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The use of performance monitoring techniques in detecting process shifts and potential root causes in a variable speed grinding application

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This paper addresses the impact of the variable speed drive on the particle size distribution in the product of a fully autogenous UG2 grinding circuit. It further discusses the impact of a varying particle size distribution in the product of the mill on the downstream classification and milling circuits. An industrial case study was used and data is presented to illustrate the techniques applied to identify the root cause of the shift in operational efficiency.

The results achieved from both the investigation into the shift in plant efficiency and the subsequent corrective action taken illustrate that the root-cause methodology used in advance control can be effectively applied on production sites to both detect the shift and identify probable root-causes. The industrial example used confirms that the variable speed drive in a UG2 autogenous milling operation is a critical control parameter to ensure that the plant operates to design specifications.

Introduction

Advance control solutions and design methodologies have proven effective not only in the control of a process but also in the monitoring of its performance. The techniques deployed in the advance control solutions are fast becoming the bases on which 'smart-alarming' and 'root-cause-analysis' systems are configured. These systems are assisting companies in monitoring the on-line performance of operations, detecting early shifts in the process and guiding engineers to identify probable root causes.

Advance control systems form an integral part of the process control solutions deployed on Anglo Platinum operations. The maturity of the systems has allowed the company to explore a wider use of control and data analysis techniques and is forming the basis of current performance analysis approaches. The control techniques are combined with multi-variate data analysis techniques to assist engineers in making sense of the modern maze of data. The process control methodologies have proven very successful in structuring the data analysis techniques and are able to handle very large sets of data within complex process flows. The techniques enhance the engineer's ability to apply his technical understanding of the process system to the measured performance variables (Groenewald J.W, *et al.*[1]).

A case study in the use of these analysis techniques was used to identify the effect of the variable speed drive in a fully autogenous mill on the performance of the downstream processes.

Performance analysis case study

Process flow description

The case study focused on a traditional MF2 (two stage milling and flotation) circuit in the platinum industry for treating UG2 ore. The run of mine plant feed is divided into coarse (+80 mm) and fine fraction (-80 mm) feeds which are fed to the primary mill in a controlled ratio. The primary milling area consists of a fully autogenous variable speed mill in closed circuit with a screen classifier. A cyclone classifier separates the primary mill product stream into chrome-rich and silica-rich streams, which are reground and re-floated separately.

Analysis methodology

The monitoring of mineral processing plants through the use of statistical analysis techniques is becoming increasingly widespread. Process plants are typically too complex to model from first principles alone, these are often complemented by the use of statistical models based on historical process data. Multivariate methods such as principal component analysis are indispensable to these analysis.

The industrial case study of these analysis techniques applied to a platinum concentrator was triggered by a noticeable deterioration in the overall process recovery. No consistent relationship which could guide the engineer along a particular process stream was noticeable between the two composite final tail streams (silica–rich and chrome–rich) and the final tail measurement. No singular dominant relationship between the defined process KPIs and the final composite losses was apparent either making singular time-based analysis very difficult. A multivariate data analysis approach was therefore required to assist the operational engineers in isolating the probable root causes.

As a general methodology, the process data are grouped into logical functional blocks. The variables associated with the blocks are determined by both the fundamental processes in the flow, such as flotation, classification, and milling, as well as events that have similar time steps. In practice this means that the plant data are grouped around process units, allowing one to customize the analysis technique to suit the fundamental drivers of particular process units. It also simplifies the impact of lead and lag indicators, since the data are grouped along similar processing times. The grouped data blocks therefore ultimately contain high (process) and low (assay) frequency data as well as metadata and information describing recorded events such as maintenance activities.

The so-called functional tree (Figure 1, Figure 2 and Figure 9) of the process links the data blocks together in a process map that represents the flow diagram. Clear objective functions are assigned to each process unit that contributes to the overall processing objectives. This methodology serves as a very powerful tool to break down the large data set into logical data groupings that capture the process performance measurements per unit operation. Each indicated block specifies the objective function of the process unit and details the related statistical techniques required to describe the unit's performance. The various process variables required to populate the analysis are pre-tagged to the software and validated for gross measurement errors. The various units comprising the functional tree are programmed into a template for easy deployment during a performance analysis exercise.

The functional tree diagram in Figure 1 can be expanded along each leg, following the flow diagram of the process, until the classification cyclone unit depicted in Figure 2, where the separation of the chrome and silica-rich streams occurs, is reached

The multivariate data analysis techniques that were used to evaluate the drivers of each process unit can be grouped into singular and multivariable types of analysis. Statistical methods were used for the analysis, monitoring and diagnosis of process operating performance over time. The statistical methods can also be used to verify whether or not a process is within a 'state of statistical control', while still allowing 'common-cause' variation (which affects the process all the time, and is essentially unavoidable within the current process).

The singular variable analysis attempts to extract features from the variable through-time series and lag plot analysis. The multi variable analysis techniques are used to determine correlations both within and between variables. Those used in the case study include singular spectrum and canonical variate analysis (Gardner S, *et al.*[2]).

Visualization of the results is fundamental in communicating the findings of the reference period for the principal component analysis plots and process

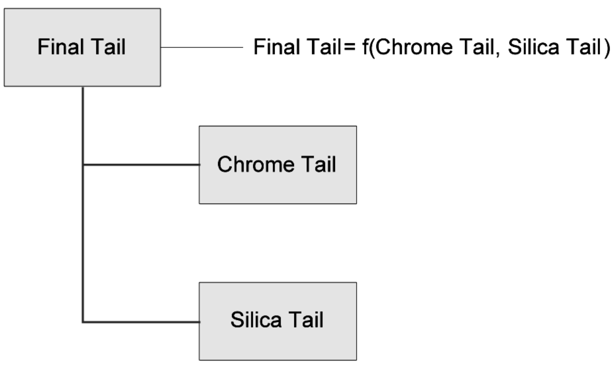

Figure 1. Functional tree describing final composite losses

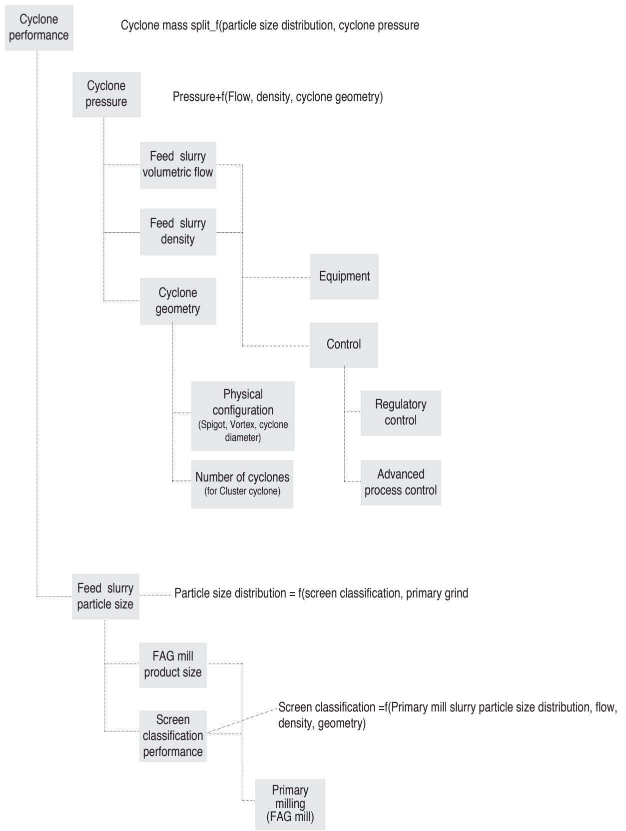

Figure 2. Functional tree expanded along the chrome classification process

performance graphs. 2-Dimensional histogram plots, density plots (Figure 8) and bi-plots (Figure 4, Figure 6, Figure 7 and Figure 11) were found to be the most effective.

The CVA biplot axis, representing the original variables used in the analysis, are rotated and superimposed on the component model. The CVA biplot captures many features of the data set. The rotation of the axes to represent the raw variables on the plot assists in visualizing the auto-correlation of the variables. Closely-spaced axes are indicative of a high degree of correlation between variables. Axes that overlay the direction of movement between the classes represent the predominant variables that capture this change. Variable axes that lie perpendicular to the movement of the classes do not directly drive or capturethe change.

Case study results

The final tail losses are sub classed into regions based on singular variable analysis. These suggest that transient areas are forming that are statistically significant on beyond 'common cause' (consistently explained variations in the process based on reference period). The transient areas are critical to the analysis since they indicate more accurately the period of change prior to the noticeable step change in performance along the time axis, and are thus essential in performing the root cause analysis. These areas are colour -coded and depicted in Figure 3. 'Class 4' in Figure 3 captures the period following the site intervention to correct for the increased losses, which was guided by the analysis.

The groupings are separated more clearly by incorporating the chrome and silica stream in distinct analysis of the variables (Figure 4). Class 1 was used as the

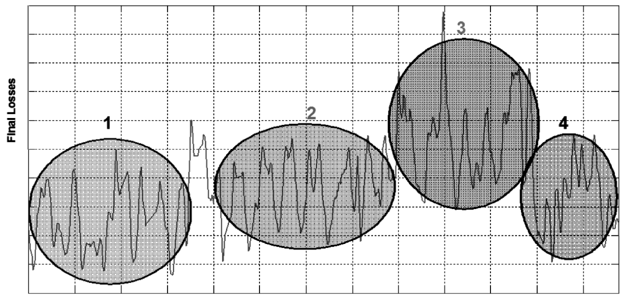

Figure 3. Final tail losses based on singular variable analysis

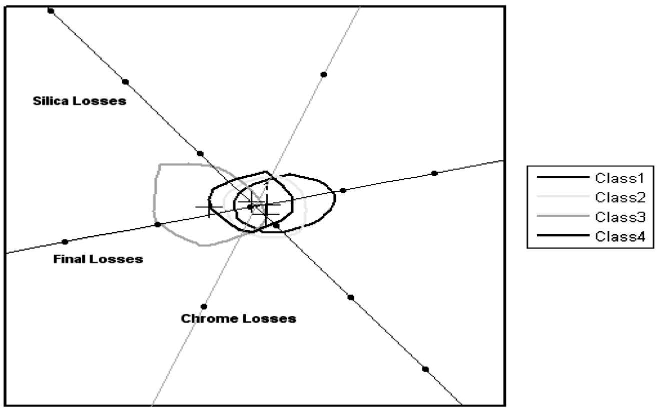

Figure 4. CVA Bi-plot of the final composite losses grouped within the predefined 4 classes

reference period for the principal component model. Class 2 is represents a transitional period, and Class 3 the recorded step-change.

The improved separation of Class 3 along the final composite losses axis is explained thus: a singular final tail value does not equate to a unique combination of the two composite tail measurements (Figure 1 indicates that the final tail is a composite of the chrome and silica tails).

It can be concluded that the correlation between the silica and chrome-rich stream to the final tails was a gradual rather than a sudden dramatic shift, as a complete separation between the classes was not achieved. The separation of the identified classes in the final composite losses is sufficient for them to be imposed on the process variables of the various processing units as described by the functional tree. The CVA bi-plots were used per process unit to visualize the class separation in relationship to the associated variables of that unit. The links between the process units, as described by the functional tree, were then used to draft a causality model to relate the shifts in the various units.

No fundamental process change was recorded for either the silica-rich or chrome-rich scavenger flotation sections. The correlated shift in losses in these processing units were discounted as the root cause (the root cause (causality model) diagram in Figure 5). The red crosses represent key performance indicators (KPIs) that have exceeded the pre-defined limit ranges for the process unit. The KPIs are grouped in three layers to assist in breaking down the causality model to the fewest possible root causes. The three layers are process, control and equipment-based KPIs. Each layer has associated performance criteria measurements such as oscillation within the control layer, and dynamic performance curves within the equipment layer. The methodology followed within the causality

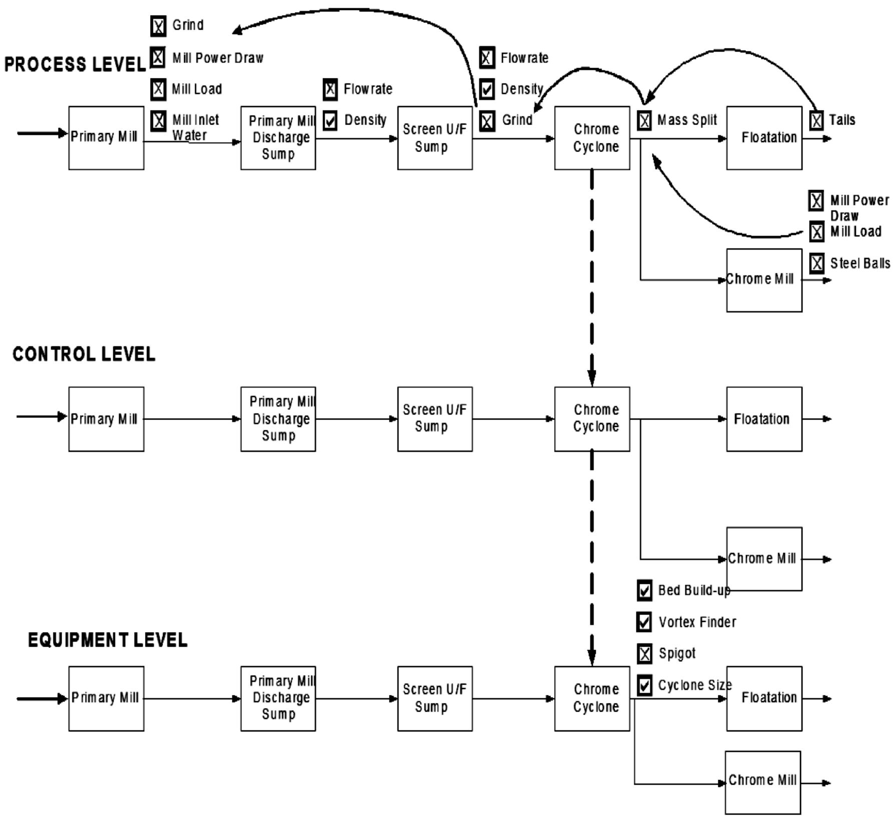

Figure 5. Root cause diagram

model is to drill up the tree (right to left) until a point is reached where no KPI limit excursions are recorded. The bi-plots complemented this approach by visually relating the specific process unit variables to the defined classes in the final tails. The root cause diagram in Figure 5 suggested that an improved separation of the classes in the final tail could be achieved by including either the milling or cyclone KPIs in the CVA bi-plot.

Figure 6 illustrates an improved separation of the final loss classes when the primary grind variables were included, clearly indicating that the primary grind is a major contributor to the increase in losses. A very distinct classing of the data was observed when the same criteria were applied to the process data of the main chrome-silica classification processes (Figure 7).

A clear mass-split shift between the overflow (silica-rich) and underflow (chrome-rich) of the cyclone was noted. The shift resulted in a dramatic change in both the composition and particle size distribution of the chrome-rich and silica-rich streams.

The classification cyclone could not be regarded as the root cause for the increased losses but only as a contributor, since a shift in the feed particle size distribution to the cyclone was also noted. This is illustrated in the root cause diagram in Figure 5.

Figure 8 is a density plot reflecting the gradual shift in the cyclone feed particle size distribution. The gradual rather than sudden shift in the feed particle size distribution supports the gradual shift detected in the final composite losses as described earlier. The recorded change of the cyclone spigot was highlighted as a potential contributor to the magnitude of the shift, as indicated on the equipment layer in the root cause map in Figure 5.

Applying the same methodology of drilling to an earlier stage on the root cause map to identify the possible root causes (Figure 5), the autogenous milling circuit seemed the likely origin of the noted shift in the classification circuit.

A clear separation between Class 1 and Class 3 was observed in the autogenous milling circuit process data (Figure 10) by applying the same classing to the data as identified by the final composite losses.

From Figure 10, it was concluded that the three variables that most support the shift from Class 1 through to Class 3 are the mill speed, mill inlet water, and the mill power. Class 4 displays a condition where the milling circuit returned to its original operational state after the intervention to correct for the increased losses. Figure 10 shows a high correlation between the mill inlet water and mill power.

Neither the mill load nor the mill feed rate data captured the change in the milling process based on the classed data. These variables were therefore excluded from the causality model. Time series plots of the mill load and feed rate data supported this conclusion. Figure 11 shows the milling circuit variables excluding the mill load and feed rate data' but including the milling circuit product grind variables.

The shifts in the milling circuit operation can also be visualized by the mill power-load curves depicted in Figure 12, by 'bagging the data' of the autogenous mill power and load, according to the predefined classes in the final composite losses.

Applying a causality model to the control and manipulated variables (captured in Figure 5) the following was concluded:

- The control range of the mill dilution water (manipulated variable) was lifted contributing largely to the shift from Class 1 one to Class 2.

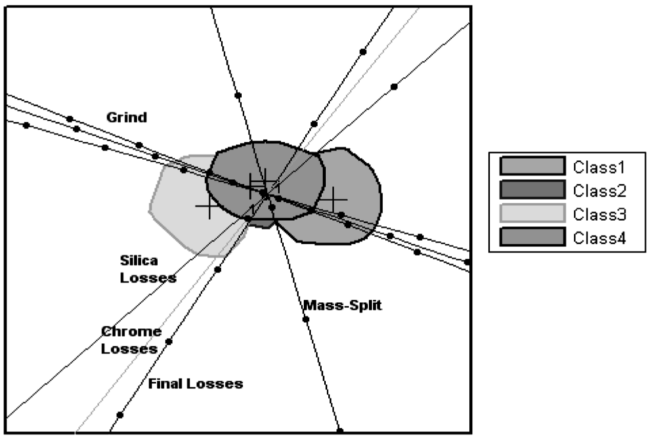

Figure 6. Improved classification of four classes in the final composite losses data (CVA bi-plot)

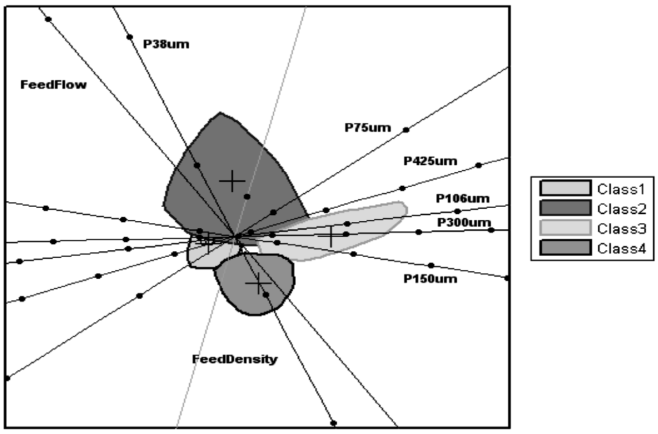

Figure 7. Classification of cyclone process data (CVA bi-plot)

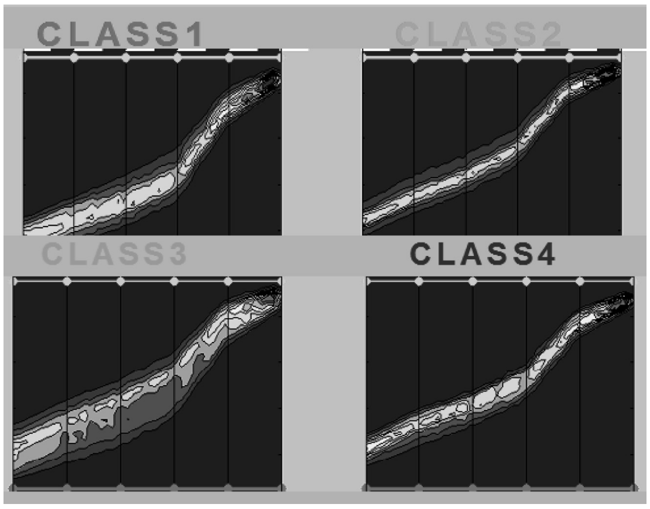

Figure 8: Cyclone feed particle size distribution curves for the predefined four classes. The size classes (x-axis) and the cumulative mass-percentages passing per size class (y-axis) has been normalised (density plots)

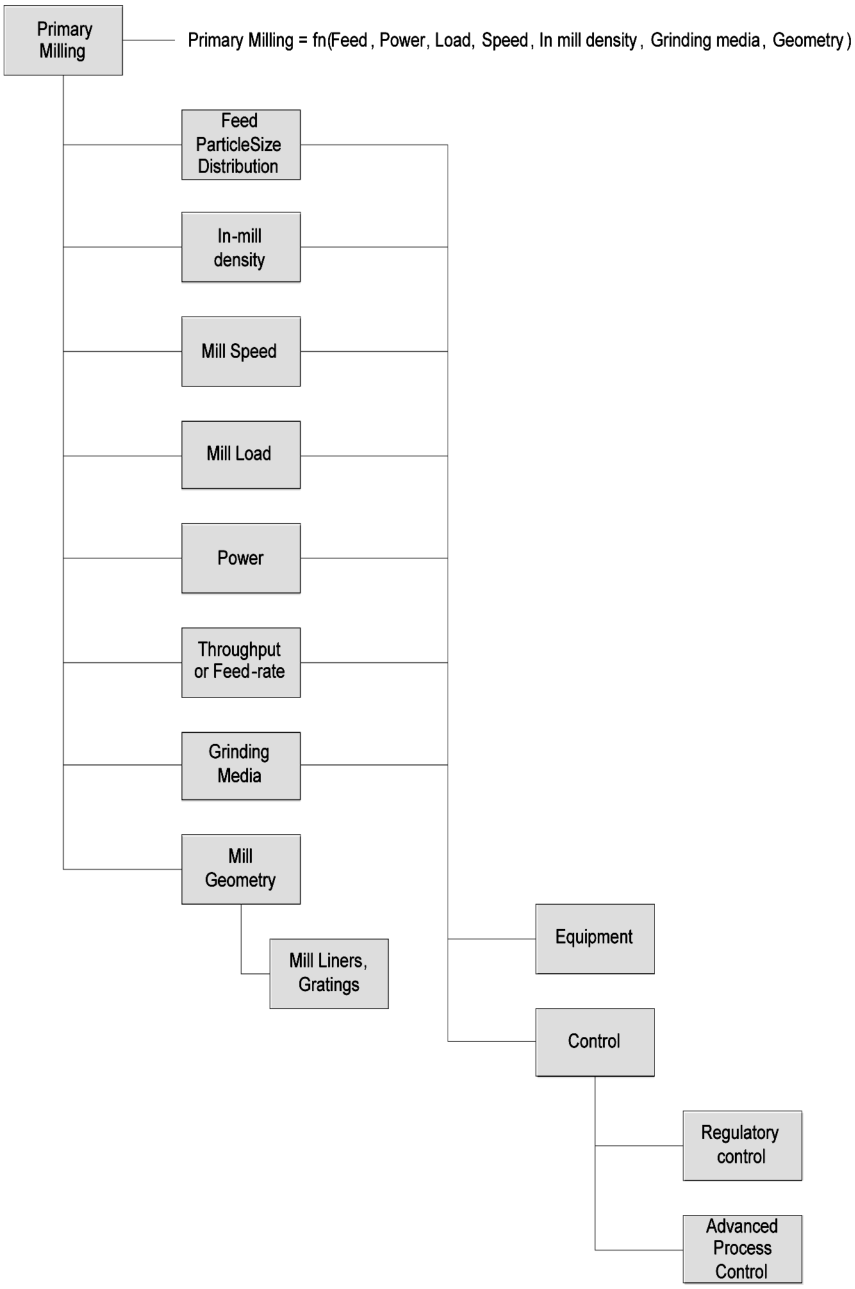

Figure 9. Functional tree expanded for primary milling circuit

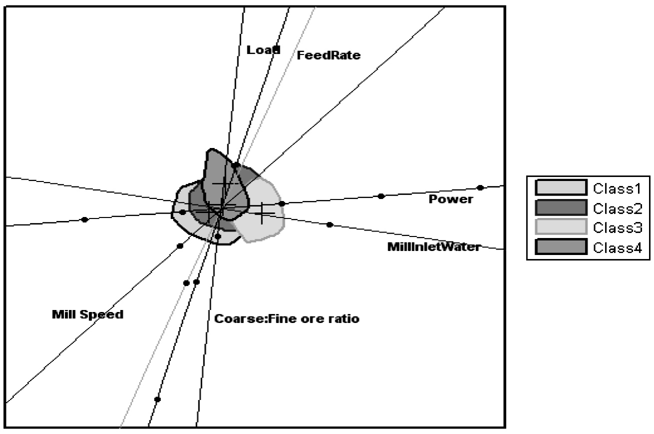

Figure 10. Classification of primary AG Mill process data (CVA bi-plot of randomly selected data)

This upward shift in the mill dilution resulted in a much tighter grind distribution, as seen in Figure 8, and a resulting drop in the mill filling. The increased mill dilution had a greater effect on the fine (-75 micron) distribution, as shown in Figure 11.

- The control range of the speed settings of the mill's variable speed drive,was lowered significantly to compensate for the increased mill dilution. The primary grind shift is not captured by a single grind variable but rather the shift in the distribution. As indicated in Figure 8. This contributed largely to the shift in the process condition from Class 2 to Class 3.
- A shift back to the reference operating regime, Class 1 in the milling operation was indicated clearly after the mill dilution had been reduced and the control ranges of the mill variable speed drive lifted.

The controller design of both the milling and

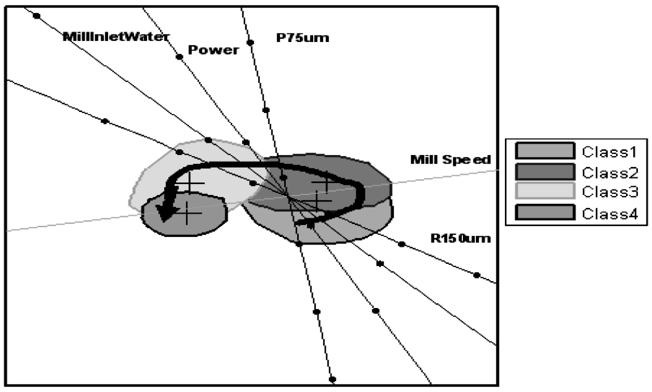

Figure 11. Classification of primary AG mill process data (CVA bi-plot of randomly selected data)

classification circuit was updated to incorporate the on-line particle size analysis as a control variable. The results of the operation illustrate the importance of using both the grind target and the shape of the grind curve in setting the control objective.

Root cause analysis results

The shift in the primary AG mill performance can be traced through the circuit to the final composite losses, as illustrated by the root cause map in Figure 5. The functional trees as depicted Figures 1, 2 and 9 allow for the use of potentially complex yet powerful statistical methods on fundamentally constrained relational variables. This methodology allows one to conclude from this case study that the root cause to the 'extra-ordinary' shift (beyond normal variance) in the final composite losses can be reconstructed as follows:

- Primary milling circuit operation shifted due to a significant drop in mill speed and increase in mill dilution water.

This resulted in:

a significant shift in the particle size distribution from the primary milling circuit, which contributed to a shift in the chrome and silica streams' particle size distributions

shift in the particle size distribution which caused a shift in the classification cyclone efficiency, thus the mass-split to the over-and underflow and resulting chrome and silica content of the over-and underflow of the cyclone

a dramatic shift in the platinum group mineral loadings of the two regrind circuits and scavenger flotation circuits

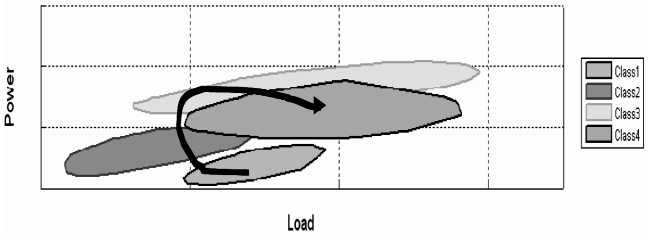

Figure 12. Power to load grouping of primary autogenous mill

aprocess shift that had a direct effect on the platinum group mineral liberation and resulting recovery.

Conclusions

The results achieved from the investigation into the shift in plant efficiency and the subsequent corrective action taken illustrate that the root-cause methodology used in advance process control, coupled with statistical analysis techniques, can be effectively applied to detect process shifts as well as to identify probable root-causes.

The industrial case study used confirms that the variable speed drive in a UG2 autogenous milling operation is a critical control parameter to ensure that set production targets are consistently achieved. It further highlights the importance of combining both the particle size measurement as well as the shape of the particle size distribution curve in an effective control philosophy.

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