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Implementing an Ore Reconciliation System Supported by Statistical Process Control

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Abstract

There are several stages within mine planning that utilize different block models to help predict future values. Ore reconciliation manages the variance observed between the forecasted values from these block models and actual production data. This paper primarily focuses on an ore reconciliation system that was developed for an open pit copper operation located in the Western United States. A monthly reconciliation approach has been setup in a stepwise format along the mine value chain. Mine call factors are calculated each month for each step within the operation's mining process to measure the variance between predicted values and production data. To monitor model performance, statistical process control (SPC) has been applied utilizing the mine call factors. Run charts have been implemented to help identify any early trends in the data. Control charts have been incorporated to separate the common cause variation (capability) from the special cause variation for each model. If the common cause variation of a model exceeds the operations error tolerance, then adjustments to the predictive model may be necessary. Primary recommendations for improving ore reconciliation and managing variance are provided based upon this study.

Introduction

Ore resource and reserve block models are intended to forecast tonnage, grade, and contained metal within a mineral deposit. Many models may be produced along the mine value chain, giving mine planning personnel the ability to plan accordingly at different stages throughout the mining process. Long range models, produced from exploration drill holes, serve as a basis in strategic mine planning to predict future cash flows; impacting overall mine design and profitability. Short range models and grade control models, typically produced from blast holes or grade control drilling, provide the basis for tactical mine planning. Having an accurate forecast of tonnage, grade, and contained metal produced is critical for planning out a mining operation. Reconciliation provides a way to monitor the variance for each model by comparing actual production data to forecasted values.

This paper provides some important background information on the primary principles within ore reconciliation. These principles are based on previous works by professionals that have extensive experience in resource estimation and the reconciliation process. One of the key focuses of this paper is the development and application of an ore reconciliation system that is monitored by statistical process control (SPC) for an open pit copper operation located within the Western United States. This ore reconciliation system has been developed to capture variance between forecasted values and actual production data at multiple stages along the mine value chain. Some basic ideas on statistical process control will be discussed and key recommendations for implementing an ore reconciliation system will be highlighted.

Literature Review and Background Information

Long Range Model

There are various stages within mine planning, and typically a different block model is utilized at each stage. Strategic planning and long range planning use the long range model to establish a sequence that will deliver the highest net present value (NPV) for an operation. The long range model used in this stage of planning is typically based on a resource estimate developed from widely spaced exploration drill holes. Because of inaccurate orebody knowledge at the time of resource estimation, the long range model is seldom true and contains errors (Parker, 2012).

Short Range Model

Tactical mine planning uses the short range model to develop detailed mine sequences to maximize production and extraction of the orebody. The short range model is developed from infill drill holes and blast holes (if available) and typically contains new information from bench, face, or stope mapping and often results in a better estimation of tonnage and grade than the forecasted values reported from the long range model.

Despite more data being used within the short range model, errors still occur. A common error is the inefficiency in the mining process to segregate ore and waste as planned by the ore control staff, resulting in higher dilution than anticipated by the short range model (Parker, 2012). Note that not all operations have a short range model and some utilize the long range model for tactical and short range planning.

Grade Control Model

The grade control model is typically used for day-to-day production planning. In many operations, the grade control model can be defined from the short range model as ore control polygons or cuts that delineate ore and waste boundaries. Internal dilution is estimated within the grade control model and mined grades should reflect the diluted ore cuts produced at this stage. The grade control model is typically the mineable portion of the short range model keeping the selective mining unit (SMU) in mind. In some surface operation the ore control polygons are surveyed out in the field defining dig boundaries.

Reconciliation Principles

Ore reconciliation primarily focuses on comparing actual production data to modeled estimates that have been used to forecast future production and cash flow values. The primary objective of a reconciliation program in a producing mine is to properly account for all ore and waste material mined (Rossi & Deutsch, 2013). Ore reconciliation can also be used to assess the accuracy of the long range, short range, and grade control models used in mine planning. Reconciliation of each model is critical for evaluating their effectiveness and may allow for optimization of the resource modeling process (Rossi & Camacho, 1999; Schofield, 2001; Parker, 2012).

Parker (2006 p. 4-1) suggests that forecasted values can be reconciled against actual values in several different ways or a combination of the following:

- By geographic area (bench, or ore zone);
- By time period (monthly, quarterly, yearly); and
- By process (short range to long range model, mill to mine production)

A combination of the above methods may provide the best fit for an operation.

Any reconciliation program is recommended to be based upon clear concise goals.

Reconciliation methods should be specifically adapted to handle the unique problems that occur at each operation. The procedures must be simple, effective, and the data should be reliable and include the full production stream from long range model through final product produced at the plant (Rossi & Deutsch, 2013; Parker, 2012).

Below is general information that should be captured to facilitate ore reconciliation:

- Obtaining mine advance positions through a reconciliation period survey (typically a monthly survey).
- Tonnage, grade, and metal from the long range model, short range model, and grade control model for the reconciliation period. Each model can be overlain by the mine advance survey capturing tonnage and grade produced for the period.
- Tonnage, grade, and metal produced from mining production for the reconciliation period. Grade from the grade control model is typically applied to a mining cut at the mining stage and may require some downgrading to account for mining dilution. Tonnage can be reported from bucket scales or truck weight. It is preferred to avoid truck factors because of inconsistencies (Rossi & Deutsch, 2013).

- Tonnage, grade, and metal produced informed as head grades and tons. Grades should be reported from direct sampling, as opposed to back-calculated from tailings grades and adjusted recoveries. Back calculated head tonnage and grades should not be used for model optimization (Rossi & Deutsch, 2013).

Within the mining industry it is a common practice to use the above information to produce factors, sometimes known as Mine Call Factors (MCF). These factors are used to evaluate the performance of the long range model, short range model, grade control model, and dilution and ore losses that occur from mining. These factors should be based off of a reasonable production period to smooth out day to day variation of waste and ore production (Rossi & Deutsch, 2013).

The factors defined below, and used within the case study highlighted in this paper are proposed by Rossi & Deutsch (2013) and are an expansion of the factors outlined by Parker (2012). The factors are defined as:

1. F_1 Factor - Measures tonnage, grade, and metal content reported from the long range model to values of tonnage, grade, and metal content reported from the short range model and is calculated as:

$$F_1 = \frac{\textit{Short range model}}{\textit{Long range model}}$$

2. F_2 Factor – Measures tonnage, grade, and metal content reported from the short range model to the tonnage, grade, and metal content reported from the grade control model and is calculated as:

$$F_2 = \frac{\textit{Grade control model}}{\textit{Short range model}}$$

3. F_3 Factor – Measures tonnage, grade, and metal content reported from the grade control model to tonnage, grade, and metal reported from mine production and is calculated as:

$$F_3 = \frac{\textit{Mine reported}}{\textit{Grade control model}}$$

4. F_4 Factor – Measures the tonnage, grade and metal content of the reported “received at mill” material versus tonnage, grade, and metal of the mine reported values. This factor directly measures ore dilution and loss from the mining and stockpiling process. The F_4 factor is calculated as:

$$F_4 = \frac{\textit{Received at mill}}{\textit{Mine reported}}$$

From these four factors, some performance measures can be obtained. To quantify the performance of the long range model to the ore delivered to the mill, the F_{LTM} factor can be used and is calculated as:

$$F_{LTM} = \frac{\textit{Received at mill}}{\textit{Long range model}} = F_1 \times F_2 \times F_3 \times F_4$$

Calculating the F_{LTM} factor measures how well the long range model forecasts material delivered to the mill, which is the basis of future cash flows from the operation (Rossi & Deutsch, 2013). Likewise, the short range model can be compared to the ore delivered to the mill by the F_{STM} Factor and is calculated as:

$$F_{STM} = \frac{\textit{Received at mill}}{\textit{Short range model}} = F_2 \times F_3 \times F_4$$

F_{STM} measures the benefits gained from infill drilling and any efforts placed in bench, face, and stope mapping to produce better geological models resulting in better estimates (Rossi & Deutsch, 2013).

Performance for the grade control model versus the material received at the mill is monitored by the F_{GCM} Factor and is calculated as:

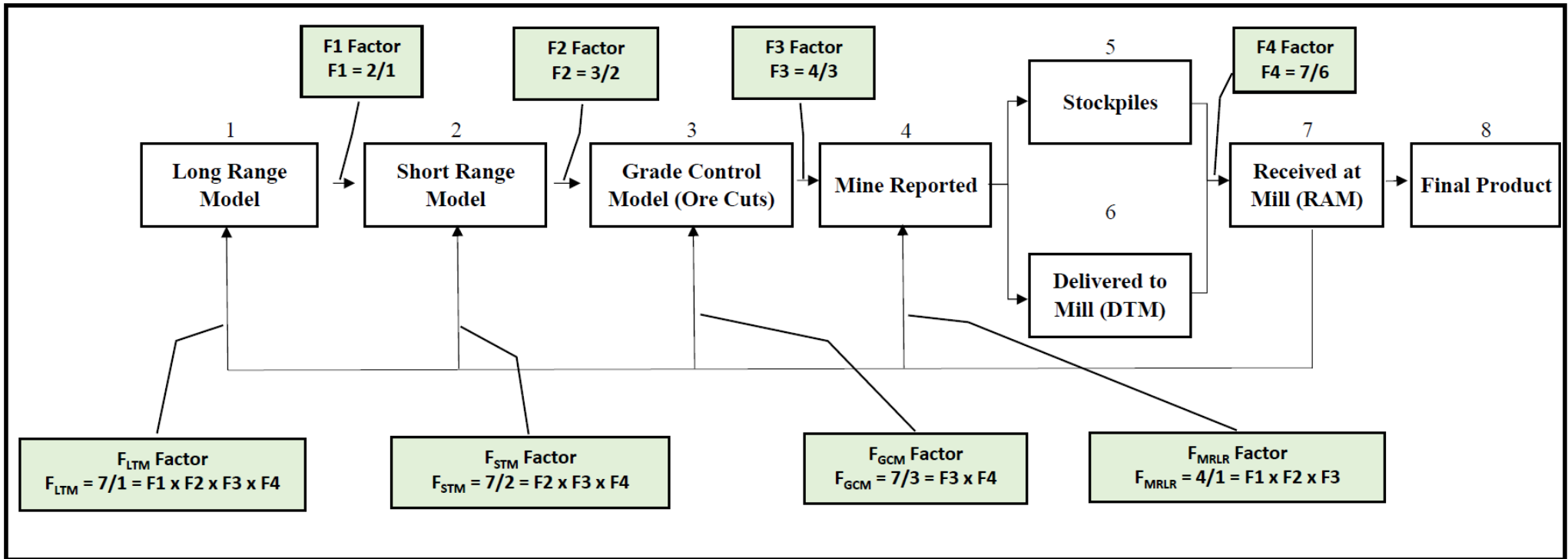
$$F_{GCM} = \frac{\textit{Received at mill}}{\textit{Grade control model}} = F_3 \times F_4$$

F_{GCM} measures the mining operation performance by evaluating any unplanned dilution and ore loss.

For the case study within this paper it is also relevant to analyze the performance of the mine reported values versus the long range model to understand how the predictive models are forecasting production in the mine. The comparison is calculated as:

$$F_{MRLR} = \frac{\textit{Mine reported}}{\textit{Long range model}} = F_1 \times F_2 \times F_3$$

Figure 1, below, is a visual representation showing the relationship of each factor along the mine value chain.



Monitoring reconciled data using Statistical Process Control (SPC)

Traditionally in mine reconciliation, the factors described above have been used to create a series of run charts (Figure 2) representing a line graph plotted over a period of time (Parker, 2006, pp. 4-3 - 4-5). Having a consistent MCF of one represents an unbiased forecast from the block model and in practice is unrealistic. Variation is likely to occur within the reconciliation system and ideally should vary around a factor of one.

The use of run charts provide an efficient tool that can be used in ore reconciliation to identify early trends in the data. However, run charts are limited in their ability to alert the analyst of process stability and need for adjustment.

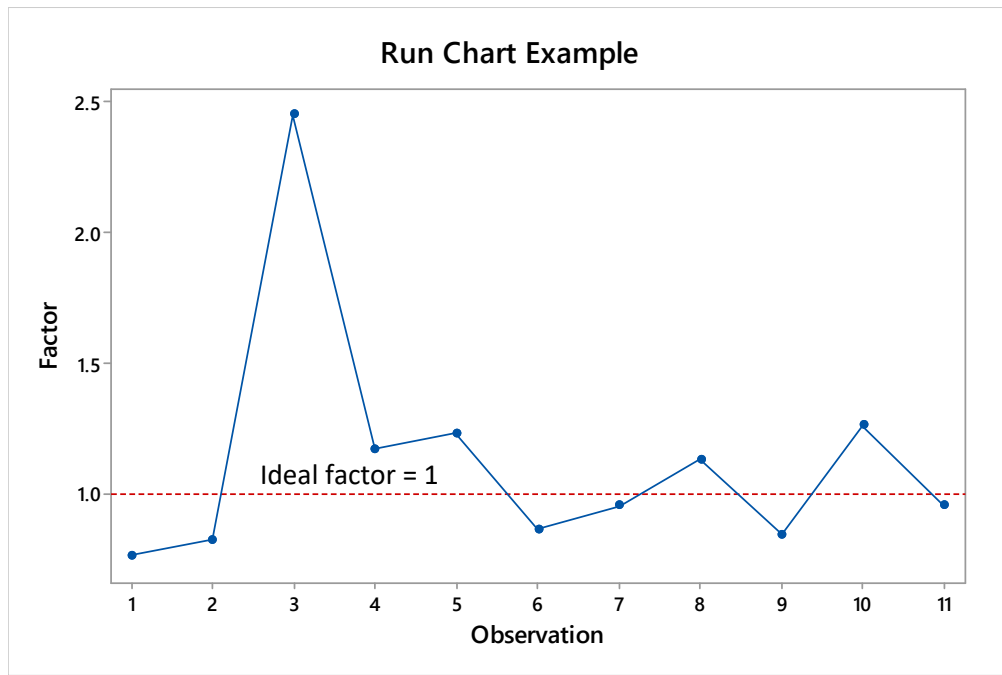


Figure 2: Example of a run chart utilizing the F1 mine call factor

To better analyze the capability of each predictive model, a set of control charts can be produced. These charts are similar to a run chart, but use the process mean and control limits to help identify if a system is stable. Control limits provide a mechanism for recognizing situations where assignable causes may be adversely affecting product quality (Devore, 2009). Control charts serve as the primary tool to filter out the probable noise within a system (common cause variation) from potential nonrandom variation (Wheeler, 2012).

Specifically, individual control charts are a type of control chart that is used for sampling intervals on relatively slow time scales where single observations are recorded (Rigdon, et al., 1994 & Montgomery, 2009 pp. 259). Data within reconciliation is typically captured as single observations from long term periods, making an individual control chart appropriate for

reconciliation purposes. This type of control chart utilizes a moving range value as a basis for estimating the process variability (Montgomery, 2009) and is defined as:

$$MR_i = |x_i - x_{i-1}| \quad (1)$$

Where MR_i is the moving range value derived from two successive observations, x_i and x_{i-1} .

The criteria for the Individual Control chart are defined as follows:

$$Upper\ Control\ Limit\ (UCL) = \bar{x} + 3 \times \frac{\overline{MR}}{d_2} \quad (2)$$

$$Center\ line = \bar{x} \quad (3)$$

$$Lower\ Control\ Limit\ (LCL) = \bar{x} - 3 \times \frac{\overline{MR}}{d_2} \quad (4)$$

Where \overline{MR} represents the mean of the moving range values and d_2 is the unbiasing constant. Because the observations of the moving range are always $n = 2$ for an individual chart the value for $d_2 = 1.128$ (Montgomery, 2009 & Rigdon et al., 1994). A value of 3 is used to calculate the control limits representing an estimate of three standard deviations away from the sample mean. If tighter control is needed for the operation this value may be modified to 2 or even 1 standard deviation.

Figure 3 represents an example of a control chart containing the control limits and the process mean (centerline) for the data. Figure 3 shows that there is one data point outside the upper control limit signifying that the system was not in statistical control at that time. This helps alert the analyst to investigate possible causes for the out of control point.

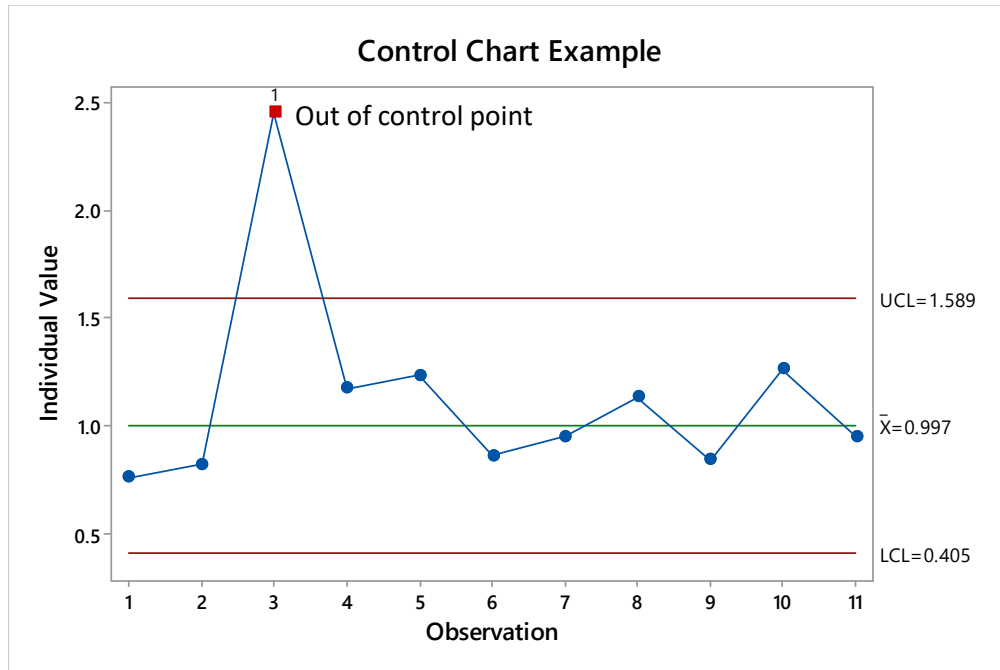


Figure 3: Example of a control chart utilizing the F1 mine call factor

Working out common cause variation will provide the analyst a way to discover each model's predictive capability. This may be achieved by comparing actual values to forecasted values; utilizing the MCFs. Figure 4, below, is an example showing the common cause variation, illustrated as dashed red lines, using the MCFs. Here, the common cause variation is consistently below one signifying an overestimation of actual values. Fluctuations of common cause variation range from 0.68 -0.96 (overestimating by 104% - 132%) and indicates the models capability of predicting future values.

Using this technique provides a powerful tool that can be used to assist with a decision to re-estimate a block model. If the model is not capable of predicting within the expected error tolerance a re-estimate for the model may be necessary.

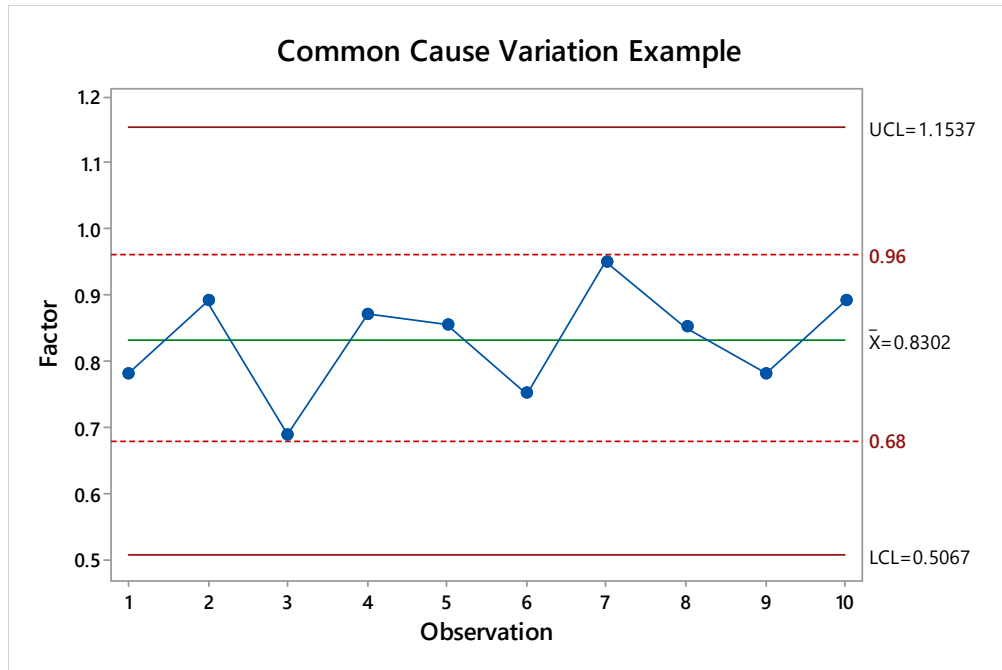


Figure 4: Control chart showing common cause variation of a predictive model

Several reconciliation periods may be needed to work out the common cause variation and gain a good estimation of the control limits. A minimum number of samples to use is dependent on the type of variation seen within the reconciliation system and will be specific to each operation. Typically for individual control charts, control limits may be setup after 5 reconciliation periods (i.e. observations gathered after a monthly reconciliation period) (McNeese, 2011). Locking in the control limits can be done once there is an understanding of the reconciliation systems common cause variation.

Case Study: Ore Reconciliation

A reconciliation system was built for an open pit copper operation located in the Western United States. This operation is in the initial stages of production and current data used in this analysis ranges from the long range model through the mine reported values. Processing plant data for this analysis is currently being gathered and due to poor sample quality in the initial stages of production, plant data was excluded from the study. The reconciliation system is modeled after (Rossi & Deutsch, 2013 & Parker, 2006) and follows the flow sheet illustrated in Figure 1.

Mine planning at the operation uses a long range model built from widely spaced exploration holes, a short range model that is created from blast hole data, and a grade control model derived by mineable ore cuts planned from the short range model. Tonnage and grade is reported from each grade control cut and for this purpose, the mine reported values are compared to the grade control cuts (F_3 Factor). Within the reconciliation system the grade control cuts are known as the grade control model.

Tonnage for the mine production is measured by a calibrated bucket scale on the loading unit and reported daily. Mined material is assigned the grade that has been stated within the grade control model.

An aerial survey is performed at the beginning of each month capturing the monthly mining advances. Digital terrain models (DTM's) are produced from the survey and can be combined with the previous month's DTM to create a solid representing total volume mined for the month. Overall tonnage and grade above cutoff can be reported using the monthly solid to constrain each block model.

Grades at the processing plant are collected as pulp samples from the fresh mill feed at regular intervals. Tonnage is captured from belt scales on the crushing unit and reported on a daily basis. Both concentrate and copper cathode is produced within the processing plant. Tonnage is reported on a daily basis for the copper cathode and concentrate is weighed and assayed to estimate pounds of copper.

All data is stored within a series of spreadsheets using Microsoft Excel that have been coded to produce reports. Figure 5 is a series of control charts that represent the F_1 factor for short tons, copper percent (Cu %), and copper pounds that were produced for the first six months of production. The UCL and LCL have been calculated using equations 1- 4, above. The reference line for the ideal factor of one has been included and is depicted in Figure 5 as a dashed red line.

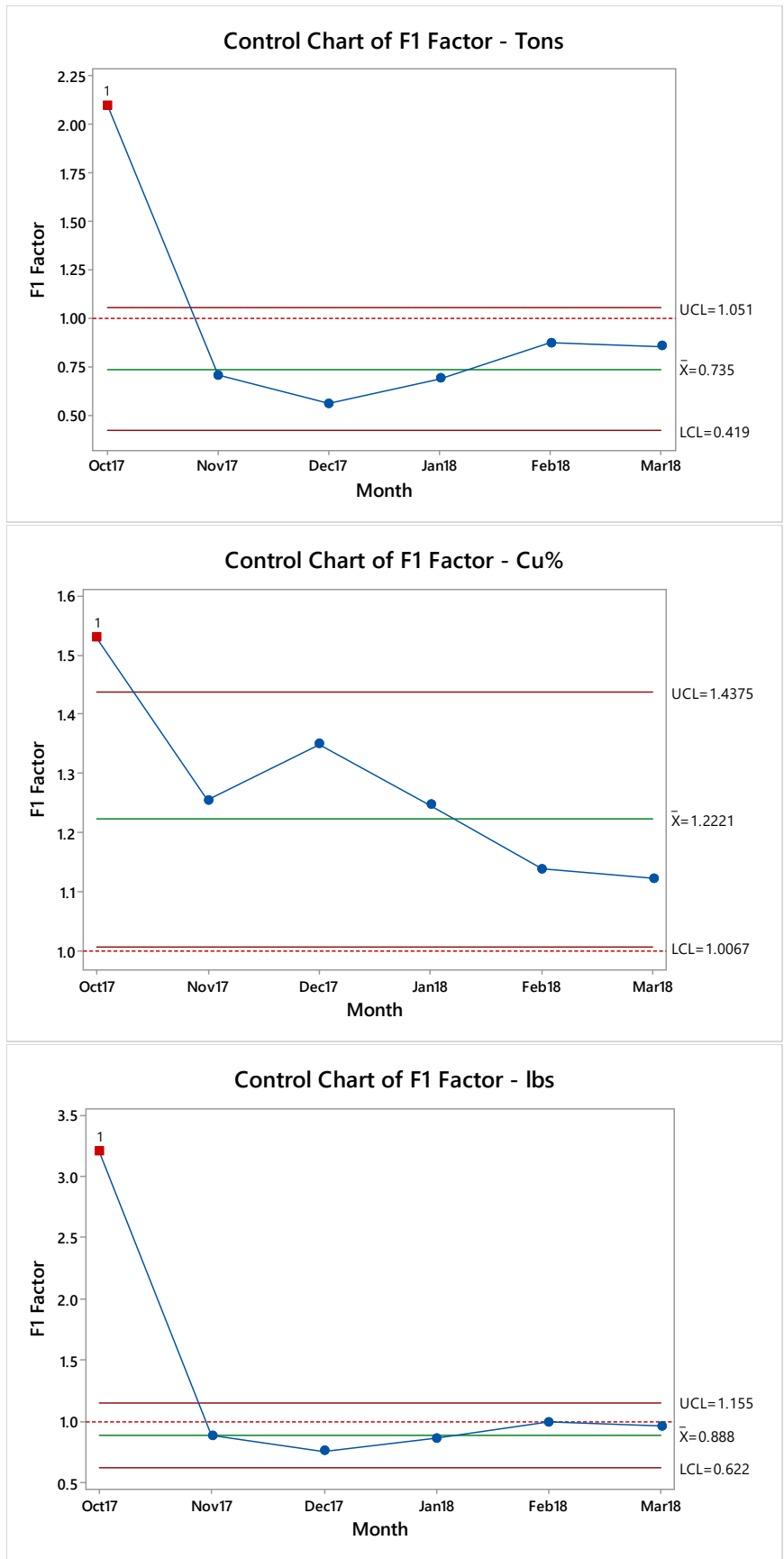


Figure 5: F1 factor control charts analyzing short tons, Cu %, and pounds of copper

From Figure 5, it can be concluded that over the six-month period the long range model has over predicted tonnage and under predicted grade. The over prediction of tonnage has resulted in an overestimation of copper pounds between the long range model and short range model, Table 1, below. All other control charts produced using the MCFs can be viewed in Figures A1 – A3 in Appendix A.

It is also important to interpret if the system was in statistical control at each time period so corrective action may be taken. From Figure 5, there is one out of control point within each chart. This occurred in the initial stages of production and at the top of the ore zone where drill holes were not concentrated. After inspecting Table 1, tonnage and copper pounds were insignificant in the month of October 2017 and no corrective action was taken. The reasons for the out of control point were identified and this point was omitted when calculating the centerline and control limits for each control chart listed in Figure 1 and each control chart within Figures A1 – A3 in Appendix A. Table B1 in Appendix B contains all reported short tons, Cu %, and copper pounds for each model and mine reported values.

The factors for copper pounds and tonnage are trending upwards as shown in Figure 5, signifying that the system may need a few more periods to completely stabilize. Locking in the UCL and LCL at this stage may not be optimum as the system is still working out common cause variation.

Table 1: Long range model versus Short range model (all tonnage reported is in short tons)

Month	Long Range Short Tons	Long Range Cu %	Long Range Cu lbs.	Short Range Short Tons	Short Range Cu%	Short Range Cu lbs.
Oct-2017	1,157	1.11	25,580	2,425	1.69	82,030
Nov-2017	36,009	0.95	681,409	25,371	1.19	602,189
Dec-2017	30,923	1.06	657,794	17,232	1.44	494,802
Jan-2018	60,183	0.95	1,148,412	42,175	1.19	1,007,082
Feb-2018	64,431	1.23	1,579,266	55,670	1.40	1,557,280
Mar-2018	69,497	1.30	1,810,420	59,384	1.46	1,734,881
Total	265,195	1.12	5,954,485	203,899	1.35	5,505,616

Comparing factors from each step within the reconciliation process is a good way to gauge how well each predictive model is forecasting. Figure 6, below, shows a run chart for the F_1 , F_2 , F_3 , and F_{MRLR} factors for the first six months of the reconciliation process. Disregarding the first month, these factors are all following the same trend for each reconciliation period showing no special causes that need to be looked into.

Analyzing the F_2 factor shows that the short range model is predicting tonnage well (varying around a factor of 1), but is overestimating grade. The ore control staff has taken the information from the short range model and has delineated ore and waste boundaries as mineable polygons. These polygons incorporate waste blocks that cannot be segregated by the loading unit resulting in higher mining dilution than anticipated in the short range model. An SMU study for the short

range model may be needed to lower the variance in grade between the short range model and grade control model

The F_{MRLR} factor shows that the long range model is over predicting short tons, under predicting grade, and is under predicting copper pounds through the mining process. However, a decision to re-estimate the block model has not been made because the F_{MRLR} factor is showing an upward trend. A table showing all the F_1 , F_2 , F_3 , and F_{MRLR} MCFs can be viewed in Table B2 in Appendix B.

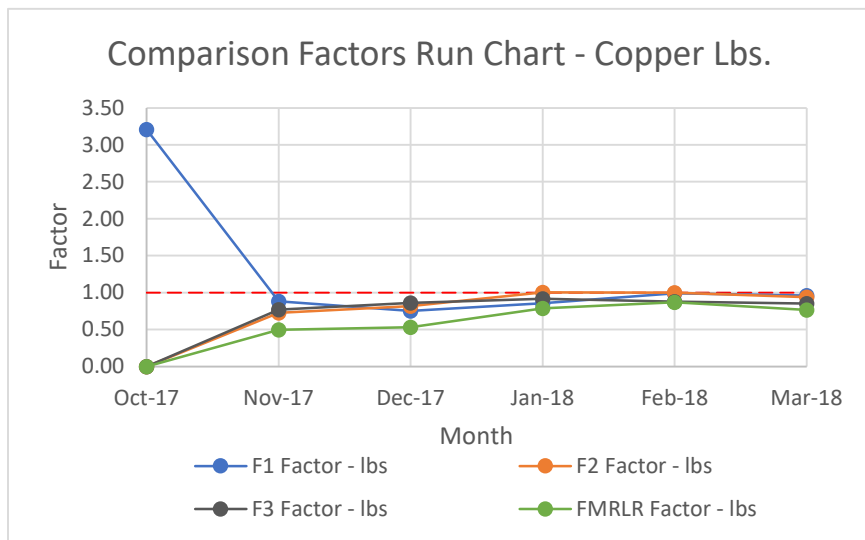
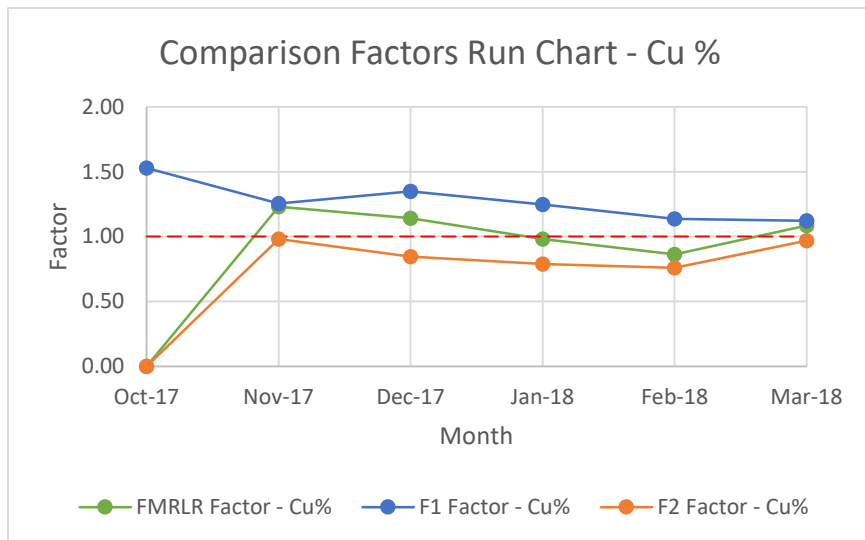
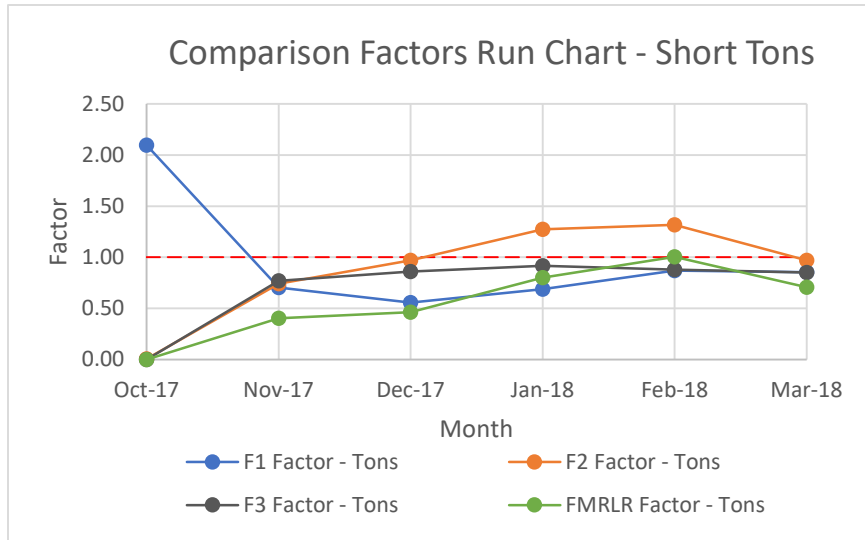


Figure 6: Graphical comparison of factors for mine production

Discussion and Recommendations

Reconciliation should be an integrated process across the operation. Geologists contain crucial information on predictive models, mining engineers create mine plans and designs based upon the predictive models, and mineral processing engineers organize the extraction of metals and non-metals from the ore. Each area has a unique piece of information that is a crucial part of the reconciliation process.

It is recommended that a reconciliation system is developed in a stepwise manner allowing each area along the mine value chain to be monitored enabling problems to be identified. For example, if the F_1 , F_2 , and F_3 factors are reconciling well, but the F_4 factor is not, there may be a problem tracking material at the processing plant. Each step can be analyzed to identify these types of problems keeping variation under control.

It is recommended that reconciliation be performed on at least a monthly basis so that early trends may be identified and corrective action can be taken (Parker, 2012). Reviewing the reconciled data on a quarterly basis will allow trends to become apparent.

Factors are suggested to monitor variance at each stage of the mine value chain as presented by Rossi & Deutsch (2013) and Parker (2012). Factors should be used as a tool to tell how well a model has predicted future values and caution should be taken when applying the MCFs to adjust a model. Factors represent global values and do not take into account spatial variation, therefore using past results may not be viable for adjusting models to predict future values. It is suggested by Rossi & Deutsch (2013) that factors should be used to calibrate a model, and not be used as correction factors. If a model is not reconciling well, go back to the estimation and use the reconciliation data along with any geostatistical tools to help with resource estimation.

A series of run charts is recommended to be used in the beginning stages of reconciliation. These charts should be setup at each step in the reconciliation process (i.e. long range model vs short range model and short range model vs grade control model) and utilize the respective MCFs. Run charts used in the initial stages will provide a way to monitor the variability and trends in the data. After five data points, run charts may be converted to control charts by applying the process average (centerline) and the UCL and LCL in the monitoring system (McNeese, 2011). Control charts should be used to determine each model's predictive capability. Locking in the UCL and LCL can be achieved once the common cause variation has been worked out.

The system should be monitored on a period-by-period basis for out of control points. When an out of control point occurs, first investigate the source of the out of control point. Then omit the out of control point from the calculations involving the centerline, UCL and LCL. Not omitting the out of control point can cause an overinflation of the control limits resulting in a lower sensitivity to capture special cause cases.

Certain things need to be evaluated in order to determine if a re-estimate of the block model is necessary. This evaluation should include reconciled data based on a series of trends over a period of time not on single data points alone. Gaining an understanding of SPC for the reconciliation process to determine the common cause variation of each model is necessary. This will help answer the question; how well can the models predict if everything were working

properly? The common cause variation for each model may be wider than what was expected and the error tolerance for the operation may be lower than the model can predict. If so, an adjustment to the model may be necessary. Gaining an understanding of a model's capability takes time and should be worked out for multiple reconciliation periods.

Note that when a re-estimation of a block model occurs each control chart should be updated. This will require the moving range, centerline, UCL, and LCL to be recalculated based on the information forecasted from the new block model and actual production data.

These are a few primary recommendations to help develop an efficient reconciliation process. In reality, every operation is unique and the reconciliation system should be developed to fit its needs. Variation at each stage through the mine value chain should be expected, and can be managed with proper reconciliation procedures.

Future Work

Properly implementing a reconciliation system requires quality control at every stage. Mill processing data in this paper was excluded from the analysis because of poor sample quality delaying the study of a full long range model through mill reconciliation system. A proper sampling method at the processing plant is now in place and reliable data is being recorded. Future work for the project will include this data providing a full mine-through-mill reconciliation solution.

Conclusion

Reconciliation methods used throughout this analysis provide a guide on how to implement an appropriate reconciliation system that is monitored by SPC. Mine call factors provide a useful measurement to analyze how each predictive model is forecasting future values. Plotting mine call factors on a series of run charts and control charts will help to identify trends in the data and determine a model's predictive capability. These principles fall within the lines of others who have performed extensive work in reconciliation. Every operation is unique and minor adjustments to the principles outlined here and in Parker (2012) and Rossi and Deutsch (2013) will enable a scientific approach for ore reconciliation to be developed.

Acknowledgements

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Appendix A: Control charts produced for mine call factors

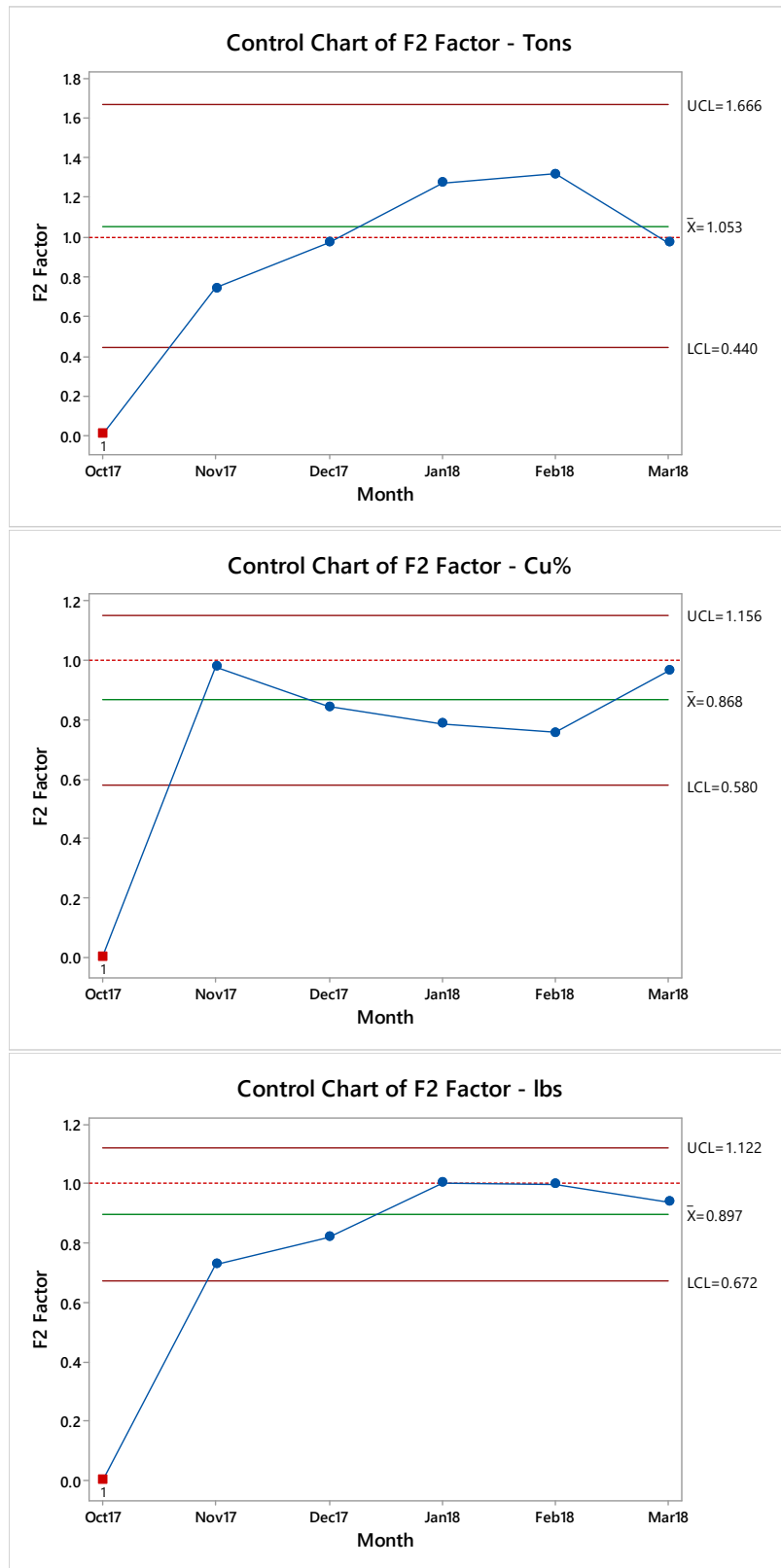


Figure A1: F2 factor control charts analyzing short tons, Cu %, and pounds of copper

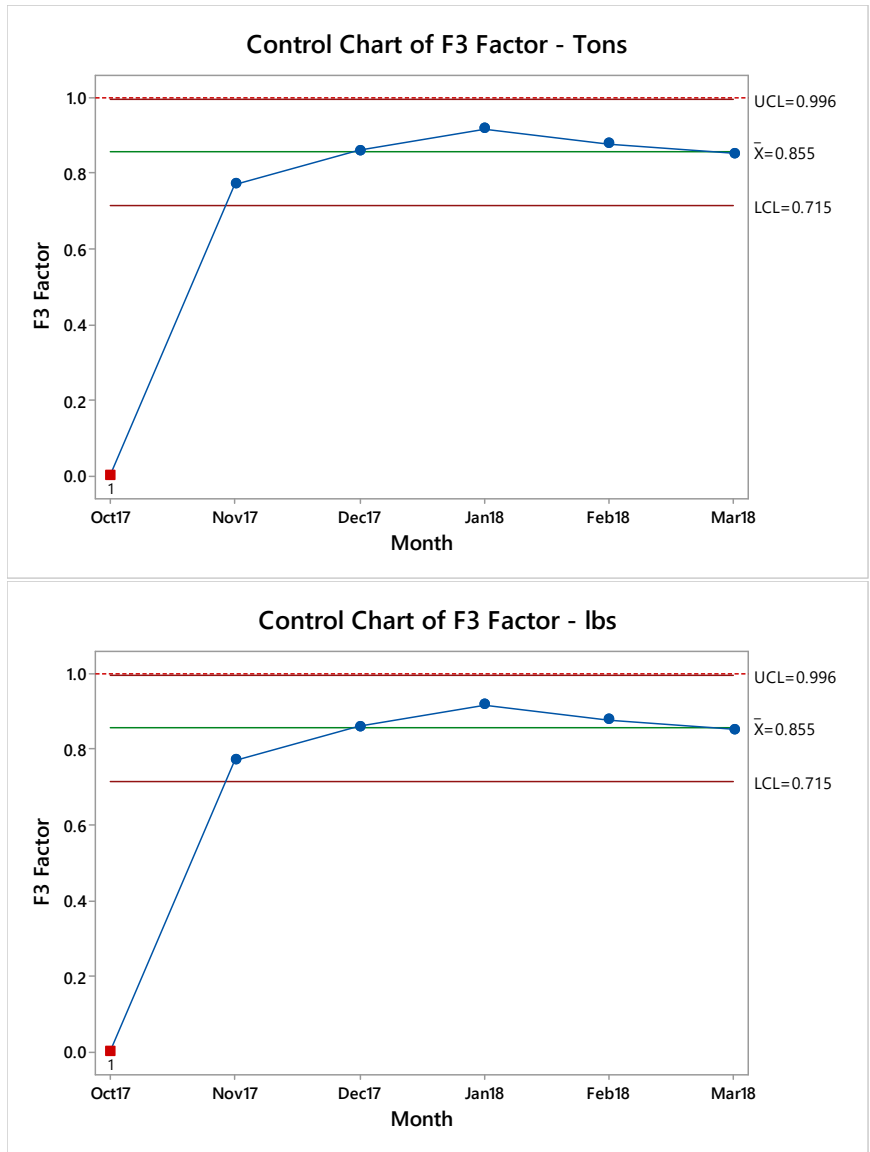


Figure A2: F3 factor control charts analyzing short tons and pounds of copper. Note that the factor of Cu% is 1 within the F3 Factor

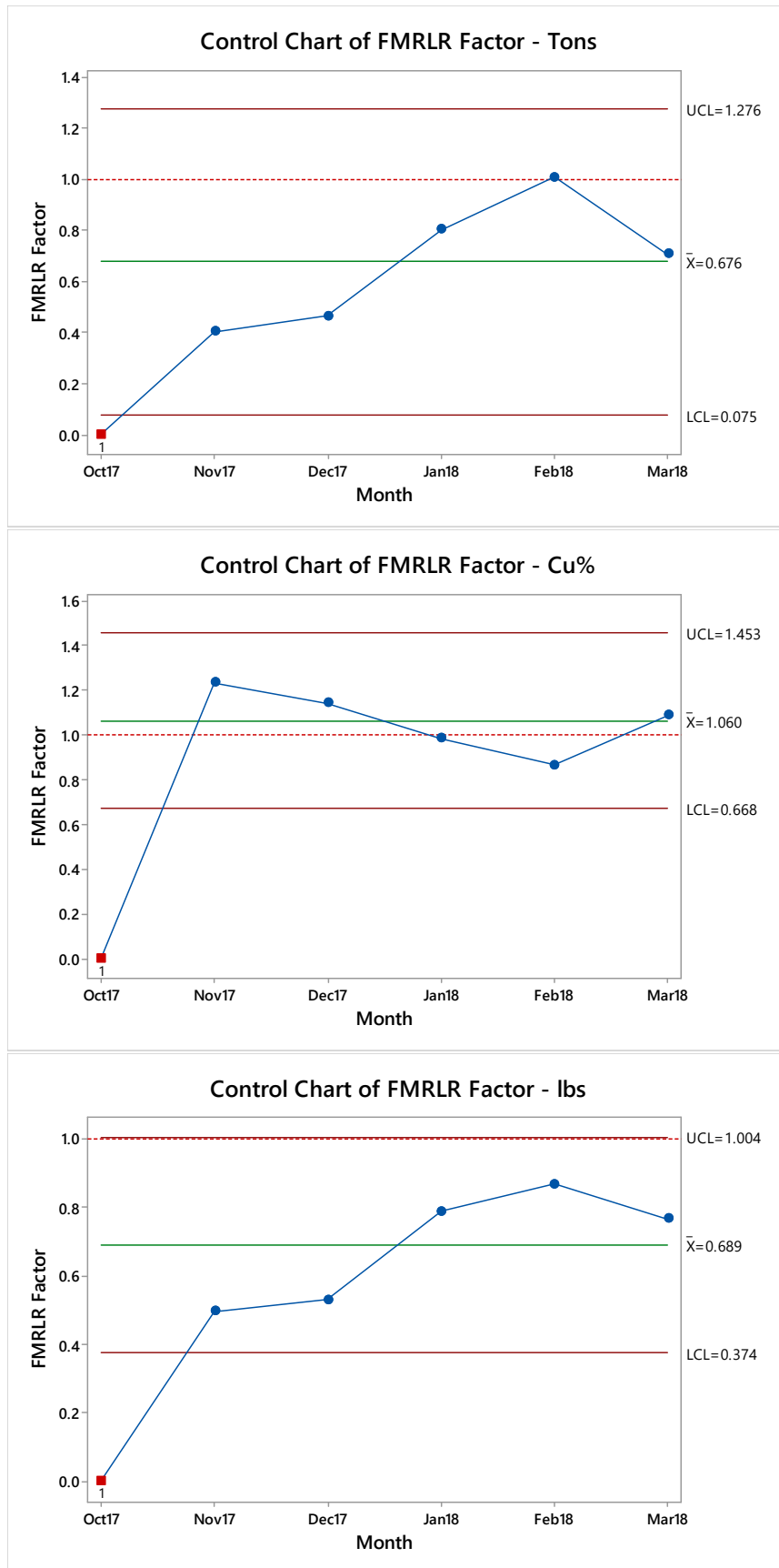


Figure A3: FMRLR factor control charts analyzing short tons, Cu %, and pounds of copper

Appendix B: Reported values for each model and mine reported value

Table B1: reported values by month for the long range model, short range model, grade control model, and mine reported values

Month	Long Range Ore Tons	Long Range Cu %	Long Range Cu lbs.	Short Range Ore Tons	Short range Cu %	Short Range Cu lbs.	Grade Control Ore Tons	Grade Control Cu %	Grade Control Cu lbs.	Mine Reported Ore Tons	Mine reported Cu lbs.
Oct-2017	1,157	1.11	25,580	2,425	1.69	82,030	12	0.00	0	0	0
Nov-2017	36,009	0.95	681,409	25,371	1.19	602,189	18,810	1.16	438,023	14,474	337,063
Dec-2017	30,923	1.06	657,794	17,232	1.44	494,802	16,691	1.21	405,168	14,349	348,325
Jan-2018	63,084	0.95	1,198,907	43,364	1.18	1,027,543	55,161	0.93	1,029,324	50,547	943,233
Feb-2018	64,525	1.22	1,580,375	56,123	1.39	1,564,170	73,870	1.06	1,560,962	64,848	1,370,321
Mar-2018	69,497	1.30	1,810,420	59,384	1.46	1,734,881	57,548	1.41	1,627,331	49,026	1,386,339
Total	265,195	1.12	5,954,485	203,899	1.35	5,505,616	222,092	1.14	5,060,808	193,245	4,385,281

Table B2: Comparison of factors from long range model through mine reported

Month	F1 Factor = Short Range Model/Long Range Model			F2 Factor = Grade Control Model/Short Range Model			F3 Factor = Mine Reported/Grade Control Model			F _{MRLR} = Mine Reported/Long Range Model		
	Short Tons	Cu%	Cu lbs.	Short Tons	Cu%	Cu lbs.	Short Tons	Cu%	Cu lbs.	Short Tons	Cu%	Cu lbs.
Oct-2017	2.10	1.53	3.21	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
Nov-2017	0.70	1.25	0.88	0.74	0.98	0.73	0.77	1.00	0.77	0.40	1.23	0.49
Dec-2017	0.56	1.35	0.75	0.97	0.85	0.82	0.86	1.00	0.86	0.46	1.14	0.53
Jan-2018	0.69	1.25	0.86	1.27	0.79	1.00	0.92	1.00	0.92	0.80	1.98	0.79
Feb-2018	0.87	1.14	0.99	1.32	0.76	1.00	0.88	1.00	0.88	1.01	0.86	0.87
Mar-2018	0.85	1.12	0.96	0.97	0.97	0.94	0.85	1.00	0.85	0.71	1.09	0.77