Energy Conservation KPI Final Report

by

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1 Introduction

Highland Valley Copper (HVC) is an operation within the Teck Copper Business Unit and continues to push itself to further embed sustainability into its culture. In its mission statement, it states that "we are a catalyst for introducing new energy and management systems that make a positive contribution to efficient use of energy", and set short-term goals (2015) to “reduce energy consumption by 1,000 TJ (at Teck)”. To further fulfill its commitment in environment and sustainability, HVC intends to use its massive data sets on energy consumption to make effective decisions towards conservation.

Key Performance Indicator (KPI) is a crucial tool to measure one’s progress towards pre-defined objectives. KPIs used by most companies primarily relate to financial or operational performance. KPIs relating to sustainability, conservation, environment, and health or safety issues do exist, but generally are not adopted cross-industry. This project aims to develop site specific KPIs for HVC.

Currently, HVC’s energy group uses a collection of complex spreadsheets to monitor energy consumption. The fundamental challenge with this is how to extract information that is informative, concise, and useful to a wide range of users at the mine.

There are many activities consuming energy at HVC, as well as in any mining operation, but the main ones are excavating, hauling, pumping, flotation, crushing, conveying and grinding. As for energy type, electricity and diesel are the two main resources that are being consumed.

In our project, we focus on the electricity side of energy because of the rich data available in electricity. We find a strong relation between the electricity intensity and mill throughput rate. Furthermore, we developed a model to predict the mill throughput rate and analyze the effects of several key input metrics with impacts on the mill throughput rate.

We would like to thank Alex Jones and Craig Haight for their efforts and deep involvement in this project. They play a very important role in coordinating the exchange of information between TRU research group and HVC. We would never be able to finish the research project without their help.

2 Milestones

- Review of KPIs used in the mining sector, other resource industries, and the financial industry (student research).
- Develop a list of current energy measurements and KPIs in use at HVC.
- Presentation of possible KPIs to HVC.
- Deliver report to HVC.

3 Literature Review

First we looked into different research papers about sustainability since energy consumption is a very important part of sustainable development. Afgan et al. (2000) suggested Resource indicator, Environment indicator, Social indicator, Efficiency indicator as sustainability indicators. In this study, we are focusing on the efficiency indicators.

There are a lot of papers introducing the methods to select KPIs in different industries. For an example, Fiksel (2002) introduced a method to select KPIs related to sustainability in cement industry. This method requires us to consider the needs of the stakeholders and establish the goals first. Then based on these goals, we identify the important factors and select the KPIs. This helps us realize the importance of getting the inputs from the managers and lead us to have the interviews with the managers from the company. Cement companies also consume a lot of energy. This report provides us a similar example of how to choose KPIs in energy intensive companies.

Then we looked into the reports produced by mining companies. Energy Efficiency Opportunities (EEO) is a mandatory Australian government initiative for organizations using more than 500 TJ that requires energy studies to be carried out. One of EEO case studies, "*Analyses of Diesel Use for Mine Haul and Transport Operations*", focuses on analyzing the diesel usage in mining operations in several mines. In this case study, Downer EDI Mining developed performance indicators that use an 'equivalent flat haul' calculation to account for elevation changes on a specific mine route. The indicators provide a more consistent measure of true energy performance, enabling the company to track energy intensity over time. But the resolution of diesel data in HVC is inadequate to conduct proper analysis, since it only has a total diesel consumption of all the equipment in the mine. So in this project, we turn our attention to the electricity consumption.

Grinding consumes over 60% of the electricity in HVC. The mill operation has a big effect on the electricity consumption. Burger *et al.* (2006) use main characteristics of the ore and blasting to predict the mill throughput in Batu Hijau.

4 Interview and Data Analysis

We had several interviews with the senior managements at HVC and they provide many useful insights to the mining and milling operations. It's important for us to get the inputs from these managers since they are the ones that are familiar with the operations. They provide us with the KPIs currently used and what features and information they want to have in the future. These inputs will eventually lead us to build the models.

The electricity intensity metric that is currently being used in HVC is kWh/DMT. This metric is affected by mill throughput rate which is mill TPOH (tones per operating hour). Higher mill TPOH usually means softer ore which requires less electricity to be grinded, and result in a lower electricity intensity. We try to build a model to confirm this relation by selecting A-line as an example. There are 5 grinding lines in total in the mill which are A, B, C, D, E. We first look at the correlation table of the mill throughput rates to see if it's suitable to choose A-line as a standard.

Figure 1. Correlation test.

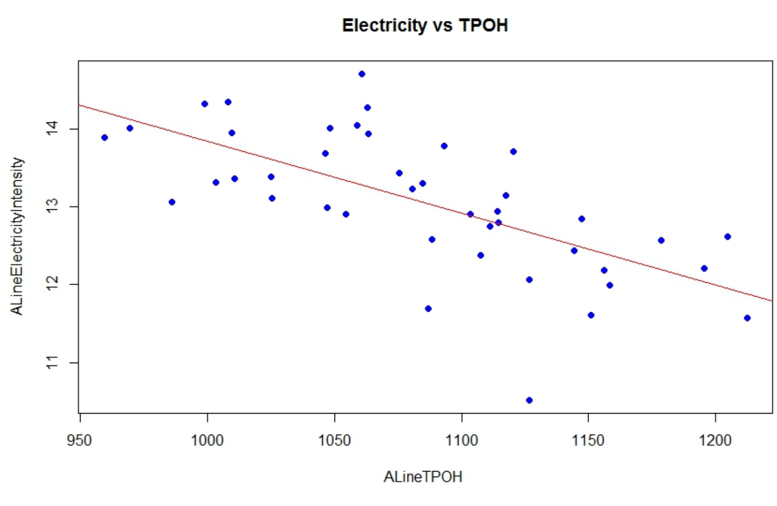
Pearson Correlation Coefficients, N = 42 Prob > |r| under H0: Rho=0					
	A_Line_Milling_Rate	B_Line_Milling_Rate	C_Line_Milling_Rate	D_Line_Milling_Rate	E_Line_Milling_Rate
A_Line_Milling_Rate A Line Milling Rate	1.00000	0.70259 <.0001	0.75155 <.0001	0.39447 0.0097	0.74793 <.0001
B_Line_Milling_Rate B Line Milling Rate	0.70259 <.0001	1.00000	0.74848 <.0001	0.38470 0.0119	0.74066 <.0001
C_Line_Milling_Rate C Line Milling Rate	0.75155 <.0001	0.74848 <.0001	1.00000	0.35819 0.0199	0.74601 <.0001
D_Line_Milling_Rate D Line Milling Rate	0.39447 0.0097	0.38470 0.0119	0.35819 0.0199	1.00000	0.51436 0.0005
E_Line_Milling_Rate E Line Milling Rate	0.74793 <.0001	0.74066 <.0001	0.74601 <.0001	0.51436 0.0005	1.00000

The upper number in each cell is the correlation coefficient, the lower number is the P-value which represents the probability of the correlation coefficient actually being 0. We can see all the P-values are smaller than 0.05 which is the threshold to identify if the coefficient is significantly different from 0. It means all lines are significantly related. The ore from different pits will get mixed before they reach the stockpile. The ore are intentionally blended so that it's roughly uniformly mixed going into different lines. That results into the strong correlation between different lines. We can also see the correlation coefficients are mostly bigger than 0.7 except for D-line. There are some technical issues with D-line resulting that D-line is always underperformed. But based on this correlation table, choosing A-line as a standard is suitable for us because the strong correlations between A-line and other lines.

4.1 Model for Electricity Intensity

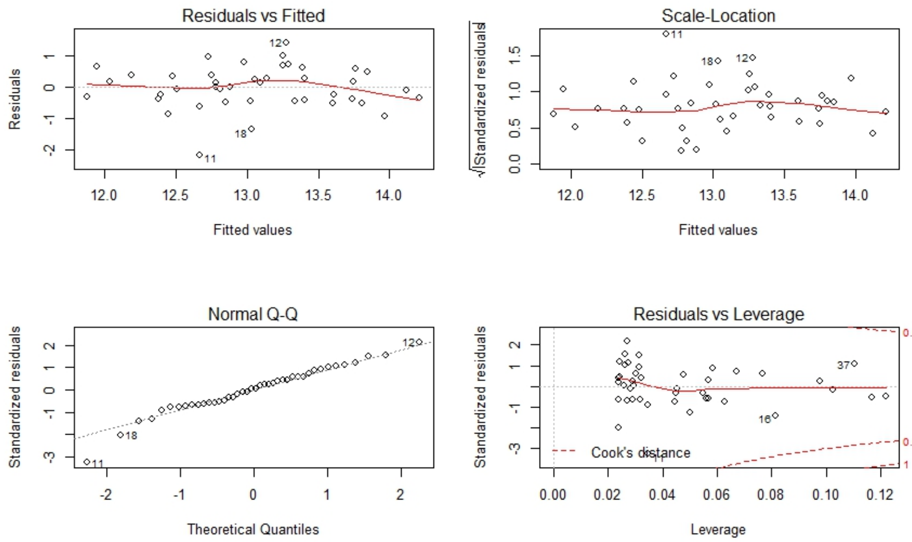
There are monthly A-line electricity intensity (kWh/DMT) and A-line mill TPOH data available back to January 2010. So in our first model, we use the A-line electricity intensity as the dependent variable (the one we want to predict) and A-line mill TPOH as the independent variable (the one we use to predict the dependent variable). First we can see how the plot looks like.

Figure 2. Electricity intensity vs mill throughput mill.



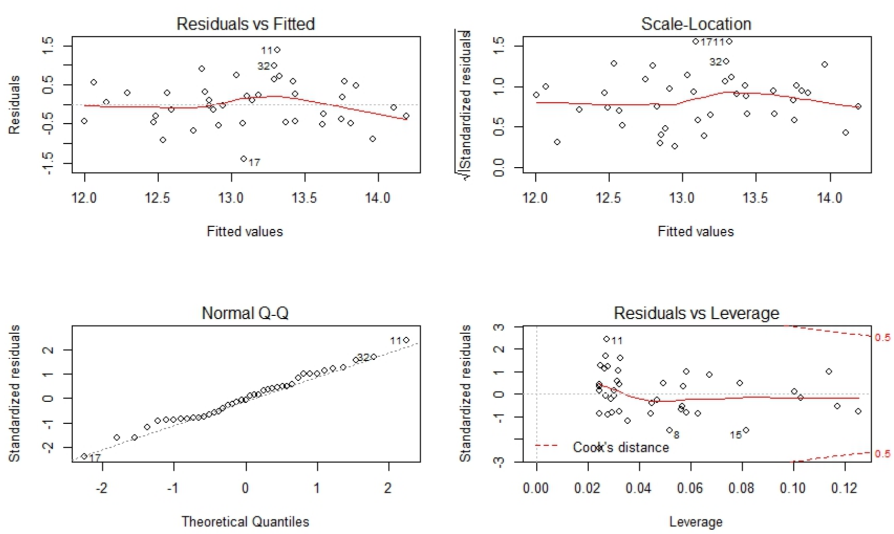
The red line is the fitted regression line. We can see that most of the data points (blue ones) are close to red line but there is only one far down that has electricity intensity smaller than 11 kWh/DMT. Let's see what the diagnosis plots look like.

Figure 3. Diagnosis plots



We use the diagnosis plots to identify the outliers. In the normal Q-Q plot, the number 11 data point is far away from the line. In the Scale-Location plot we can also see number 11 data point has the biggest standardized residual. This indicates it's an outlier. This is possibly caused by some mistake of recording the data. After delete this data point, the diagnosis plots become the following:

Figure 4. Diagnosis plots after deleting the outlier



There is no outlier anymore based on these new diagnosis plots. So finally let's see summary of the model after deleting the outlier. (We will only display the summary information for each of models in the rest of report.)

Table 1. Summary for electricity intensity model (Model 1)

```
Call:
lm(formula = ALineElectricityIntensity ~ ALineTPOH)

Residuals:
     Min       1Q   Median       3Q      Max
-1.39180 -0.44208 -0.03852  0.31987  1.38384

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 22.504432   1.551357  14.506  < 2e-16 ***
ALineTPOH   -0.008662   0.001430  -6.059 4.29e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5822 on 39 degrees of freedom
Multiple R-squared:  0.4849,   Adjusted R-squared:  0.4716
F-statistic: 36.71 on 1 and 39 DF,  p-value: 4.294e-07
```

The R-suqared represents the percentage of the variation of the dependent variable can be explained by this model. The R-squared is close to 0.5 here which indicates that it's a good model. The Pr(>|t|) is the P-value which is the probability that the corresponding independent variable is 0. So a small P-value means the independent variable is significant and this independent variable does have an impact on the dependent variable, and the threshold we use is 0.05. Here the P-value for AlineTPOH is much smaller than 0.05 which means the mill TPOH has a very significant effect on the electricity intensity. We can also see the estimated coefficient for AlineTPOH is negative. So when *the mill TPOH increases, the electricity intensity will decrease*. It confirms our expectation.

4.2 Linear Models for Mill Throughput Rate

Now we've found the strong relation between the electricity intensity and the mill TPOH in the mill. Next, we want to find the key input metrics that will affect the mill TPOH. So we will eventually link the electricity intensity to these key input metrics. In No. 48 SRK Consulting's International Newsletter, they mentioned the effect of feed size on mill throughput. In HVC, there is a camera system being tested which can be used to take the pictures of the ore and calculate the size automatically. But this system hasn't been fully configured and operational yet. So in our study, we can't utilize the feed size to build the model for throughput. African Mining (2012) investigated the effect of blasting on the mill. Valery et al. (2011) investigated the effect of different blasting design on the mill throughput. Ben Burger et al. (2006) use the hardness and powder factor as key input metrics to predict the mill TPOH.

Powder factor is the amount of explosives we use to blast per tonne of ore. It's measured in kg/DMT. Hardness is measured in the drill and it's recorded in Leica system. The original hardness is a standardized number from 0 to 100. But there is a polynomial formula used to transfer this original hardness to A-line equivalent TPOH before it gets recorded in Leica system. We call this number Mine TPOH and it represents the information of hardness. From this point on, the hardness will always refer to this Mine TPOH number and it's recorded when the ore get removed from the ground. In the second model, we still use monthly data. The average hardness value is a weighted average of the ore from different pits. We choose the mill TPOH as the dependent variable, average hardness and powder factor as the independent variables in model 2. The summary of the model is following:

Table 2. Summary for *monthly* mill throughput rate model (Model 2)

```
Call:
lm(formula = ALineTPOH ~ AverageHardness + PowderFactor, data = a)

Residuals:
     Min       1Q   Median       3Q      Max
-134.749  -42.974   -2.477   40.816  123.398

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)     1080.47775  224.81956   4.806 2.31e-05 ***
AverageHardness    0.03188    0.17016   0.187    0.852
PowderFactor    -113.23913  201.46890  -0.562    0.577
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

Residual standard error: 65.25 on 39 degrees of freedom
Multiple R-squared: 0.009705,  Adjusted R-squared: -0.04108
F-statistic: 0.1911 on 2 and 39 DF,  p-value: 0.8268
```

We can see both P-values are very big which indicate the independent variables are both not significant. It means these two key input metrics don't have significant effect on the mill TPOH. And the R-square is very small. The model is not fitted well. We found there are some problems with the powder factors we use in the second model. After the ore get blasted, it takes a couple of weeks before the ore get removed from the ground and goes into the mill. Since we are using monthly data here, a couple of weeks of time lag will have a great effect on the model we built. Also since the time lag varies for different ore, there is no way we can correct the time lag of the data. We found another problem with using powder factor. We will give more details in the following model.

After encountering this problem, we had a meeting with the blasting group. They suggested to use high energy blasting rate and trim and buffer rate. High energy blasting rate is the percentage of total ore blasted that is done with high energy blast design. Trim and buffer rate is the percentage of total ore blasted that is done with trim and buffer blast design. High energy blasting started at the end of 2012. The reason we use these two key input metrics instead of powder factor is that high energy blasting use more explosives to blast (higher powder factor), and it will result in smaller size of ore. Then it finally leads to less work to be done in the grinding and increase the mill throughput rate. Trim and buffer use lower powder factor to blast to protect the wall, so it will result in decreasing the mill throughput rate. These two variables have the same information as powder factor in some degree. Figure 5 shows the powder factor we use for different blasting designs.

Figure 5. Blasting table

Current Blast Designs vs. Blastability vs. Blast Goal

Increasing hardness ----->

<-----Increasing Energy

	Good	Medium	Poor
Wall Control (T&B)	0.17	0.2	0.24
Standard Production	0.29	0.33	0.37
High Energy Production	0.37	0.48	0.48*

The advantage of using these two key input metrics is that they are recorded when the ore get removed from the ground (the same time as the hardness gets recorded). The delay before these ore going through the mill will be less than 12 hours.

First we try to use the daily data to build the model. The daily mill TPOH we use here is calculated in “Optime data”. This mill TPOH is an indicator of the performance of 5 lines, and it also incorporates the information of extra tonnes of ore it can produce if there haven't been those holdback inefficiencies while the mill is running. These accidents will slow down the mill but the mill is still running. So these accidents can't be accounted in the availability. This calculated mill TPOH is a more accurate measure of the mill throughput rate. So in model 3, this daily calculated mill TPOH is the dependent variable and Mine TPOH (hardness), trim and buffer rate, high energy blasting rate are the independent variables. After deleting the outlier, we got the following result:

Table 3. Summary for *daily* mill throughput rate model (Model 3)

```
Call:
lm(formula = MillTPOH ~ TandB + HighEnergy + MineTPOH)

Residuals:
     Min       1Q   Median       3Q      Max
-188.491  -53.377   -8.412   47.506  211.211

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 566.48858   98.40682   5.757 3.35e-08 ***
TandB        63.76489   30.24816   2.108   0.0363 *
HighEnergy  138.91564   25.96162   5.351 2.48e-07 ***
MineTPOH      0.50917    0.08372   6.082 6.29e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 80.87 on 192 degrees of freedom
Multiple R-squared:  0.2518,	Adjusted R-squared:  0.2401
F-statistic: 21.54 on 3 and 192 DF,  p-value: 4.561e-12
```

We can see now the P-values are all smaller than 0.05, it means all 3 independent variables are significant. The estimated coefficient for Mine TPOH is positive like we expected. Because higher Mine TPOH means softer ore, and it will increase the Mill TPOH. The estimated coefficient for high energy blasting rate is also positive, which is the same as expected because of the reason stated before. The estimated coefficient for trim and buffer is positive. We expected it to be negative because it uses less explosives and it will reduce the mill throughput rate as we said before. After communicating with the geologist in HVC we find there actually can be some reasons why this is the case. The Lornex Fault is a fault line that runs parallel to the main wall being mined in the valley pit. This may have caused an increased grindability of the ore there blasted in trim and buffer design. This may cause the coefficient of trim and buffer to be positive. This is another reason why powder factor might not be a good independent variable here, it doesn't incorporate the extra information that trim and buffer rate has. We can also see the R square is 0.2518 which is much better than model 2.

There are a lot of data points lying out of the 10% error range (red lines). The time delay that is about 12 hours may have a big effect on the daily model. So one way to increase the performance of the model is to use the weekly data instead of the daily data. The 12 hours' time delay won't have a big effect on weekly model. We don't incorporate the data of August because of some tailing issues (the time of changing system). The summary of model 4 is following:

Table 4. Summary for *weekly* mill throughput rate model (Model 4)

```
Call:
lm(formula = MillTPOH ~ TandB + HighEnergy + MineTPOH, data = a)

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 *
HighEnergy  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
```

We can see the R square is now bigger than model 3. There is only one point lying out of 10% error range. This model is much easier for us to analyze outliers. There are a couple of data points not fitting well with big deviations from actual Mill TPOH to prediction produced by the model.

4.3 Polynomial Model for Mill Throughput Rate

Now we have confirmed that Mine TPOH, trim and buffer rate, high energy blasting rate are strongly related to the Mill TPOH and built a linear model for them. One way to improve the model is to introduce the polynomial terms (including interaction terms) into the model. After some importance tests of these 3 independent variables, high energy blasting rate and Mine TPOH turn out to be better ones. We add the polynomial and interaction terms of hardness and high energy blasting rate up to degree 5 as new independent variables in the model.

We use stepwise method to select the model based on the criterion of AIC. The following is the summary of the model after selection.

Table 5. Summary for polynomial mill throughput rate model (AIC-Model 5)

```
Call:
lm(formula = MillTPOH ~ HighEnergy + MineTPOH + HM + M2 + H3 +
    M3 + H4 + M4 + H5 + M5 + H1M2 + H2M1 + H2M2 + H1M3 + H3M1 +
    H1M4 + H2M3 + H3M2 + H4M1 + TandB, data = a)

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
HighEnergy  -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
```

We can see the R square is much better now. But there are still too many terms in the model, and it will usually perform badly outside the range of independent variables. When we use this model to fit the 2012 data where high energy blasting rate is 0, there are a lot of data points have much bigger prediction value than the actual one. One of the reasons is that there are several data points having a very bigger Mine TPOH in 2012 than in 2013. These data points are outside of the range of the independent variables we use to fit the model. And it results into these big deviations.

Next, we try a different criterion, BIC, which is similar to AIC. It will usually choose a model with fewer independent variables because it penalizes more when we include 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 we use AIC in this case.

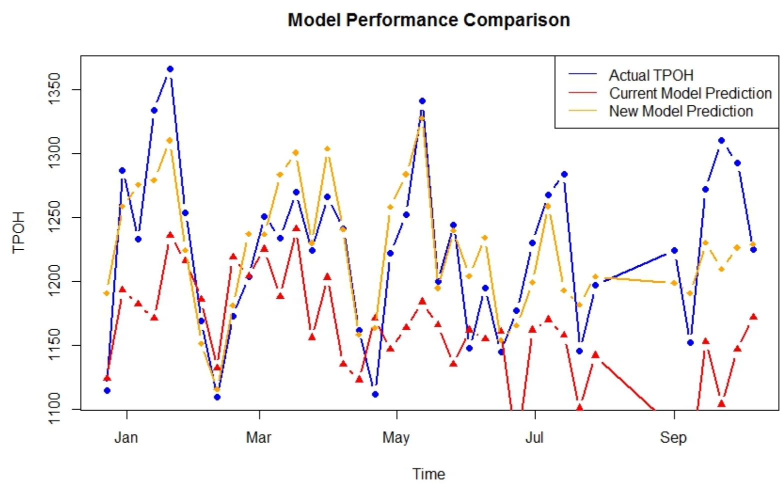
Then we turn to Cp criterion. This is another selection criterion, it usually tell us the appropriate number of independent variables to be included in the model. The following is the summary of the best model after selection:

Table 6. Summary for polynomial mill throughput rate model (Cp-Model 5)

```
Call:
lm(formula = MillTPOH ~ MineTPOH + HM + H2 + H4 + H5 + H1M2 +
    TandB)

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
```

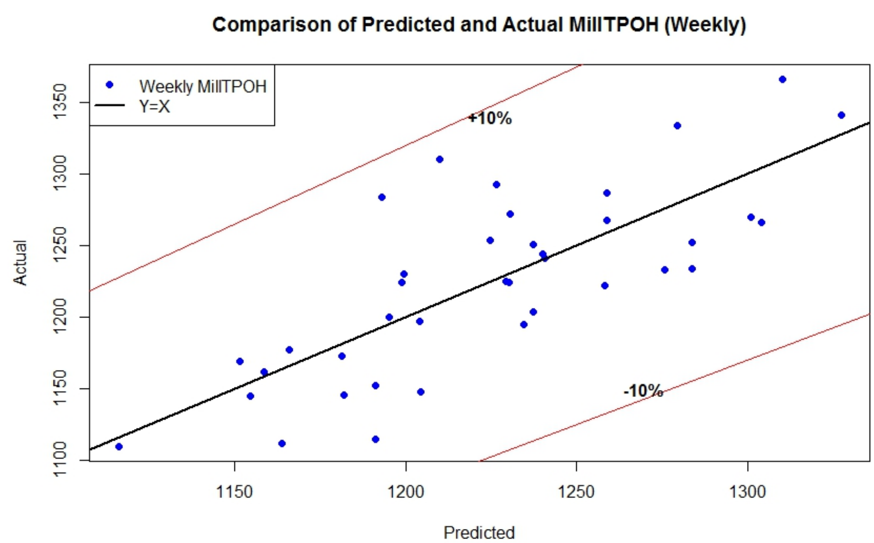
We can see the R square is smaller now but the adjusted R square doesn’t drop so much. The adjusted R square is another indicator that balances the number of independent variables and the fit of the model (R square). The following is the plot of comparison between the prediction currently used in HVC (Mine TPOH) and our new polynomial model prediction:

Figure 6. Current HVC Model vs New Model



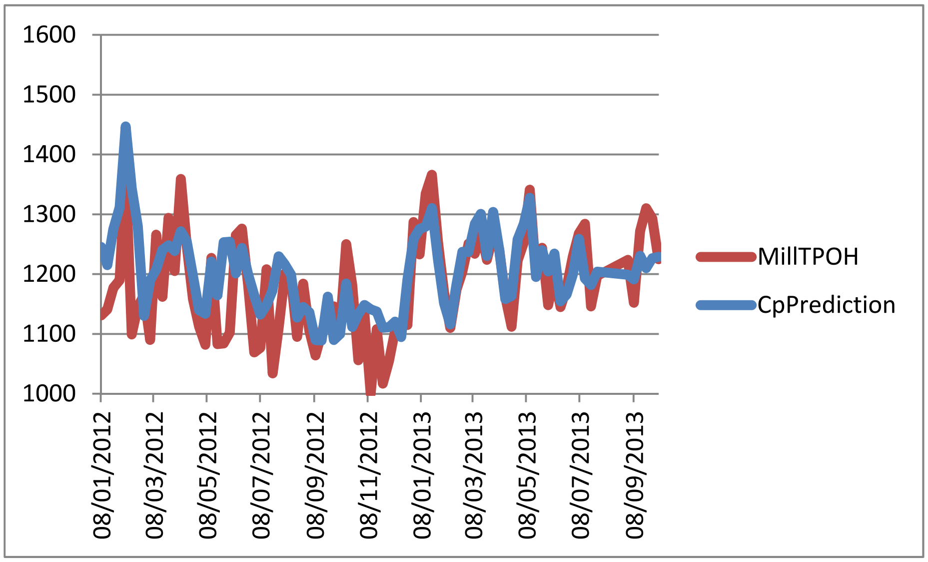
The old model only considers the hardness and then uses a polynomial formula to transfer it to Mine TPOH. We can see that it always underperforms the actual mill TPOH because the high energy blasting starting in 2013 is not considered. We incorporate the high energy blasting in our new model and the prediction is much better now.

Figure 7. New model performance



We can see the polynomial model is much better now. All the data points fall into the 10% error range. We can also apply this model to 2012 data.

Figure 8. New model prediction back to 2012



Cp prediction is the prediction of the new model. We can see it's not fitted as well in 2012 as in 2013. But the two plots are still somewhat close. Since we don't have the trim and buffer data in 2012, we set it to be 0. We will expect the plots to be closer if we have the trim and buffer data in 2012.

5 Major Findings and Future Investigation

Based on the models we've built, we can made the following observations:

- First model indicates that increasing Mill TPOH will significantly reduce the electricity intensity in the mill operation.
- From model 2, we can see that powder factor is not a good measure for mill performance.
- Based on model 3-5, trim and buffer, high energy blasting and hardness are confirmed to have a significant effect on Mill TPOH.
- Model 5 predicts the mill TPOH better than the model currently used in HVC which only considers the effect of hardness.

These findings from this project can further benefit the operations in HVC. We suggest the following future refinements and expansion of investigations.

- Understanding underlying reason for singular data points (outliers) in model 5 plot. After we find out the reasons and events for those points with big deviations, we can utilize potential opportunities to boost production by either avoiding those events that will cause underperformance of the mill or adopting those events that will increase the mill throughput.

- There is strategic planning in HVC which decides when and which part of the ore in the mine will be put into the mill with a blasting design. Then based on the information, and models 1 and 5 we built (also with budgeted mill availability), we could predict the electricity consumption in the future. AA rating in TSM requires the mining company to set the energy consumption target in the future, so this prediction we make for the electricity consumption will help HVC achieve this AA rating.

- When there is a future project coming in and it will affect the mill throughput rate, we can update the model. If there is a new variable introduced by this project (like high energy blasting rate), we update the model by adding this new variable and see how the model changes. Then comparing the old model and new model, we can assess how much mill throughput rate this project has raised and further the value of the project in raising the mill throughput rate. Based on the change in mill throughput rate, we can then assess how much electricity consumption has been saved by the project. AAA rating in TSM requires the company to set a reduction target of energy consumption in the future. When a new technology or procedure is introduced in the future, the models will help us to evaluate the reduction towards the target of electricity consumption.

- The new camera system and tracking system are being tested currently in HVC. One of the reasons we are incorporating blasting in our model is because the blasting will affect the size of the ore and we don’t have means to measure the size of the ore currently. The new camera system will enable us to measure the size of the ore and it can be a more direct and accurate variable for building the model for mill throughput rate. The tracking system will eliminate the time lag of the data and the model will be more accurate without time lag.

- The old strategic planning is based on the prediction of a model only considering hardness. As we mentioned, this prediction is not accurate anymore because of the high energy blasting project starting from the end of 2012. The new model obtained can replace the old one and get more accurate prediction of mill throughput rate. So we can update the strategic planning and make production and profit in HVC more stable and sustainable.

- We’ve talked about the effect of high energy blasting on mill throughput rate. We then can identify how much energy we have saved by this high energy blasting project. We can set the high energy blasting rate all to 0 during this period and get the predicted mill throughput, and further the electricity consumption. Then we compare this predicted electricity consumption by setting high energy blasting rate to 0 and the actual electricity consumption during this period to see the difference, and that’s the amount of electricity we’ve saved during this period by conducting the high energy blasting project.

- Include recovery process to the models in the future. The recovery will be affected by the mill throughput rate and type of ore going into the mill. Mill throughput rate and percentage of Bornite can be used to build a model for the recovery. Then we can predict the recovery rate in the future by combining this recovery model and the model we use to predict the mill throughput recovery (although use the information in strategic planning to decide the percentage of Bornite). The recovery model will also need to be improved because of the various operations by different groups. This can further help the groups achieve an optimal practice in flotation by incorporating the parameters they can change into the recovery model.

References

Afgan, N. H., Carvalho, M. G., & Hovanov, N. V. Energy system assessment with sustainability indicators. *Energy Policy* (2000), 603-612.

Analyses of diesel use for mine haul and transport operations. *Energy Efficiency Opportunities* (2010). Department of Resources, Energy and Tourism, Australia.

Blasting Process Improved. *African Mining* (2012), 47-50.

Braun, W. J., & Murdoch, D. J. *A First Course in Statistical Programming with R.* Cambridge University Press, 2007.

Burger, B., McCaffery, K., McGaffin, I., Jankovic, A., Valery, W. & La Rosa, D. Batu Hijau model for throughput forecast, mining and milling optimisation, and expansion studies. *Advances in Comminution*, edited by S. Komar Kawatra, SME publication. March, 2006, 461-479.

Ebrahimi, A. An attempt to standardize the estimation of dilution factor for open pit mining projects. *World Mining Congress*, *Montreal*, *Canada*, 2013.

Fiksel, J. *Toward a Sustainable Cement Industry Substudy 5: Key Performance Indicators.* World Business Council for Sustainable Development, 2002.

Geyer, C. J. *Model Selection in R.* unpublished manuscript, 2003

Gorp, J. C. Uing key performance indicators to manage energy costs. *Strategic planning for energy and the environment* (2005), 9-25.

Khandker, S. R., Koolwal, G. B., & Samad, H. A. *Using key performance indicators to manage energy costs.* World Bank Publications, 2010.

The downer energy and emissions measure. *Energy Efficiency Opportunities* (2011). Department of Resources, Energy and Tourism, Australia.

Valery, W., Jankovic, A., & Sonmez, B. New methodology to improve productivity of mining operations. Balkan Congress 2011.