positive, which is what we expected. But the estimated coefficient for T&B rate is also positive, which is a surprise. We expect that the coefficient is negative because it uses less explosives and reduces the mill throughput rate due to less fragmentation. The explanation is that there is a fault line that runs parallel to the main wall being mined in a pit. This may cause an increased grindability of the ore blasted in T&B design and thus yield a positive coefficient for T&B. Additionally, with finer material entering the mills as a result of high energy blasting, the larger chunks of ore from the trim and buffer section may actually serve the function of crushing ball to improve the grinding rate– particularly in the two AG mills where the process is reliant on the ore breaking itself up.

To reduce the impact of 12-hour delay from crushers to stockpiles and to consider the stability of data sets, the data with finer resolution (e.g., daily data) may not be the most appropriate and so we choose to build a weekly model of throughput.

Table 2. *Summary of linear weekly model (Throughput ~ TandB + High Energy +Hardness).*

Residuals:				
Min	1Q	Median	3Q	Max
-101.883	-31.613	-7.516	27.981	122.576
Coefficients:				
	Estimate Std.	Error	t value	Pr(>|t|)
(Intercept)	351.1834	230.8155	1.521	0.137384
TandB	160.8893	61.4587	2.618 *	0.013116
High Energy	216.9825	55.1700	3.933	0.000392 ***
MineTPOH	0.6657	0.1949	3.415	0.001666 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Residual standard error: 50.65 on 34 degrees of freedom				
Multiple R-squared: 0.4263, Adjusted R-squared: 0.3757				
F-statistic: 8.422 on 3 and 34 DF, p-value: 0.0002539				

In this model, the R-square is 0.4263 and the estimated coefficient for T&B is 160.8893. Figure 2 shows the actual mill throughput and the prediction generated by the weekly model.

Figure 3 shows the performance of the weekly model. Here, closer to the central line the data points are, the better the model is. The two parallel dotted lines are ±10% range, i.e., the data points inside this range are within 10% difference to the prediction. We can see that only one data point lies outside this range.

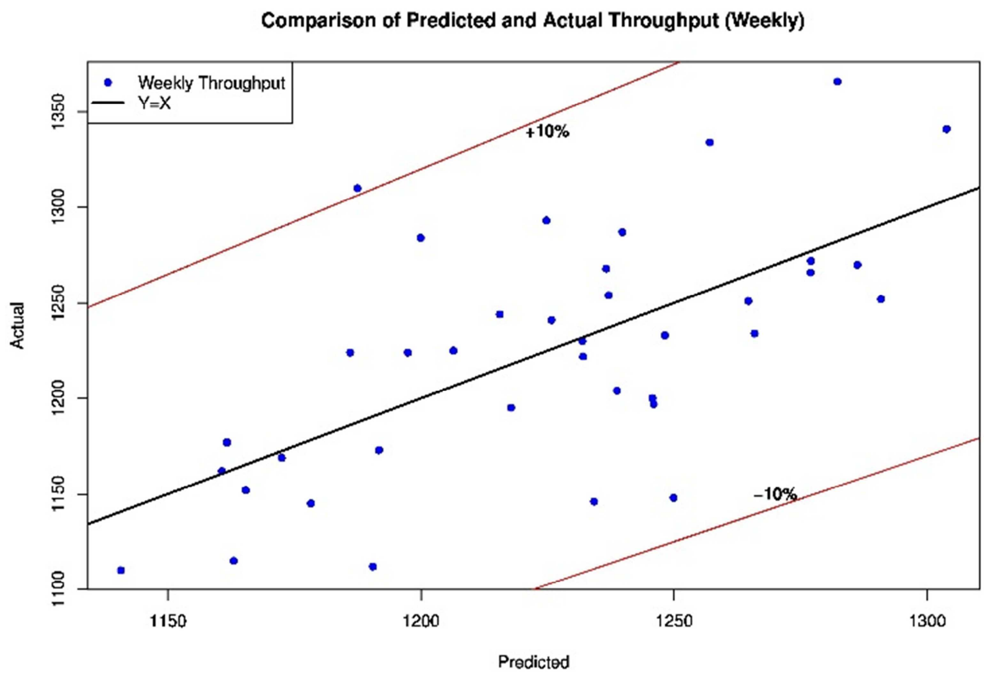

Figure 3. *Accuracy of the prediction.*

3.3. Polynomial Models for Mill Throughput Rate

We confirm that hardness, T&B rate, high energy blasting rate are strongly related to the throughput and built a linear model for them. To improve the accuracy of the model, we introduce the polynomial terms (including interaction terms) into the weekly model.

At below, we present the relative importance of the independent variables, hardness, high energy blasting rate, T&B rate, in the weekly linear model.

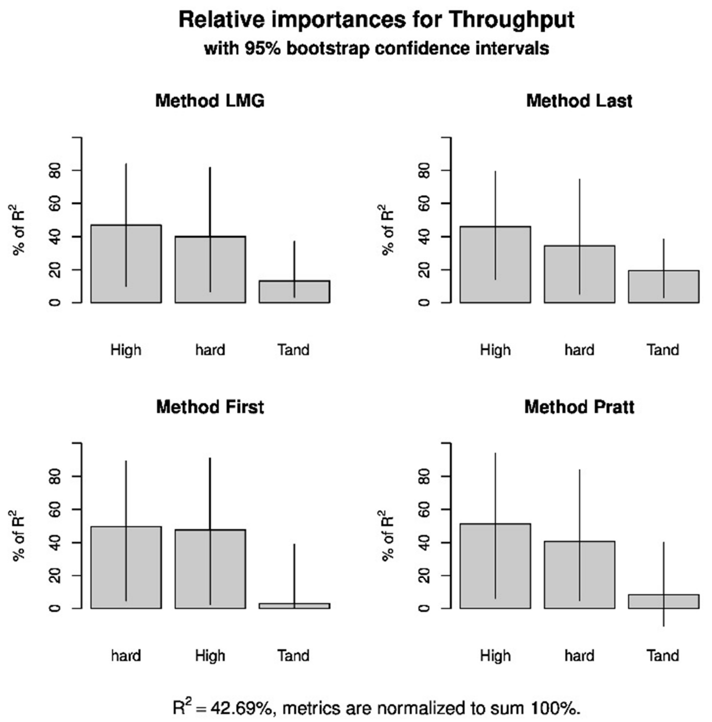

Figure 4. *Four methods to test the importance of independent variables.*

Figure 4 shows the importance of test results by four different methods, and all of them indicate that high energy blasting rate (High) and hardness (Hard) are relatively more important than T&B rate (TandB). It means high energy blasting rate and hardness can explain more about the variation of the dependent variable (i.e., mill throughput rate). So in the polynomial model, we add the following terms:

HM = High · Hard
H1M2 = High · Hard^2
H2M1 = High^2 · Hard
H1M3 = High · Hard^3
H2M2 = High^2 · Hard^2
H3M1 = High^3 · Hard
H1M4 = High · Hard^4
H2M3 = High^2 · Hard^3
H3M2 = High^3 · Hard^2
H4M1 = High^4 · Hard
H2 = High^2
M2 = Hard^2
H3 = High^3
M3 = Hard^3
H4 = High^4
M4 = Hard^4
H5 = High^5
M5 = Hard^5

At first, we use stepwise method to select the model based on Akaike Information Criterion (AIC). The stepwise method first includes all the independent variables in the model. Then it calculates all the AIC values for each model without one of the independent variables and choose the model with the smallest AIC value. Iteratively, we do the same for this chosen model, and pick up the model with the smallest AIC by adding or deleting another independent variable. Table 3 shows the summary of the model after selection.

Table 3. *Summary of polynomial model after AIC selection (Throughput ~ TandB +High + Hard + other interaction terms).*

Residuals:				
Min	1Q	Median	3Q	Max
-60.546	-16.620	-1.089	11.588	63.088
Coefficients:				
	Estimate Std.	Error	t value	Pr(>|t|)
(Intercept)	-1.259e+08	9.049e+07	-1.391	0.1822
High Energy	-6.643e+07	5.156e+07	-1.288	0.2149
MineTPOH	5.683e+05	3.908e+05	1.454	0.1640
HM	2.312e+05	1.783e+05	1.297	0.2121
M2	-1.024e+03	6.756e+02	-1.516	0.1478
H3	-3.844e+06	2.419e+06	-1.589	0.1305
M3	9.214e-01	5.846e-01	1.576	0.1334
H4	-1.486e+06	7.344e+05	-2.023	0.0591.
M4	-4.137e-04	2.532e-04	-1.634	0.1207
H5	2.099e+05	9.353e+04	2.244	0.0384 *
M5	7.417e-08	4.390e-08	1.689	0.1094
H1M2	-3.022e+02	2.310e+02	-1.308	0.2082
H2M1	2.806e+03	1.874e+03	1.497	0.1527
H2M2	-5.411e+00	3.203e+00	-1.689	0.1094
H1M3	1.759e-01	1.328e-01	1.324	0.2030
H3M1	8.262e+03	4.141e+03	1.995	0.0623.
H1M4	-3.847e-05	2.863e-05	-1.344	0.1967
H2M3	2.533e-03	1.377e-03	1.839	0.0835.
H3M2	-4.085e+00	1.826e+00	-2.238	0.0389 *
H4M1	9.613e+02	5.768e+02	1.667	0.1139
TandB	6.466e+01	6.595e+01	0.980	0.3406

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				
Residual standard error: 41.65 on 17 degrees of freedom				
Multiple R-squared: 0.8061, Adjusted R-squared: 0.5779				
F-statistic: 3.533 on 20 and 17 DF, p-value: 0.005593				

The R-square 0.8061 is good. But there are too many terms in the model, and it usually performs badly outside the range of independent variables and results in relatively large deviations.

Next, we experiment another criterion, BIC, which is a similar criterion to AIC. It usually chooses a model with fewer independent variables because it penalizes more when there are more independent variables in the model. We still use the stepwise selection method to choose the model. The chosen model by BIC ends up being the same as the one selected by AIC.

Thirdly, we turn to C_p criterion. This is a well-known selection criterion, which suggests the appropriate number of independent variables to be included in the model:

$$C_p = SSE_p / MSE_{all} - (n - 2p)$$

where MSE_{all} is the mean squared error for the model including all the available independent variables, and SSE_p is the sum of squared error of the model with p independent variables.

We use the forward method to select the model. It adds parameters to the model and choose the best one for each model with different number of parameters. For each best model we can calculate C_p and choose the one that has the smallest difference between C_p and the number of parameters which is p. The model with eight parameters including the intercept turned out to be the best one. Table 4 shows the summary of this model.

Table 4. *Summary of polynomial model after C_p selection (Throughput ~ Hard + TandB + HM + H2 + H4 + H5 + H1M2).*

Residuals:				
Min	1Q	Median	3Q	Max
-75.98	-35.23	-1.90	23.27	100.06
Coefficients:				
	Estimate Std.	Error	t value	Pr(>|t|)
(Intercept)	2.929e+02	4.475e+02	0.655	0.5177
MineTPOH	7.331e-01	3.953e-01	1.854	0.0735.
HM	-9.320e-01	1.251e+00	-0.745	0.4622
H2	4.900e+03	2.527e+03	1.939	0.0619.
H4	-2.808e+04	1.164e+04	-2.413	0.0221 *
H5	3.031e+04	1.219e+04	2.487	0.0187 *
H1M2	2.756e-04	9.954e-04	0.277	0.7838
TandB	1.450e+02	5.650e+01	2.567	0.0155 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				
Residual standard error: 45.15 on 30 degrees of freedom				
Multiple R-squared: 0.5977, Adjusted R-squared: 0.5039				
F-statistic: 6.368 on 7 and 30 DF, p-value: 0.0001237				

We see that the R-square is smaller now but the adjusted R-square doesn’t drop too much. The adjusted R-square is another indicator that balances the number of independent variables and the fit of the model. Figure 5 is the plot of comparison among the prediction currently used in HVC, actual throughput and the prediction by the new polynomial model.

The current model used at HVC for predicting throughput consistently undervalue the actual throughput, partly because the high energy blasting stared in 2013 was not accounted for. The new polynomial model includes both the high energy blasting rate and T&B rate, and results a much better fitting, and all the data points fall within the 10% error range (see Figure 6).

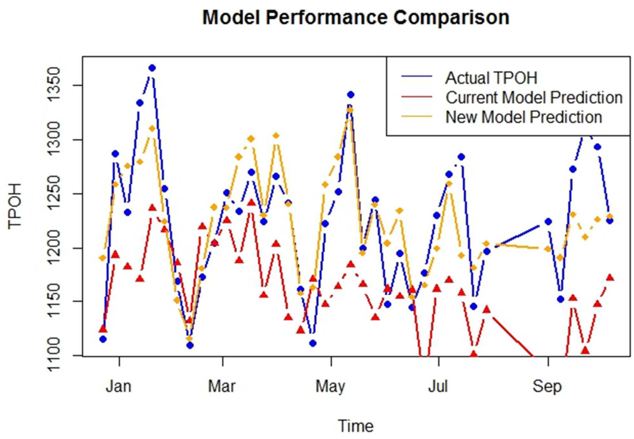

Figure 5. *Model performance comparison.*

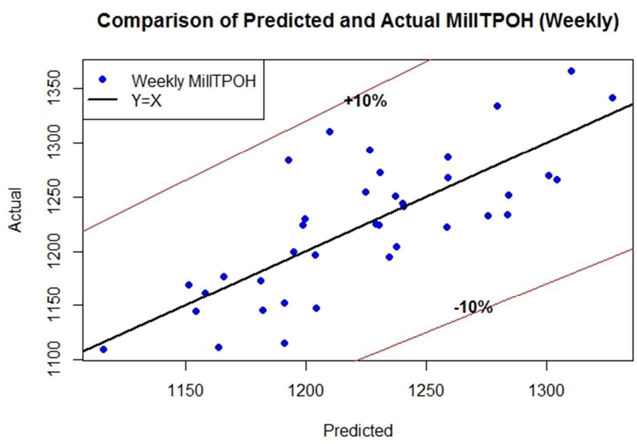

Figure 6. *10% error range.*

4. Conclusions

In this project, we attempt to determine the key performance indicators in the mining process which have significant impact on mill throughput. Taking advantage of the high-resolution data collected at HVC, we use statistical techniques to analyze the relation among mill throughput, energy consumption and key operational factors. Linear regression models and polynomial models are deployed for the purposes. Based on the statistical analysis of the models given in the Section 3, we obtain the following findings:

- There is strong correlation between mill throughput and electricity intensity. By improving the performance of mill throughput, it will significantly reduce the electricity consumption in the mill.
- High energy blasting, hardness and T&B are confirmed to have a significant impact on mill throughput.
- The polynomial model presented in Section 3 provides a better prediction of the mill throughput than the model currently in use.

The more accurate prediction from the new model will be helpful to the management to improve production efficiency by controlling the high energy blasting and useful in its operation management and production planning. In the investigation, we determined the key performance indicators in relation to mill production and proposed several regression models for mill throughput. For the further investigation, we suggest the following refinements and directions:

- Develop a model to link electrical consumption and mill production directly, and use the model to monitor energy consumption targets.
- The polynomial model fits the current data set well. However, it is necessary to conduct the sensitivity analysis to determine how the model reacts to the high energy blasting rate beyond the range of current practice so that the model is suitable for spectrum of all possible blasting design and avoid the over-fitting and dependency to the current data set. In the meantime, conduct cross-validation to verify the fitness of the polynomial model to other deviations, which is an important step to take in order to replace the existing prediction model and to implement the new model in strategic planning at HVC.
- Identify energy savings contributed to high energy blasting using polynomial model to quantify the impact of blasting designs on mill throughput.

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