Acoustic estimation of the particle size distributions of sulphide ores in a laboratory ball mill

by C. Aldrich and D.A. Theron*

Synopsis

The acoustic signals emitted from a laboratory-scale ball mill were used for the estimation of the comminution of two complex sulphide ores, viz. Merensky and UG2 ores from the Bushveld Igneous Complex in South Africa. The digital acoustic signals were transformed to power spectral densities that could be related to particle size distributions (-75 μm to 4000 μm) in the mill by use of continuum regression. This approach is more general than principal component regression methods or Kalman filtering used previously and resulted in significantly more accurate calibration in the case of the Merensky ore, where approximately 93.4% of the variance in the particle size distributions could be explained. With fewer data available, the variance in the particle size distributions in the UG2 ore could be explained less accurately (82.4%), but still satisfactorily. In addition, smaller particle sizes (less than 300 μm) could be modelled more accurately in the case of the UG2 ore.

Introduction

The high-intensity vibrations emitted by comminution equipment are a useful indication of the state of the process and plant operators responsible for controlling comminution circuits often exploit this knowledge. The feasibility of diagnostic monitoring and control systems based on interpretation of the acoustic signals emitted from milling equipment was already established in the early 1960s (Anon, 1963, Rowland, 1963). The first controllers merely caused an on-off action with the feeders, but later incremental control was used. The largest drawback of these controllers was their vulnerability to extraneous noise that was difficult to eliminate at the time. Furthermore, the equipment was not particularly sensitive and could only detect large changes reliably. In these early stages it was noted that acoustic control of pebble mills was easier than that of mills with steel grinding media that had higher and more varied noise levels.

In the early 1970s the approach was used to monitor the performance of an industrial SAG mill in Cyprus Pima (Lynch, 1977), among others. Similar studies were conducted by Watson (1985) and Watson and Morrison (1986), but instead of attempting to isolate the parts of the sound spectrum associated with the particle breakage, they focused on the changes in the mill noise related with changes in ore types or size. Other unreported investigations in industry have been aimed at predicting liner wear in mills, particle size, etc. However, on-line capability was limited, especially in the early stages. On the Cyprus Pima site, for example, acoustic data were captured on magnetic tape and had to be analyzed mostly off-site afterwards.

More recently, Zeng and Forssberg (1992, 1993a, 1993b, 1993c, 1996) and Zeng *et al.* (1993) have shown that the signals can be used to assess particle size and other comminution parameters on-line, with a high degree of accuracy. In these and earlier studies, the digital acoustic signals were usually transformed to power spectral densities, typically resulting in several hundred variables that had to be related to the parameters of interest in the comminution process. The high degree of redundancy in the spectral variables was naturally accommodated by factor analytical methods, such as principal component regression or Kalman filtering.

Although previous investigations have demonstrated the potential advantages of using acoustic emissions to monitor a wide range of equipment and comminution conditions, much work still needs to be done with regard to the interpretation of these acoustic spectra. The accuracy of process and measurement models is an important issue. For example, model maintenance becomes a problem as machinery wears and operating conditions change. Also, more accurate models would allow more sensitive control systems, capable of detecting changes in grinding parameters, ore types, etc.

* *Institute of Mineral Processing and Intelligent Process Systems, Dept of Chem. Eng, University of Stellenbosch, Private Bag X1, Matieland, 7602.*

 SA ISSN 0038–223X/3.00 + 0.00. Paper received Aug. 1999; revised paper received June 2000.

Consequently, in this paper these investigations are extended to complex sulphide ores from the Merensky and UG2 reefs in the Bushveld Igneous Complex in South Africa. In particular, in this preliminary study the different comminution behaviours of the two ores are considered, as well as a more general approach to the development of linear latent variable models to estimate particle size distributions. With this approach it is shown that better diagnostic models can be developed by fully exploiting the covariance structure of the spectral and operational data combined and not just that of the spectral data.

Experimental setup

A diagrammatic representation of the experimental setup is shown in Figure 1. The laboratory mill used in all experiments was lined with rubber and fitted with a flanged lid to facilitate loading and to provide watertight closure during wet grinding. The mill had an inner diameter of 200 mm and an inner length of 280 mm. It was fitted with a 1.1 kW motor that could be controlled by means of a variable speed drive, as well as a set of pulleys that permitted mill speeds of up to 98 r.p.m., as measured by a tachometer.

Two directional microphones with cardioid pick-up patterns and a frequency response from 50-15 000 Hz were used to record the sound emission from the mill. One microphone was placed approximately 10-15 mm from the shell of the mill, close to the toe of the charge as shown in Figure 2, since this is the region in the mill where most of the sound is generated by the tumbling media. The other microphone was used to record ambient noise, which could be used to improve the composite signal of the first microphone via adaptive filtering.

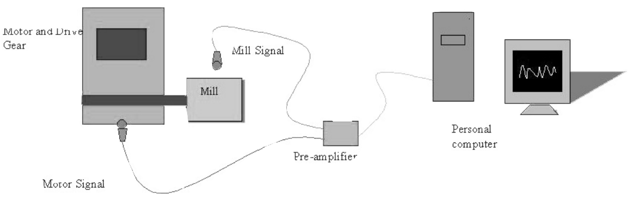

Figure 1—Schematic diagram of (a) experimental setup and (b) the position of the microphone with regard to the mill charge

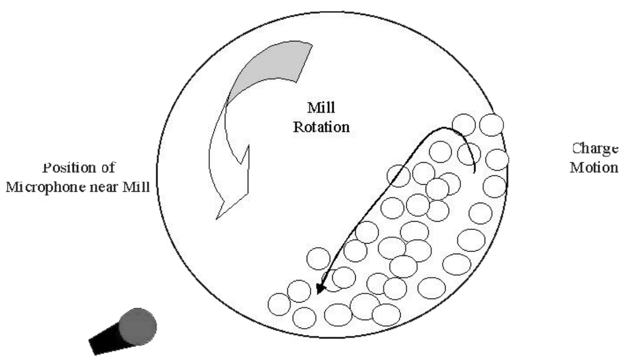

Figure 2—Positioning of microphone near mill

The signals from the microphones were amplified before further processing. A pre-amplifier was designed and constructed by the Centre for Electronic Services in the Department of Electronic Engineering at the University of Stellenbosch for this purpose. The gain on the two input channels could be adjusted independently, with the amplified output signal sent to a personal computer for further processing.

An Intel Pentium II, 200 MHz with 32 megabyte RAM and a 2 GB hard disk was used for signal and data capturing purposes. The amplified stereosignal from the pre-amplifier was routed to a sound card in the PC for processing. The sound card facilitated 8-bit and 16-bit digitizing in stereo- and mono-mode, with programmable sampling rates of 5-44 kHz. The signal was converted to digital form by the sound card and stored on the computer's hard disk.

Experimental procedure

Pre-crushed Merensky and UG2 ores were milled in order to study the effect of changing particle size on the sound emission. In all experiments the mill was loaded with a charge of approximately 3 L, that is approximately 38% of the total volume of the mill. The charge consisted of 290 steel balls with a diameter of 25 mm, 1 kg of ore and 667 mL of water. This resulted in a slurry concentration of approximately 60% by mass.

Since sampling of the particle sizes during runs led to significant disturbance of the mill load through loss of fines, mill loads were only sampled at the end of each run. The runs differed in duration, i.e. runs could last 5, 10, 15, 20, 25, 30, 35, 40, 45 or 50 minutes. In all, 63 runs were recorded for the Merensky ore, while 39 runs were recorded for the UG2 ore, i.e. runs were replicated approximately 6 and 4 times on average for the Merensky and UG2 ores respectively. The large particle size fractions, e.g. 425–600 µm, 600–1400 µm, 1400–2800 µm, 2800–4000 µm and, 4000+ µm, were sieved by hand to reduce fines build-up on the wire mesh, while the smaller fractions, e.g. -75 µm, 75–106 µm, 106–150 µm, 150–212 µm, 212–300 µm and 300–425 µm were sieved using a mechanical shaker.

Acoustic signals were collected for a duration of one minute just before the end of a particular run. For example, in runs that were terminated after 10 minutes, recording would have taken place from the 9th to the 10th minute of the run, for 20 minute runs, recording would have taken place from the 19th to the 20th minutes, etc. The amplified signal of the microphone fixed close to the mill shell was recorded onto the hard disk of a personal computer via a sound card. By making use of Nyquist's sampling theorem, requiring that the sampling rate should be at least $2^1/_2$ times higher than the highest desired frequency, a sampling rate of 11025 Hz was selected. This gave a highest recorded frequency of 4410 Hz. Analysis of the signal showed that the lower frequencies contained most of the information from the grinding process. Samples were thus recorded at 11025 Hz with 16 bit linear quantization. All sound files were saved in the standard Windows PCM *.*wav* format.

The recorded signals were converted by means of Fast Fourier transforms to a series of power spectral densities, where each density was associated with a different frequency, as described in more detail in the Appendix. The

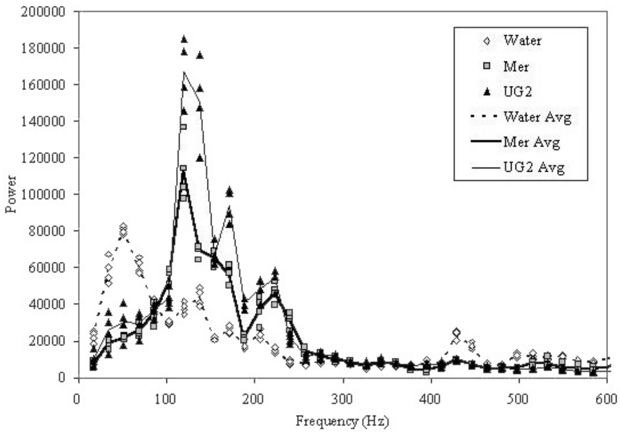

Figure 3—Average power spectra of Merensky ore (bold solid line), UG2 ore (thin solid line) and water (broken line) obtained after 5 minutes of milling. The diamonds, squares and triangles indicate the individual observations on which the respective averages were based. Average standard deviations over the frequency spectrum for Merensky ore, UG2 ore and water are 9.47%, 12.24% and 12.25% respectively

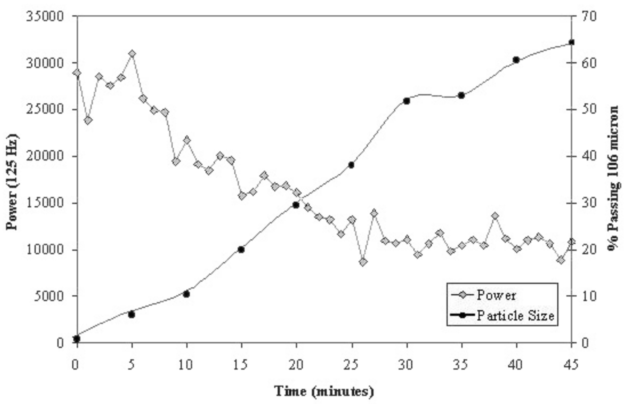

Figure 4—Decrease in the power associated with the 125 Hz frequency over time (shaded diamonds, left axis) and increase in the percentage of particles smaller than 106 μm (solid circles, right axis) versus time. Note that particle sizes were sampled at five minute intervals only, while the power spectra were sampled at one-minute intervals. Lines simply connect observations to emphasize trends

power spectral densities of typical samples obtained after 5 minutes of milling are shown in Figure 3. These spectra tended to flatten out after prolonged milling (i.e. smaller particles), as indicated in Figure 4. Figure 4 shows the trend for the power densities associated with the 125 Hz frequency, as well as the associated trend in the particle sizes. As indicated by the Figure, the power decreased approximately 67% over a 45 minute period, while the percentage of particles smaller than 106 μm showed a concomitant increase. These samples were saved in ASCII format from where they could be exported to a spreadsheet (Microsoft Excel®). Owing to limitations in the spreadsheet software, only 239 samples of the power spectrum vectors were used in subsequent analyses.

Continuum regression modelling

Each experiment yielded an observation of the form $(\mathbf{x} \mid \mathbf{y}) = (x_1, x_2, \dots x_{239} \mid y_1, y_2, \dots y_{10})$, where x_i denoted the power spectral density or FFT spectrum associated with the i'th frequency (i = 1, 2, ... 239) and y_j denoted the percentage of particles smaller than the j'th particle size (j = 1, 2, .. 10). The next step was to estimate the particle size distributions from the acoustic signals, as explained in more detail below.

The model used to estimate the particle size distributions was determined by the nature of the data. Although 239 variables (and far less observations) were nominally available in each case to estimate a particular particle size fraction, these variables were not independent and could be represented by just a few independent latent variables. Likewise, the particle size distributions (the output variables) were also correlated, albeit to a lesser degree than the spectral variables. For this reason, it was desirable to use a latent variable model, such as the principal component regression used by Zeng and Forssberg (1993a, 1993b). In this case, the method of continuum regression (Stone and Brooks, 1990; Wise and Rickert, 1993) is used, since it is a more general approach than principal component regression that can also accommodate correlation in the output variables. Moreover, it is a linear approach that suits the relatively few data available, as well as the fact the relationships between the spectral variables and the particle size distributions appeared to be approximately linear (see Figure 4, for example).

The continuum regression model is characterized by the number of factors used in the model, as well as the order of the model. Detailed algorithms are described elsewhere (Stone and Brooks, 1990), but essentially the first step in the derivation of continuum regression models is the singular value decomposition of the matrix of p predictor (spectral) variables on n observations ($\mathbf{X} \in \Re^{n\mathrm{x}p}$), that is

$$\mathbf{X} = \mathbf{USV}^T \qquad [1]$$

where $\mathbf{U} \in \Re^{n\mathrm{x}n}$ and $\mathbf{V} \in \Re^{p\mathrm{x}p}$ are orthonormal matrices and $\mathbf{S} \in \Re^{n\mathrm{x}p}$ a diagonal matrix, with elements (singular values) $s_{11}, s_{22}, s_{33}, \dots$ placed in descending order on the diagonal. The diagonal matrix is subsequently raised to a power of m, that is each of the singular values in the matrix is raised to a power of m, to derive a new $\mathbf{X}^m$-block

$$\mathbf{X}^m = \mathbf{US}^m\mathbf{V}^T. \qquad [2]$$

A partial least squares algorithm (Geladi and Kowalski, 1986; Höskuldsson, 1996) can consequently be used to produce a regression vector and the final models.

The continuum regression algorithm can be understood in terms of the stretching of the space of the predictor variables when the singular values are raised to powers exceeding unity. The directions of greatest variance in $\mathbf{X}^m$ are therefore emphasized more than in $\mathbf{X}$. The larger the power m, the more pronounced the emphasis and the closer the character of the model resembles that of a principal component regression (PCR) model. Conversely, the smaller the m-value (less than unity), the less emphasis is placed on the correlation of the prediction variables, and the closer the resemblance of the continuum regression model to that of an ordinary multivariate regression model.

Partial least squares models can be seen as lying somewhere between these two extremes (i.e. at $m = 1$), in that both the correlation between variables in the $\mathbf{X}$-block (spectral variables) and variables in the $\mathbf{X}$- and $\mathbf{Y}$-blocks (particle sizes) are taken into account. Since relatively few observations were available, the number of latent variables and the continuum parameter or power of the continuum regression models were determined by 10-fold cross-validation, repeated three times. The powers (m) that were considered in each case were 0.01, 0.05, 0.1, 0.5, 1 and 5, which covered the range from multivariate regression to principal component regression models.

Results and discussion

Figures 5 and 6 show the regression coefficients of the Merensky and UG2 ore models respectively, reconstructed from the latent variables. It is interesting to note the five or six large regression coefficients associated with the spectral frequencies of less than 1400 Hz in the Merensky ore (Figure 5). In the UG2 ore, the regression coefficients are spread more or less evenly among the 239 different frequencies, ranging up to approximately 4000 Hz (Figure 6).

Figures 7 and 8 show the cumulative predicted error sum of squares (PRESS) as functions of the number of latent variables and continuum parameters for the Merensky and UG2 ore models respectively. Both these surfaces are typical for continuum regression models. The level regions to the right of these surfaces are sometimes referred to as multivariate regression planes and represent models identified with so many latent variables, that they have converged to the multiple linear regression (MLR) solution. On the left of these Figures are models with large errors, sometimes referred to as principal component regression (PCR) mountains, i.e. models identified with too few latent variables. These regions include a so-called valley of best models.

In the case of the Merensky ores (Figure 7), the best model was one based on seven latent variables and a power of unity, i.e. a partial least squares (PLS) model. The best UG2 model (Figure 8) was obtained with only one latent variable and a power of 0.1, i.e. closely resembling an MLR model in character. The predictive power of the best models is shown in Figures 9 and 10. As can be seen from these Figures, the PLS model for the Merensky system was able to explain more than 93% of the overall variance of the particle size distributions. The smaller particles could be modelled nominally better than the larger particles, but these differences are probably not significant.

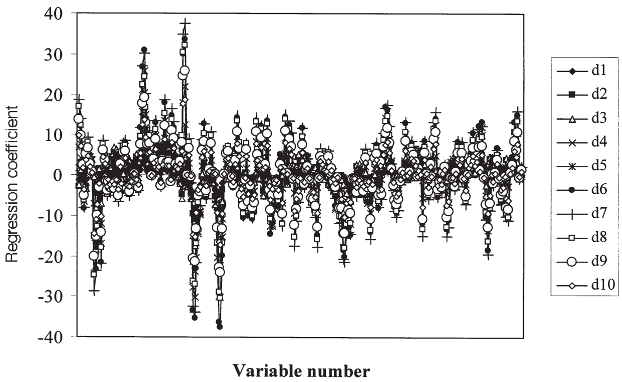

Figure 5—Regression coefficients for the best PRESS model for the Merensky ore. The best PRESS model was based on 7 latent variables and a power of 1

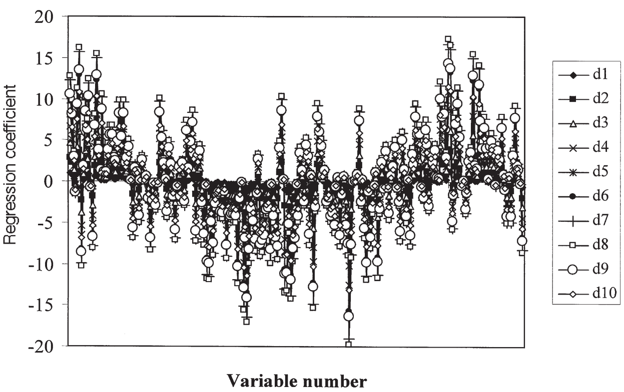

Figure 6—Regression coefficients for the best PRESS model for the UG2 ore. The best PRESS model was based on 1 latent variable and a power of 0.1

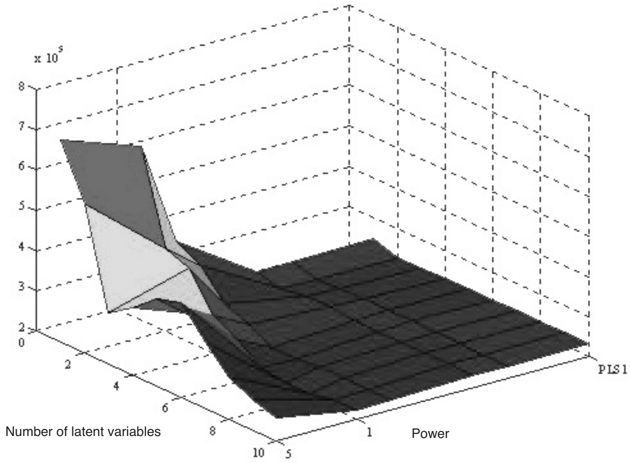

Figure 7—Cumulative PRESS for the Merensky ore as a function of number of latent variables and power (continuum parameter)

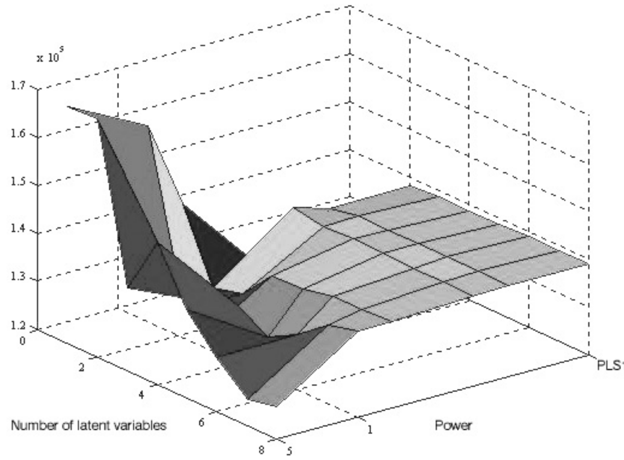

Figure 8—Cumulative PRESS for the UG2 ore as a function of number of latent variables and power (continuum parameter)

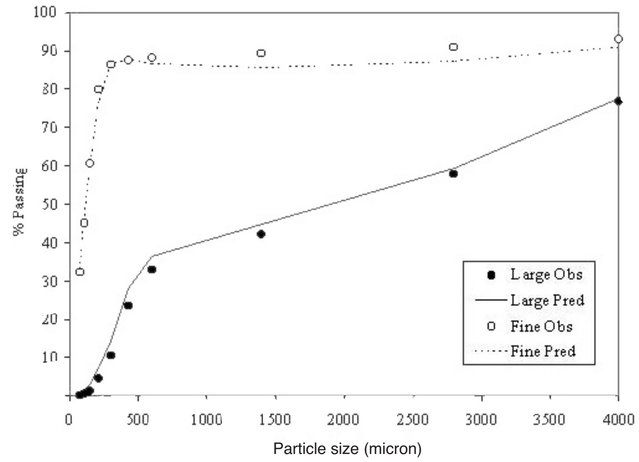

Figure 9—Typical continuum regression model fits of the Merensky ore size distributions. Solid and empty circles indicate the observed values of the large and small particles respectively. The solid line indicates the model fit to the larger particles, while the broken line indicates the model fit to the finer particles. The explained variances associated with all the particles, the large particles only and the small particles only are 93.5%, 92.1% and 94.1% respectively

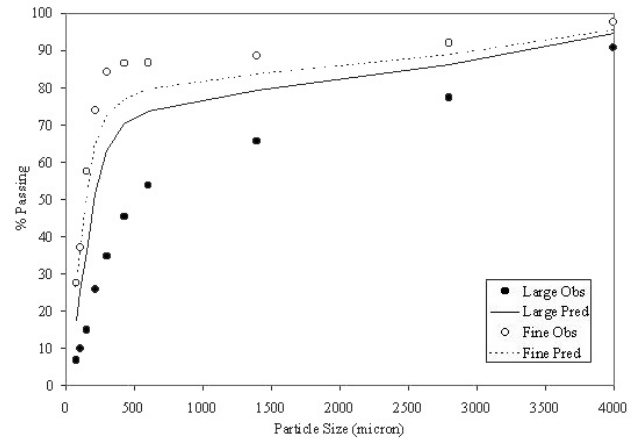

Figure 10—Typical continuum regression model fits of the UG2 ore size distributions. Solid and empty circles indicate the observed values of the large and small particles respectively. The solid line indicates the model fit to the larger particles, while the broken line indicates the model fit to the finer particles. The explained variances associated with all the particles, the large particles only and the small particles only are 82.0%, 76.8% and 83.4% respectively

In the case of the UG2 ore, the best model was able to explain 83.0% of the overall variance in the particle size distributions. The smaller particles could be modelled more accurately (explained variance of 83.4%) than the larger particles (explained variance of 76.8%). The lower accuracy of the UG2 models could possibly be attributed to the smaller data set that was used in the development of the model and future work may include a more rigorous comparison of the models done on larger data sets.

In addition, the mechanisms controlling the characteristics of the noise signals also need to be addressed by further experimental work. For example, the overall decrease in the noise emitted from the mill (similar to the trend indicated in Figure 4) can possibly be explained by the increase in the pulp viscosity associated with the build-up of fines in the slurry. As the viscosity of the pulp increases, the ball-ball collisions inside the mill are damped and the noise inside the mill is decreased. However, this needs to be investigated more extensively, as the temperature would also rise with prolonged grinding, which would tend to decrease the viscosity of the pulp.

Although the models developed in this investigation could be used to monitor the performance of a tumbling mill, it seems reasonable that they could be extended to other systems where on-line particle size analysis is important. For example, by disturbing the particles on a conveyor belt or in other particle feeder systems, it should be possible to measure particle size distributions on-line via the acoustic signals emitted by these particles.

Conclusions

- ➤ The covariance structures of the power spectra and particle size data of the two ores (Merensky and UG2) differed appreciably. In the Merensky ore, a better model could be derived by use of partial least squares, rather than a principal component regression model. In fact, a PCR model for the Merensky ore could only explain 82.4% of the total variance in the size distributions, compared with 93.4% for the PLS model for the same data. In contrast, in the UG2 ore the continuum regression model was similar to a principal component regression model (both of which could explain approximately 82%-83% of the variation in the data).
- ➤ In the Merensky model, a number of frequency bands ranging up to 1400 Hz appeared to dominate in their contribution to the size distribution model. This was not the case with the UG2 ore, where the entire range of frequencies up to 4000 Hz appeared to contribute towards the particle size models.
- ➤ In addition, the UG2 ore differed from the Merensky ore in that the smaller particle fractions (<400 μm) could be modelled significantly more accurately than the coarser particle size fractions (400 μm–4000 μm).

Acknowledgements

The assistance of Prof. David Weber and the Digital Signal Processing group at the University of Stellenbosch with the experimental setup is gratefully acknowledged.

References

Anon. Acoustic controller for improving grinding mill output. *Measurement and Control,* 2(11), 1963. pp. 444–446.

Geladi, P. and Kowalski, B.R. PLS tutorial. *Analytica Chimica Acta,* 185(1). 1986. pp. 1–17.

Höskuldsson, A. Prediction Methods in Science and Technology, *Thor Publishing*, Denmark. 1996.

Lynch, A.J. Mineral Crushing and Grinding Circuits. *Elsevier Scientific Publishing Company*, Amsterdam, Netherlands. 1977. pp. 287–297.

Proakis, J.G. and Manolakis, D.M. Digital Signal Processing. 3rd ed. *Prentice Hall International Editions,* New Jersey, USA. 1996.

Rowland, C.A. Automation of grinding circuits. *Pit and Quarry,* 56(1). 1963. pp. 176–179.

Stone, M. and Brooks, R.J. Continuum regression: Cross-validated, sequentially constructed prediction embracing ordinary least squares, partial least squares and principal components regression. *Journal of the Royal Statistical Society B,* 52, 1990. pp. 337–369.

Stremler, F.G. Introduction to Communications Systems. 3rd ed. *Addison-Wesley Publishing Company,* Massachusetts, USA.1990.

Watson, J.L. An analysis of mill grinding noise. *Powder Technology*, 41. 1985. pp. 83–89.

Watson, J.L. and Morrison, S.D. Estimation of pulp viscosity and grinding mill performance by means of mill noise measurements. *Journal of Mineral and Metallurgical Processing*, AIME-SME, 4. 1986. pp. 216–227.

Wise, B.M. and Rickert, N.L. Identification of finite impulse response models using continuum regression. *Journal of Chemometrics,* 7(1). 1993. pp. 1–14.

Zeng, Y. and Forssberg, K.S.E. Effects of operating parameters on vibration signal under laboratory scale ball grinding conditions. *International Journal of Mineral Processing,* 35. 1992. pp. 273–290.

Zeng, Y. and Forssberg, K.S.E. Application of digital signal processing and multivariate data analysis to vibration signals from ball-mill grinding. *Transactions of the Institute of Mining and Metallurgy*, 102. 1993a. pp. C39–C43.

Zeng, Y. and Forssberg, K.S.E. Application of vibration signals to monitoring crushing parameters. *Powder Technology*, 76. 1993b. pp. 247–252.

Zeng, Y. and Forssberg, K.S.E. Monitoring grinding parameters by signal measurements for an industrial ball mill. *International Journal of Mineral Processing*, 40. 1993c. pp. 1–16.

Zeng, Y., Zheng, M. and Forssberg, K.S.E. Monitoring jaw crushing parameters via signal measurement. *International Journal of Mineral Processing*, 39. 1993. pp. 199–208.

Zeng, Y. and Forssberg, K.S.E. Vibration signal measurement from mono-particle breakage. *International Journal of Mineral Processing.* 44–45. 1996. pp. 59–69.

Appendix: Processing of acoustic signals

The Fast Fourier transform (FFT) was used to decompose the signal into its frequency components (Proakis and Manolakis 1996), that is

$$F(w) = \frac{1}{T_p}\int_0^{T_p} f(t)e^{-j2\pi}dt \qquad [A.1]$$

with T_p the period and F(0) the fundamental frequency. Parseval's theorem gives the relation between a time signal f(t) and its Fourier transform F(w) as

$$\int_{-\infty}^{\infty}\left|f(t)^2\right|dt = \frac{1}{2\pi}\int_{-\infty}^{\infty}\left|F(w)^2\right|dw \qquad [A.2]$$

This relation makes it possible to obtain the frequency components of the signal from the time dependent form.

Stremler (1990) summarized the power spectral density of a signal as the energy per unit of frequency, which displays the relative energy contributions of the various frequency components. The area under the power spectral density function gives the energy within a given band of frequencies.

Welch's method (Proakis and Manolakis, 1996) for averaging periodograms was used to estimate the power spectra of the signals, since the signals recorded were not all of the same duration. The method allows data sections to overlap and windows the data segments before computing the periodogram, viz.

$$P(f) = \frac{2}{T_p}\left|\int_0^{T_p} w(t)f(t)e^{-j2\pi}dt\right| \qquad [A.3]$$

with w(t) the windowing function. The final periodogram is averaged, unbiased and consistent. The windowing function used in this investigation was the triangular Bartlett function (Proakis and Manolakis, 1996).

$$w(n) = 1 - |2n - M - 1|/(M-1), \text{ for } 0 \le n \le M-1 \qquad [A.4]$$

where n is the bin number and M-1 the length of one section for the calculation of the FFT.

The signal was divided into 512 overlapping sections, each of which was detrended in MATLAB, then windowed by using the Bartlett window. The signal was zero-padded to a length of 512 points. The power spectrum was formed by squaring the length of the overlapping sections and averaging their discrete Fourier transforms. The sections were overlapped with 128 points per neighbouring section. The result was a power spectrum vector with 257 samples. These samples explain the intensity or volume of each respective frequency in the mill signal. ◆

Above: The winners (from Left) David Phillpotts (Crawford College), Marvin Mashiwane (Mamelodi High), and Dylan Clement (HS Silverton with Dr Kelvin Kemm of Stratek, and Mintek CEO, Dr Aidan Edwards

Gauteng North take Science Quiz*

The Gauteng North team has won the national finals of Mintek's Minquiz annual school's science competition. Other teams that competed in the finals were Mpumalanga, Northern Province, Eastern Cape and Free State ◆

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