Continuous Monitoring of Mineral Processes with Special Focus on Tumbling Mills

– A Multivariate Approach

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Cover illustration:

Visualisation of the ball charge movement in a tumbling mill using Distinct Element Modelling technique.

The force exerted on a lifter bar by the mill load measured with an embedded strain gauge sensor.
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Abstract

Increasing emphasis on productivity and quality control has provided an impetus to research on better methodologies for diagnosis, modelling, monitoring, control and optimisation of mineral process systems. One of the biggest challenges facing the research community is the processing of raw sensor data into meaningful information. Information that to some extent express quality parameters such as chemical assays, size distribution and other metallurgical variables in the different process streams.

This thesis shows how multivariate statistical methods can be used with great advantage to model process data as well as sensor data of spectral character. The modelling approach has been applied on a large process section, a cobbing plant, as well as a single unit operation, a tumbling mill. As a signal pre-processing method for spectra-like data the discrete wavelet transform is used. It distinctly shows a capability of signal feature extraction where both time and frequency are of interest. Its well-known ability to achieve good data compression without loss of information is also demonstrated, here a data reduction ratio of 20:1 is obtained.

A strain gauge sensor that measure the deflection of a lifter bar when it hits the charge inside a tumbling mill is studied for different operating conditions in a pilot scale ball mill. The deflection of the lifter bar during every mill revolution gives rise to a characteristic signal profile that is shown to contain information on both the charge position and grinding performance.

The results presented for prediction of grinding performance suggest that the strain gauge signal, in combination with wavelet transformation and multivariate data analysis, provide a promising mean for monitoring and control of process fluctuations. The low prediction error achieved for the calculated grinding performances clearly highlights the importance of well-planned experimental strategy including experimental design, signal pre-processing, multivariate modelling and validation. Results demonstrate that different operating conditions are well distinguishable from each other and by that the finding of proper operating regimes are highly feasible. Grinding parameters that are normally measured in the laboratory are now readily modelled from the on-line signal. As a consequence this opens new possibilities for real-time monitoring and control of the grinding process.

A further objective of this work is to link computational results to the experimental data obtained from an instrumented pilot ball mill. The approach taken is to simulate the behaviour of a rubber lifter when it is exposed to forces from the grinding charge in a two-dimensional DEM mill model using a particle flow code. Typically walls in a DEM model are made up of rigid bodies where the equations of motion are not satisfied for each individual wall - i.e., forces acting on a wall do not influence its motion. Here the instrumented rubber lifter is represented as an assemblage of bonded particles rather than walls in order to simulate deflection. The deflection profile obtained from the DEM simulation shows a reasonably good correspondence to the pilot mill measurements. The difference is attributed to the fact that time-dependent behaviour of the rubber lifter is ignored, resulting in a too rapid relaxation of the lifter when the exerted force is released. Mill charge features such as toe and shoulder position of the charge are well marked. However, DEM prediction shows lower values compared to measurements which is most likely an effect of the two-dimensional model used and the inability to model the effect of slurry present in the mill.

The novelty of the thesis work is in the method for analysing the signal profile as well as the experimental verification in both pilot and full-scale operation. The result is a contribution to improved mill lifter design and continuous monitoring of the grinding process.

Keywords: Grinding, Process monitoring, Simulation, Modelling, Strain gauge sensor
To my wife and family
LIST OF PUBLICATIONS

This thesis is based on the work contained in the following papers, referred to by Roman numerals in the text:

I. Continuous monitoring of a tumbling mill
   K Tano, B Pålsson and S Persson

II. Monitoring of a tumbling mill using PLS-regression on a wavelet transformed strain-gauge signal
   K Tano, B Pålsson and S Rännar
   Submitted to Sensors and Actuators A: Physical

III. On-line Measurement of Charge Position and Filling Level in Industrial Scale Mills
    K Tano, A Berggren and B Pålsson
    Accepted for publication in Minerals & Metallurgical Processing

IV. On-line monitoring of rheological effects in grinding mills using lifter deflection measurements
    K Tano, B Pålsson and A Sellgren
    Minerals Engineering, In press

V. Comparison of experimental mill lifter deflection measurements with DEM predictions
    K Tano, M Pierce and J Alatalo
    Submitted to International Journal of Mineral Processing
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1 INTRODUCTION

1.1 General

The term data analysis and process monitoring, as used in the context of process applications, collectively refer to the interpretation and evaluation of sampled process measurements. Data analysis as used in this work is intended to describe how data are manipulated and used together with fundamental understandings to infer the state of a physical process. Monitoring, on the other hand, refers to the classification of the data based upon a calibration model of expected behaviour so that unwanted situations can be detected and proper control actions can be made.

The first part of this research work which resulted in a licentiate thesis (Tano, 1996) focused on the use of a multivariate statistical model to monitor a mineral process with the aim to detect deviations from normal operation and in some extent predict quality properties in the processed material. The method is characterised by a good ability to visualise course of events but a disadvantage is the need of a great number of relevant measurements. Unfortunately, in many cases process data are of poor quality. Instrument failure, poorly or uncalibrated instrumentation, high noise levels, which all contributes to data problems. Without proper pre-treatment, the necessary interpretation is difficult, if not impossible. This principally limited the application of the method to few and relatively large process sections.

Substantial progress in the development of intelligent real-time sensors and data pre-treatment methods has opened new possibilities to study single unit operations. The second part of this work focuses on methods for measuring and modelling of the grinding process. Size reduction is an inevitable unit operation in mineral processing, and comminution is by far the most energy consuming part in mineral concentrators and extremely inefficient, less than 10% of supplied power produce new mineral surfaces, great efforts have been made to improve grinding operations. The economical potential is substantial if efficiency can be increased just a couple of percent. In general, the only grinding control is to maximize the power drawn by the mill. Unfortunately, the relation between power and grinding performance is a complex and non-linear function. Development of advanced control systems has helped the situation considerably. However, these systems still are lacking relevant information such as mill load, charge position or slurry properties. Sensors capable of delivering this information are therefore of great value.

Pre-treatment by wavelet transformation to locate and identify significant events combined with multivariate statistics presents good prospects to estimate the magnitude of variables not directly measurable. Furthermore the application of fundamental physical modelling techniques such as DEM has developed considerably lately, which in the case of grinding has lead to increased knowledge and understanding of process phenomena taking place in a tumbling mill.

Accordingly, the combined use of advanced measuring techniques as well as the use of both empirical and fundamental mathematical modelling applied on mineral processes is a key approach to increase knowledge and create control strategies for improved product quality and process performance.

1.2 Scope of this work

The overall aim of the present work is to show how an advanced sensor system can be used to collect data that contain information of the grinding process and from these data derive multivariate models to monitor and characterise changes in operating conditions.

An objective of this thesis is also to determine the influence of the significant factors that vary in an ordinary grinding process and how these variations are reflected in the measured signal. To further understand the behaviour in the grinding mill DEM technique is applied and an attempt to validate the modelling results with obtained practical mill measurements is demonstrated.
Application of the thesis work will form a foundation for an on-line system that can be used to improve process performance in mineral process operations.

1.3 Outline of the thesis

Chapter 2 of this thesis introduces the concept of using multivariate statistical methods in the modelling of process data from mineral processes. The applied modelling techniques form the basis for the second part of the work where focus is on a sensor embedded in a lifter bar inside a grinding mill. In Chapter 3 is the applied sensor system as well as the most common methods to measure mill load characteristics described. The purpose of the two introductory chapters is to relate the methods used in the papers included in this thesis to other well-established techniques. Chapter 4 describes the grinding mills studied and gives a brief overview of the data pre-treatment method used. Included in chapter 4 is also a conceptual description of how DEM technique is used in this work to link the measurement with fundamental knowledge of charge movement in a tumbling mill. The results obtained from the measurements under different operating conditions are presented and discussed in Chapter 5. Finally, some conclusions and future perspectives are presented in Chapter 6 and 7.
2 INTRODUCTION TO MONITORING OF MINERAL PROCESSES USING MULTIVARIATE STATISTICAL METHODS

2.1 Background

Nowadays an operator plays a very central role in the operation of a plant, it is not unusual that only one person controls an entire plant from a remote control room. Automated process control have lead to operators that to a larger extent are left with a passive monitoring task with few active interactions with, or manipulations of, the process under normal and stable operation of the plant. This leaves few opportunities for ‘learning by doing’ about how the process works and for applying, and thereby retaining and raising the reliability of trained skills. The operators generally have to intervene in the process only when disturbances exceeding some alarm criteria occur. A requirement is therefore that the control and information system shall support the operator in maintaining their process knowledge. Also, to be competitive many industries, and especially the mineral industry, have to improve their efficiency in utilisation of raw material and energy that have directed higher demands towards the operators for optimisation and trimming tasks. A development in this direction means that operators will be faced with more strategic tasks, which in turn, means that they will interact with the process on a higher supervisory level (Olsson and Lee, 1994).

A general trend in process industry is the development towards more and more complex processes with very specific demand on the final products. The customer have become more conscious about the quality and the demand is that quality should be uniform and of high level. Modern processes are inherently multivariate with many variables contributing to the overall process quality. The number of functions and measurements that the operators have to handle has lately increased dramatically. This put high demands on the interface that shall support the operator in interpreting changes that are taking part in the process. There is at the same time a limit on how much information an operator can process simultaneously. Therefore the interface of the control- and information system have to be adapted to the way humans process large data sets. Humans are very skilled in interpretation of pictures and recognising patterns. This complexity often limits the application of theoretical models, developed from first principal differential equations, to the monitoring of industrial processes. On the other hand, most processes now are equipped with automatic data acquisition systems linked to computerised databases that collect large amounts of information about the process operation. This allows for the possibility of using data based statistical models to better understand the process or to detect and analyse process upsets and sensor errors, and finally for process control (Veltkamp, 1993).

2.2 Multivariate statistical modelling techniques

Many processes are multivariate in the sense that many variables contribute to the overall process quality. A process system can roughly be described as in Figure 2.1.

Ideally, the characteristics of the product can be described according to Eq. (2-1). Unfortunately the reality is not as nice, there are often a number of process variables that are non-controlled and also unmeasured.

\[ P(\text{quality, quantity}) = \Gamma(F, C) \quad (2-1) \]
Therefore there is a great need to get information about the state of these variables when trying to control the process. If the relations between the different variables are known, it is possible to set up model equations for the system and use them in active control. But in many processes this is not the case because of lack of knowledge about the system. Hence, you are obliged to methods that use process measurements for the development of models (MacGregor et al., 1992). It is then possible to set up relations between the measurements (M) and the feed (F), product (P) and non-controlled (N) variables.

\[
F, N = q(M, C) \quad \text{(2-2 A)}
\]

\[
P = t(F, N) \quad \text{(2-2 B)}
\]

Since the measurements of the process often are done at a sampling rate of seconds or minutes this gives an opportunity to get predictions of F, N and P at a much higher frequency than normally is achieved by manual sampling. This gives the operator an possibility to follow the changes in the process on a moment to moment basis and by this act much faster when process upsets appears.

It is in this context that multivariate statistical modelling (MSM) technique is interesting and during the last years received a lot of interest and a number of work has been done in this area (MacGregor et al. 1995; Wise et al. 1989; Kvalheim O.L., 1996).

MSM is a collective term for methods that extract information from data tables and by projection technique, model complex process relationships. Two basic statistical tools for this are principal component analysis (PCA) and partial least square regression (PLS).

### 2.2.1 Theoretical background of principal components

The mathematical and statistical properties of PLS have been discussed in detail by a number of workers (Wold et al., 1987; Lorber et al., 1987; Martens & Naes, 1989; Höskuldsson, 1988; Helland, 1988). In these papers many variations of the basic algorithm used to do the calculation appears.

PLS is a regression technique, regressing \( Y \) onto \( X \), where \( X \) is an \( N \times K \) matrix (\( N \) is the number of measurements and \( K \) is the number of input process variables) and \( Y \) is an \( N \times M \) matrix (\( M \) is the number of output variables). This method is especially useful when the variables within \( X \) and within \( Y \) are correlated (Kresta et al., 1991). Consider first the case where only one of the data matrixes is of interest, eg. \( X \).

PCA is a procedure (Andersson, 1984; Mardia et al., 1982) which attempts to explain the structure of the variation in the data matrix in terms of a number of latent variables called principal components. Generally the \( X \) matrix is mean centred and scaled before PCA is applied. The methodology of PCA is to decompose the data matrix into the following bilinear form:
\[ X = \sum_{a=1}^{A} (t_a * p_a^T) + E_A \]  

(2-3)

Where \( t \) is the score vector for \( X \) and \( p \) is the loading vector for \( X \), \( E_A \) is the residual matrix, \( a \) is the model dimension index (\( a = 1, \ldots, A \)).

Since the \( t_a \)'s and the \( p_a \)'s are orthogonal it can be shown (Helland, 1988) that the \( t_a \)'s are the eigenvectors of \( XX^T \) and the \( p_a \)'s are the eigenvectors of \( X^TY \). This points to the equivalency between PCA and singular value decomposition, SVD (Höskuldsson, 1988). In SVD the eigenvalues are calculated in descending order starting with the largest, in both methods the corresponding eigenvectors are also in descending order. For detailed discussions of PCA see Jackson (1991). For correlated data sets \( A < < K \) using SVD to calculate all the principal components is inefficient. The NIPALS algorithm (Wold et al., 1987) calculates the PC's iteratively, the correct number of PC's (\( A \)) can be determined from stopping criterions, one of the more popular techniques being cross validation (Wold, 1978). The \( Y \) matrix can be similarly decomposed into

\[ Y = \sum_{a=1}^{A} (u_a * q_a^T) + F_A \]  

(2-4)

Where \( u \) is the score vector for \( Y \) and \( q \) is the weight vector for \( Y \), \( F_A \) is the residual matrix.

Performing the regression of \( u \) onto \( t \) leads to principal component regression. PLS follow a similar procedure except that it performs both of the decomposition simultaneously and in an iterative manner in order to get a better prediction of \( Y \). The method can be described by the following algorithm (Wold et al., 1987).

1. Start: set \( u \) equal to a column of \( Y \)
2. \( w^T = u^T X u / u^T u \) (regress columns of \( X \) on \( u \))
3. Normalize \( w \) to unit length (\( w \) is weight vector for \( X \))
4. \( t = Xw / w^T w \) (calculate the scores)
5. \( q^T = t^T Y t / t^T t \) (regress columns of \( Y \) on \( t \))
6. Normalize \( q \) to unit length
7. \( u = Yq / q^T q \) (calculate new \( u \) vector)
8. Check convergence: if YES to 9, if NOT to 2
9. \( X \) loadings: \( p = X^T t q / t^T t \)
10. Regression coefficient: \( b = u^T t q / t^T t \) (often set to one)
11. Calculate residual matrices: \( E = X - tp^T \) and \( F = Y - btq^T \)
12. To calculate the next set of latent vectors replace \( X \) & \( Y \) by \( E \) & \( F \) and repeat

The latent vectors (\( t \) and \( u \)) now depend upon both the \( X \) and \( Y \) spaces and are related through the linear inner relationship \( u_a = b_a * t_a + \epsilon_a \) where \( \epsilon_a \) is a residual and \( b_a \) is the least squares regression coefficient. Non-linearities can be incorporated into the model by using a non-linear inner relationship \( u_a = f(b_a, t_a) + \epsilon_a \) and estimating the parameters (\( b_a \)) by non-linear regression in step 10 (Wold et al., 1989). Höskuldsson (1988) showed some interesting relationship between PCA and PLS. These are of interest because PCA is conceptually easier to grasp than PLS. PLS works on the \( X \) matrix, and the loading vectors calculated using NIPALS are, as mentioned before, the eigenvectors of the covariance matrix \( XX^T \). PLS on the other hand, works on both \( X \) and \( Y \), the first loading vector calculated in this case is the eigenvector of the matrix \( YY^T \). This last matrix can be thought of in two ways: (1) the covariance of \( Y \) has been scaled using the “size” of the \( Y \) matrix (\( YY^T \)), or (2) PLS is simply PCA pre-formed on the covariance matrix of \( X \) and \( Y \) (\( Y^T X \)). Next loading vector is then calculated after updating of matrices \( X \) and \( Y \).
2.3 Monitoring via multivariate plots

Since the operator nowadays has a central role in running an industrial plant, it is of great importance that the control system has functionality to support the operator. This means tools that help the operator to monitor actual process status, detect process upsets and also give guidance to keep the process at best conditions.

Traditionally the operator gets information presented as numerical figures or univariate trendcurves on a display. But in a multivariate situation where one is faced with perhaps 10 to 100 variables, individual plotting is not feasible. In this situation, approaches based on PCA and PLS are very attractive. Jackson (1980) provided early approaches to multivariate monitoring using PCA methods. More recent extensions of the PCA methods and the introduction of PLS approaches were considered by Wise et al. (1989) and by Kresta et al. (1990).

It can often be assumed that the underlying dimensionality of the process, when it is operating normally is quite low. Under these circumstances it is possible to represent the most important elements of its behaviour in low dimensional plots defined by the dominant latent vectors obtained via PCA or PLS. The low dimensional planes defined by these latent vectors provide a low dimensional window on the behaviour of the very high dimensional process. For e.g. a cobbing plant with an underlying dimension of three, the first two axes of the score plot (T1 and T2) form the two axes of the monitoring chart and each observation is located on this plot via its score, see Figure 2.2.

![Figure 2.2: Score plot presentation of a low dimensional PLS model.](image)

The observations included in the reference data set, data from the experiments that were set up in order to build the model, are plotted as ‘star dots’ on this chart. In order to really get an understanding of the cause and effect relationship it is of great importance to run the experiments according to a statistical design. If this is the case, it is then possible to mark different areas in the score plot as ‘good’ and ‘bad’ regions depending on the correlation structure between the manipulated variables and the response variables. Otherwise an appropriate reference data set could be chosen which defines the ‘normal operating conditions’ (NOC) for a particular process. The choice of this reference set is critical for a successful application of the procedure.

To get a correct interpretation of the mutual dependencies between the variables also the loading plot, Figure 2.3, have to be analysed. The loading plot do not needed to be presented continuously for the operator since the information in this plot is static as long as the model is not updated. It is of course essential that the operator can interpret the loading plot since it contain information about
how the controlled variables correlate to the quality variables. Interpretation of loading plots will be discussed in more detail when describing the case studies.

Consequently there are two main tasks for a multivariate statistical process control (MSPC) system to deal with, namely

- Detect if a new observation is an outlier, a process disturbance of some kind
- Indicate the variable(s) which have contributed to the disturbance


The first task, detection of an outlier is accomplished by either calculating the squared prediction error (SPE), Eq.(2-5), or the measure called the distance to model (DmodX), Eq.(2-6). The SPE value represent the squared distance of a new observation from the model hyperplane, plots illustrating the use of SPE are to be find in papers by MacGregor et al. (1991 and 1995).

$$\text{SPE}_i = \sum_{k=1}^{K} (x_{\text{new},k} - \hat{x}_{\text{new},k})^2$$

(2-5)

The rows in matrix $E_A(e_{ik})$ in Eq.(2-3) contains the residuals, i.e. the part of the data that is not explained by the model. The row i's standard deviation of the residuals, $s_i$ calculated according to Eq.(2-6), is a measure of the distance between the i:th observation and the PLS model. This measure is called distance to model, DmodX. High values in SPE and DmodX indicate probable outliers in the X-space.

$$\text{DmodX} = s_i = \sqrt{\frac{1}{K} \sum_{k=1}^{K} e_{ik}^2 / (A-K)}$$

(2-6)

The second task, variable contribution can be calculated in different ways depending on the objective. If the interest is to give information on how an observation differs from another in the t-score and how it influence on the outputs $Y$, the so called score gap contribution is calculated according to Eq.(2-7).
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\[ \text{Gap}_s \text{ (scores)} = \Delta X \ast \text{weight} \]  \hspace{1cm} (2-7)

Where \( \Delta X \) is the difference between two observations or between one selected observation and the average process observation, default \( \text{weight} \) is the component loading, \( p \).

Often there is an interest to calculate the gap contribution when monitoring a principal plane, e.g. \( t_1 / t_2 \), then \( \text{Gap}_s \) is the sum for both components. If on the other hand the interest is to give information on which variable(s) that have contributed to an high value in DmodX, in other words which variables caused the new observation to move away from NOC, the DmodX gap contribution is calculated according to Eq.(2-8).

\[ \text{Gap}_d \text{ (DmodX)} = e_k \ast \text{weight} \]  \hspace{1cm} (2-8)

Here, \( e_k \) represents variable residuals and the default \( \text{weight} \) is the square root of the explained sum of squares for each variable. In the same manner it is possible to sum the DmodX gap contribution for two components when monitoring a principal plane. With this information it is possible to present the calculated gap contribution for the operator in a bar graph form. Sorting the variables in decreasing order in respect to the calculated \( \text{Gap}_d \) offer an very convenient way for the operator to get a fast overview on which variables that caused a process upset, see Figure 2.4.

By combining these different charts (score, gap contribution and time-plot) together in one display, Figure 2.5, it can be used to monitor the process. The scores for a new observation can be located on the principal plane according to the calculation in Eq. (2-9).

\[ t_1 = X \ast w_1, \quad t_2 = (X - t_1 p_1) \ast w_2 \]  \hspace{1cm} (2-9)

Connecting each new calculated score \( t_1 / t_2 \) (n) to a previous one \( t_1 / t_2 \) (n-1) with a line, presents the process as a dynamic line, a worm. The movement of this worm shows whether the process is approaching or deviating from the model centre. A proper length of the worm has the be chosen depending on time constants in the process but also how long time backwards there is an interest to follow the process. The structure of these plots reflects the two ways in which abnormalities can enter the system and provides powerful diagnostic capability to determine the
cause of the abnormality (MacGregor, 1991). If the abnormality is caused by a larger than normal change in one or more of the process variables, but the basic relationship between the process and quality variables does not change, then the abnormality will manifest itself as a shift in the principal plane, and the DmodX will remain at an acceptable level. If on the other hand the abnormality enters through a new event not captured in the reference set, it will change the nature and possibly the dimension of the relationship between the process and quality variables. This will show up in an increase in DmodX. Future development of the algorithm has to make the model adaptive by recursively updating it with new samples.

In order to retain the ease of interpretation it is of importance to keep the number of principal components low, this means that normally the monitoring procedure would be restricted to a maximum of three to four latent vectors. For very complex processes, where the bulk of variation is not explained by few principal components, the system should be divided into logical modular sections that can be monitored separately.

An example how an operator display could be designed is presented in Figure 2.5. Here, the upper left corner shows the dynamic score plot where the operator continuously receives information regarding changes in the process. If a sudden process disturbance of the earlier mentioned types occurs, the operator can intervene and call for the gap contribution chart, shown to the right. The variables are sorted in such a way that the most influenced variable are at the top, with the colour (dark or grey) indicating if the variable influence is positive or negative. By activating one of the variable bars, the time plot of the corresponding variable is presented in the lower left part of the display. Normally the time plot shows the value of DmodX. This value is of great importance since it tells the operator if the process is within the model space or not. It must be mentioned that the multivariate charts do not replace, but rather complement, the traditional displays that are used by the operators.

Figure 2.5: Operator display showing scores, gap contribution and DModX.
2.4 Application - Cobbing plant

2.4.1 Process description

The cobbing plant at LKAB Malmberget, shown diagrammatically in Figure 2.6, has an incoming feed where the iron content varies between 45-55%. As a consequence of this, the operator has to run the plant in such a way that the lowest grade crude ore gives an acceptable final quality. The adjustable variables are the amount of fresh feed and the speed of the magnetic separators. The problem for the operator is to decide, with certainty, when the iron content is high or low. An experienced operator can judge this by studying via a video-camera the colour of the material when the incoming feed passes a screen. If there were time enough for the operator to continuously monitor the video display there would be a possibility to act at the right moment. Unfortunately, the operators tasks are so many and so varying that there is seldom time for detailed monitoring. It is in this context that PLS modelling is interesting.

![Figure 2.6: Flow chart of the cobbing plant at LKAB, Malmberget.](image)

Since the main interest for modelling of this process was to develop a strategy for controlling the quality variation in the PAR product, it was necessary to run designed experiments. The manipulated variables were the amount of fresh feed and the speed of the magnetic separators. The interesting responses were the silica content in PAR and the iron content in the crude ore. Through the development of a model that predicts the responses with enough precision and then applying the model for the graphical presentation of the process status, hopefully sufficient information will be made available to the operator for taking the necessary control actions.

2.4.2 Results and discussion

Detailed results and interpretations using the calibrated model are given in Tano (1996). The model deals with a delicate problem, namely the quality of the fresh feed. It is very difficult, mainly due to the large sampling problem, to measure the iron content so frequently that it can be used for control. In practice, one value is delivered from the laboratory every 24 hours. No values are reported during weekends. For silica content, the agreement is fairly good with a prediction error of approximately +/- 0.8%-units. Unfortunately, this is somewhat too large for direct control purposes. The agreement, however, for the iron content in the crude ore is very good with the prediction error in this case being approximately +/- 0.9 %-units. This accuracy is satisfactory enough to fulfil the goal for this model.
In order to test the predictive capability of the model, the iron content in the incoming feed to the sorting plant was predicted during the validation period (comprising 3.5 months). This is shown in Figure 2.7. The model provided a prediction of the iron content every minute. In order to make it possible to compare the predictions with the 24 hours value provided by the Quality Department, the average value was chosen for comparison with the predictions. The first month of the validation period shows a constant deviation, probably due to the change of screen size just before the validation period started. After the first month, it was decided to make a small correction to the model and the following 2.5 months showed a very good accuracy in the prediction.

The monitoring part in the modelling of the sorting plant yielded some very interesting results. First of all, a thorough training of the involved operators was conducted. This involved both process analysis as well as an introduction to MVA. Results from the modelling showed that component t1 and t2 explained approximately 87% of the variation in the response variables. This implies that the operator only has to contemplate the principal plane t1 and t2 which considerably simplify the handling of the score plot. The operators found the functionality in the MVA system to be very useful, especially the gap contribution chart. Unfortunately, the implemented MVA system had to use an old graphical system in the process control computer. This led to some dissatisfaction with the response time when exchanging windows and also with the design of some displays. Another interesting observation from the operators viewpoint was that the MVA system overreacted to trivial changes such as a stop in a feeder which caused the worm to spread over the whole score chart. Such process disturbances are so elementary that they can be handled by the ordinary alarm system. In the MVA system they are more bothersome than helpful. The overall opinion from the operators was very positive. Today the MVA system has characteristics, which are helpful to conducting the daily activities, and with some polishing of details it will be useful in operation.

Experience gained from the modelling of the sorting plant led to the following recommendations:

- If the predictive capability of the model is good enough, use the predicted value as one of the signals in the control system.
- If the complexity of the process is relatively low MVA charts should not be used since they do not bring any new information to the operator.
- The interface of the MVA system must be easy to use preferably integrated into the ordinary control system.
- An interlocking module bypassing the model should be used to handle trivial disturbances.
The recommendations and the overall results are so encouraging as to demand that similar work should be continued on the other mineral processing plant sections.

2.5 Conclusions

Models are only simplified approximations, intended to have structural or functional analogy to some phenomena in the inaccessible more complex reality. Hence it is important to use methods which yield a reasonable compromise between simplicity and completeness. A statistical multivariate modelling method, PLS regression has been presented for steady state modelling of a mineral process.

Experience with the technique has shown that PLS stimulates users to take an open-minded approach to data analysis in general and to the calibration of process models in particular. The applications have shown that it solves the multivariate prediction problem for collinear data with satisfactory predictive ability. The resulting model often has good interpretation properties as well, due to its dimensional parsimony.

By approximating complicated multivariate input data by a few principal components, the operator can plot simplified ‘maps’ of the main relevant information from the process. This allows the operator, who knows the data and their context, to interactively bring important background knowledge and intuition into their interpretation. The information would otherwise be far too complex to be represented as explicit numerical information in statistical modelling. This also gives the operator the ability to detect major changes in the behaviour of the process caused by new events.

PLS modelling has also shown to be very useful in mineral processing unit operations e.g. grinding, where the direct measurement of certain physical parameters is infeasible. Experimental modelling work, where data from an embedded strain gauge sensor, a lifter deflection profile, has been regressed to a number of mill operating parameters, has indicated promising and satisfactory results with respect to reliability and accuracy. This will be further elaborated in following chapters.
3 OVERVIEW OF MILL LOAD MEASUREMENTS

3.1 Literature review of previous work

Grinding in tumbling mills are inefficient, much of the energy is wasted in impact, that do not break particles. Autogenous (AG) and semi-autogenous (SAG) mills often operate in an unstable state because of the difficulty to balance the rate of replenishment of large ore particles from the feed with the consumption in the charge. This has led to an increased interest in obtaining an accurate and direct measurement of mill load and the behaviour of the mill charge. Several parameters do significantly influence the effectiveness of the grinding operation, however, some of these parameters are either difficult or laborious to measure. Intermittent in-situ measurements of some of the parameters are most often prone to errors and there is often a long time-delay before the acquired data is fed to the control system. Also, an understanding of the charge motion within the mill is of importance in mill optimisation (Agrawala et al., 1997). Both the breakage of ore particles and the wear of liners/ball media are closely linked to the charge motion. Therefore, it is essential to use a method that can provide a precise, as well as, real time information of the charge to the control system.

Work done in the past can be divided into two main categories of methods of load measurement; off-shell and on-shell, c.f. Figure 3.1. One method of the first category that has been used in many plants is to measure the bearing back-pressure on the mill’s feed and/or discharge end. It gives an idea of the weight of the charge and it can be correlated to the filling level. A method developed by Bradken Mineral calculates the weight of the charge load by the measurement of bearing pressure, power draw and mill speed. One system installed on a 28ft SAG-mill at Noranda Mine in Brunswick showed that it is theoretically feasible to relate mill load with bearing pressure, provided that wear of mill lining as well as the mill drive system is taken into account. (Evans, 2001) The great disadvantage is that the pressure is not stable, e.g., shifting temperature causes sensor drift. Moreover, since bearing pressure is related to overall mill weight, changes to the ball charge as well as the wear of the lining will affect the signal. As a consequence, it is hard to develop a robust calibration. Despite these problems, one can still make use of bearing pressure for SAG load control. In an attempt to circumvent some of the problems associated with bearing pressure, load cells can be used under SAG mills. Proper installation is of great importance, ensuring that the sensors are located beneath all elements bearing weight, including pinions for example, to measure load when the mill is running.

Acoustics have been used in different kinds of setup; single microphones (Watson et al, 1985) correlated sound power with pulp viscosity, arrays of microphones (Jaspan et al., 1986) designed to detect changes in the position of the toe of the mill charge. Koivistoinen et al. (1989) used high frequency sampling of the power draw, and more specifically the amplitude of the power oscillations corresponding to each lifter passing through the pulp/charge, to infer mill loading. The phase shift in power draw can be correlated to the change in toe position of the charge. Järvinen (2004) showed that the method produced result comparable to intrusive methods. In Chile, a device from CIMM (Centro de Investigacion Minera y Metalurgica) known as MONSAG (Monitoring SAG mills) also employs the power draw, and through a complex signal processing algorithm estimates torque, which can be correlated with volumetric filling. The system is well suited to detect under- and overfilling of the mill. A validation of the system was performed on a 15 kHp SAG-mill where Pontt (2004) established a 3.2 % increase in throughput and a better understanding of the mills optimal operation.

A similar method, using a mill power draw model, described by Apelt et al. (2001) showed that the method can be used to predict total filling level as well as ball charge level.
The other category of measurements is those involving some device that is resident on the mill shell. These devices are not as well developed yet, largely because of electro-mechanical issues arising from the service demands. This approach certainly holds some appeal, since these systems are capable of inferring the nature of the load more directly. A well-known method (Moys, 1988, Vermeulen et al., 1988) is to measure the conductivity inside the mill with two probes that are mounted on a lifter. This method has shown some good results but a disadvantage has been the wear of the probes and also the drift that this wear causes. Berggren et al. (2000) has developed a similar system that is running at one of their operations deducing the toe and shoulder position of the load.

Acoustic or vibration sensitive devices such as ELAC (Electro-Acoustic) from CIMM provide a non-contact indication of where the toe and shoulder of the load are located. Using geometrical considerations, an estimate of the load is obtained. There is some current research (Pax, 2001) looking at a more sophisticated non-contact acoustical approach using Fourier transformation for relating the measured signal to process parameters. The proposed equipment is relatively simple, placed outside the mill making it independent of maintenance stop for exchange of components.

Within the AMIRA project a SAG mill monitoring system is developed measuring the surface vibrations directly by accelerometers mounted on the mill shell (Campbell et al., 2001). Changes in the vibration signal indicate changes in the charge motion and provide a warning of the onset of sub-optimal or undesirable operating conditions. Zeng and Forssberg (1994) also used accelerometers but mounted on the trunnion bearings at both ends of the mill. They showed that vibration signal measurement is a viable method for monitoring some of the parameters in ball grinding operations.

An approach that is more or less a category in itself is a technique utilizing a soft-sensor for load estimation. In most cases this involves the use of phenomenological models describing the mass balance around the mill, coupled with field measurements. Generally speaking, the more field measurements, the better the soft-sensor, and in such cases it can often be employed to infer more than load and the dynamic angle of repose, for example ore grindability could be estimated on-line. Examples in this category, model-based methods, are a softsensor developed at University of Utah and a system (ComMINSens) developed by Herbst and Pate (1996). The latter system has been implemented on a SAG-mill, result shows that it predicts mill performance within 2% accuracy and can be used to secure maximum throughput for varying ore qualities.

Techniques that measure the force acting on the lifter or a lifter bolt (Herbst et al, 1988) when it hits the charge inside the mill have got an increased interest recently because of the ability to combine it with DEM modeling. Process Engineering Resources Inc (PERI) markets a unit called CVM - Continuous Volume Measurement, and this uses the relaxation in strain in an instrumented lifter washer or bolt to infer the normal forces on the lifter. These are negligible unless the lifter is in the charge, making it possible to estimate the toe and shoulder positions. Kolacz (1997) used a
piezoelectric strain transducer for the measurement of mill load. Here the strain arisen on the mill shell due to the charge load is measured and is directly proportional to the ball charge load.

In this work is a strain gauge sensor used, which is embedded in a rubber lifter, detailed description in section 3.2. The sensor is integrated in a complete measurement system that is marketed by Metso Minerals (Dupont et al., 2001) under the name CCM (Continuous Charge Measurement system).

3.2 Strain gauge sensor system

The CCM system is a quite newly developed electronic measuring system (Persson, 1994-1999). It is dedicated to continuous measurement of the charge volume and the angle of repose provided that the mill has a rubber or rubber-metal mill lining or that a sensor-equipped rubber lifter bar can be installed in a steel-lined mill.

The equipment consists of three main parts; the sensor, the telemetry system and the computer for data analysis and presentation. The most exposed component is the sensor, since the mechanical environment is very stressful due to the number of deflections of the sensor spring is far above the normal fatigue limit, usually in the order of 10 million. Furthermore, the sensor is exposed to moisture/water with temperatures between 30-60°C and also to high stress during parts of every revolution. Consequently, the system is constructed and built with great attention placed on the included components.

Figure 3.2: Pilot mill showing the lifter bars where one of them has a strain gauge sensor installed, the right part shows the lifter (1) with a strain gauge (2).

A simplified view of the sensor is shown in Figure 3.2. The mill has a number of lifters on the inside of the mill shell. One of these lifters (marked 1) is equipped with a leaf spring whose deflection is measured by the strain gauge (marked 2). As the mill rotates and the lifter with the sensor dips into the charge, the force acting on the lifter increases, which in turn, causes a deflection. The strain gauge mounted on the leaf spring converts this deflection to an electric signal. The signal is then amplified, filtered and transformed to a pulse with a modulated HF-signal in the transceiver and by the antenna wired around the mill transmitted to the receiver placed close to the mill, c.f. Figure 3.3. A pendulum driven generator placed on the mill end produces the power to the transceiver, or in the pilot mill case by a battery pack mounted on the mill shell. The receiver has also a trigger pulse that is activated once every revolution. This is for the system to know when a new revolution occurs. Finally the signal is transmitted by cable to the measurement computer where the calculation, analysis and presentation of the signal is done. Data acquisition by the A/D-converter in the computer is done at a frequency of 100 Hz. All the data are stored in the computer for further processing.
For both ball mills (pilot and full scale) there is only one sensor installed at the center of the mill. In the AG mill application the sensors are placed as marked in Figure 3.3.

![Figure 3.3: Overview of the mill with its mounted system components.](image)

3.2.1 Strain-gauge signal features

A typical deflection profile of the sensor signal and a corresponding graphical representation of a simulation of a mill are shown in Figure 3.4. The numbers in Figure 3.4, indicate important dynamic events during the passage of the sensor-equipped lifter bar under the mill charge.

1. The sensor lifter bar (SL) is still in the air
2. The SL hits the surface of the slurry
3. The SL starts to get submerged in the slurry
4. The SL hits the ball charge and starts to get submerged in the charge (T4)
5. The SL starts to bend forward due to turbulence in the toe area
6. The SL grips the ball charge again
7. The SL is at peak bending
8. The SL has gradually decreased the bending and is at take-off position
9. The SL is leaving the ball charge and starts slowly rise to an upright position (T9)

![Figure 3.4. CCM raw signal, showing the bending of a rubber lifter during the passage of the charge.](image)

Calculation of fractional filling $J$ and dynamic angle of repose $\alpha$ (radians) from a CCM system raw signal is quite straightforward since the change in force acting on the lifter relates to both $(J, \alpha)$ of the mill charge. A simple method for estimating those parameters is shown in equation (1) and (2), where $N$ is mill speed (rps) and $T$ is time (s) when lifter enter and leaves the charge.
Continuous Monitoring of Mineral Processes with a Special Focus on Tumbling Mills – A Multivariate Approach

\[ J = (T_9 - T_4)N - (\sin 2\pi( T_9 - T_4)N) / 2\pi \]  

\[ \alpha = \pi (T_9 + T_4)N - (\pi /2) \]  

The toe and shoulder angle can also be calculated from the CCM raw signal. One method is to look at the derivative of the signal and chose the position of \( T_4 \) as the toe angle and position \( T_9 \) as the shoulder angle. Metso CCM uses a proprietary algorithm to determine toe and shoulder angles as well as to estimate mill load volume. There is no established practice when stating toe and shoulder angles. In this work the measurement system used for the ball mill applications use the horizontal line as the reference. For the AG mill the corresponding reference is the vertical line, c.f. Figure 3.5.

![Figure 3.5: Angular reference for the Ball Mills (left) is the horizontal line and correspondingly for the AG Mill (right) is the vertical line.](image)

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4 EXPERIMENTAL SET-UP AND METHOD

4.1 Pilot scale Ball mill

The pilot mill is 1.414 m in diameter and 1.22 m in length. It is a grate-discharge mill, equipped with 12 rubber lifters of square size 0.1 m, face angle 45 degrees. Steel balls in the size range 10-30 mm and density 7800 kg/m³, were used in the experiments. Figure 4.1 shows a photo of the pilot mill and the mounted system components (described in Chapter 3.2).

A frequency converter and a conveyor scale controlled the mill feed. Mill Power is measured in the switch gear room giving total power, i.e., mill, transmission and gearbox. Load cells are used to measure the mill weight and slurry temperature is measured by a handheld IR-sensor on the mill discharge sample. Charge behavior was monitored using the strain gauge and an average of the signal profile was stored every minute. After steady state was reached in each experiment, data were logged and the mill discharge was sampled, approximately for 10 minutes. Analyses of the particle size were done with a laser diffraction instrument, Malvern Mastersize S (optical mode-polydisperse, dry).

The test material, a hematite pellet feed with \( d_{50} \) around 35\( \mu \)m and a solids density of 5200 kg/m³, was chosen to get stable grinding conditions with respect to feedsize variations. Particle size distributions from which the grinding performance indices were calculated are given in Figure 4.2.

![Figure 4.1: Pilot ball mill with mounted system components.](image)

![Figure 4.2: Particle size distributions for ground hematite ore, dotted line represent the feed.](image)
Two experimental campaigns were performed. The first experimental campaign was meant as a test of the equipment’s performance, and to study how the sensors responded to changes in some operating variables [Paper I and II]. To get an understanding of, and distinguish between correlation and causality, the experiments were performed according to a full factorial design with two levels, and in addition two replicates of the experiments at a centerpoint in the charge level setting. Twelve experiments were performed and the variables Fractional mill volume, Mill speed and % -solids were varied according to design region depicted in Figure 4.3.

The objective for the second experimental campaign was to further study how well the strain-gauge sensor detect changes in product slurry resistance, here evaluated in terms of bench scale viscosity measurement, and its influence on grinding performance [Paper IV]. The term flow resistance is used here to reflect that rheological (viscous) properties are mainly characterized by a medium formed by water and particles with sizes less than 20-30 microns. The resistance to flow is then a combination of viscous influence and effects of two-component hydrodynamic and mechanical behavior of larger particles.

In this campaign is the pilot mill deliberately stressed to its maximum with respect to slurry flow rate and flow resistance, aiming to test the sensor’s ability to detect such possible process states. To assess the joint influence of the variables (feed, solids content, dispersant) an experimental design of experiments (DOE), is used (Eriksson et al., 2001). The mill was run at 24.4 RPM corresponding to 73 % of critical speed. The ball mill charge filling was approximately 28 % of total mill volume. The feed rate and solid content in the mill were varied according to Figure 4.4, which shows the design region spanned by all 10 experiments. Addition of the dispersant to the mill feed was achieved using a peristaltic pump with a rate of approximately 90 ml/min. Bench scale measurements with a vane type viscometer (Bohlin CS10 Rheometer), roughly evaluated in terms of apparent viscosity is used as a character for the resistance to motion of the slurry. Design variables and measured responses are listed in Table 5.1 and Table 5.2, Chapter 5.
4.2 Full scale Ball mill

Figure 4.5 shows a typical flowsheet for concentrating iron ore. The coarse materials at 10-15 mm in size are fed to a primary wet magnetic cobbing separator (M1). The magnetic concentrate is discharged into a primary ball mill (#1), and the ground product (pulp) is transferred to a secondary magnetic separator (M2). The resultant magnetic concentrate is then pumped into a secondary ball mill (#2). The ground product is finally upgraded by a tertiary magnetic separation unit (M3) and the concentrate is used as feed for the tertiary grinding stage (#3). The strain-gauge sensor was installed in the tertiary-grinding mill (#3).

![Figure 4.5: Flowsheet of multi-stage grinding and magnetic separations.](image)

The overflow ball mill used in the tertiary grinding stage has an outside diameter of 4.9 m and a length of 5.7 m, and is run in open circuit. The grinding charge consists of approximately 400 tons of 25-mm diameter chromium steel balls corresponding to 40 % in charge volume. The height of the new rubber liner lifters is about 70 mm. The mill is driven by two 1800 kW AC motors. The mill speed is set at 14.7 rpm giving a fraction of critical speed $K_c = 78\%$. Under normal grinding condition, the rated power draw, the pulp density and the feed rate are 2550 kW, 72 weight-% solids and 250 t/h respectively.

This experiment was the first full-scale test of the equipment’s performance [Paper III]. Until then the development had concentrated on work with sensor accuracy and tuning of the data acquisition system. The equipment had been installed 1.5 months before the test period started, in order to ensure reliability.

Nine experiments were performed and the variables Ball Charge and Feed were varied according to Table 4.1. To accomplish the different fillings the mill was stopped and emptied of balls, in the first case 25 ton of the charge and in the next case additional 25 tons. In each case when the mill was stopped the height of the charge was manually measured. With these measurements it was possible to calculate the percent volumetric mill filling level, see Table 4.1.

<table>
<thead>
<tr>
<th>Manually measured filling level</th>
<th>Normal charge</th>
<th>-25 ton of charge</th>
<th>-50 ton of charge</th>
</tr>
</thead>
<tbody>
<tr>
<td>44.6 %</td>
<td>38.8 %</td>
<td>31.6 %</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Feed rate</th>
<th>Normal charge</th>
<th>-25 ton of charge</th>
<th>-50 ton of charge</th>
</tr>
</thead>
<tbody>
<tr>
<td>235 t/h</td>
<td>235 t/h</td>
<td>215 t/h</td>
<td></td>
</tr>
<tr>
<td>250 t/h</td>
<td>250 t/h</td>
<td>230 t/h</td>
<td></td>
</tr>
<tr>
<td>265 t/h</td>
<td>265 t/h</td>
<td>245 t/h</td>
<td></td>
</tr>
</tbody>
</table>
4.3 Full scale AG mill

The flowsheet for the grinding line at Aitik where the experiments was conducted is shown in Figure 4.6. The ROM material is fed to the primary autogenous grinding mill, $\Omega 6.7 \times 12.2 \text{ m}$ with installed power of 6000 kW. From the primary mill, 40 to 80 mm pebbles are extracted to the secondary pebble mill, $\Omega 5.2 \times 6.8 \text{ m}$, motor power of 3000 kW. The primary and secondary mill is running in closed circuit with a spiral classifier where the coarse material goes back to the primary mill. During normal operation, the primary mill is controlled using a simple and effective optimizing control strategy implemented in the DCS. The objective for the optimizing control is to maximize the throughput. This is done by always keeping the mill at one of two constraints limiting the throughput. The two constraints are maximum allowed mill filling or maximum allowed power draw. Which of the constraints that is active depends on the ore type and fragmentation. The strain-gauge sensor is installed in the primary AG-mill.

![Figure 4.6: Flowsheet of a grinding line at the Aitik plant.](image)

The Aitik experiments [Paper III] were conducted with three strain gauge sensors mounted in lifters at different locations along the shell of a primary AG mill. One was mounted at the feed, one in the middle and one at the discharge end, c.f. Figure 3.3. The system used for transmitting the data is slightly different from the one described earlier. Instead of using a modulated HF-signal, the Boliden system has a radio modem with a baudrate of 4800 kBit/s. For each revolution the signal shape from the previous revolution is sent by a radio modem to the receiver beside the mill. From the radio modem, data is transmitted with short distance modems to a computer in the control room where it is received by the serial port. Since only one signal, i.e. from one analog input channel, can be transmitted at a time for one mill the system scans the three input channels consecutively. Each signal is sampled with 125 Hz for 246 degrees of the total revolution. With a mill speed of 12.8 rpm this corresponds to 400 measurements each revolution. A LabView™ application filters the signal and calculates the toe-angle of the grinding charge. Observe, that here is the toe-angle defined as the angle between a vertical line and the point where the lifter hits the charge, c.f. right part of Figure 3.5 (Chapter 3.2). A higher value corresponds to either a higher mill filling or a charge that is more horizontally positioned due to mill speed, slurry rheology etc.

This part of the work had a focus on studying the ability of the sensor to detect how changes in operating conditions and variables influence the grinding charge, this with respect to both position and filling level of the charge. The changes were aimed to be within what could be seen as a normal operating range during production. The final goal with these experiments was to find out if the charge measurement could be used in a control strategy where throughput is maximized. A number of different step changes were made, summarized in Table 4.2.
Table 4.2: Step changes made at the Boliden Aitik plant.

<table>
<thead>
<tr>
<th>Exp. nr</th>
<th>Operating condition/variable changed</th>
<th>Water addition</th>
<th>Ore type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Feed</td>
<td>400 [t/h]</td>
<td>60 [wt-% solid] Coarse ⇒ Fine</td>
</tr>
<tr>
<td>2</td>
<td>Feed</td>
<td>600 [t/h]</td>
<td>60 [wt-% solid] Normal</td>
</tr>
</tbody>
</table>

Changing feeders under the stockpile made it possible to use the natural segregation in the stockpile to achieve the aim of change in the feed ore fragmentation. During the experiment the ore feed was kept constant at a level of 400 ton/h and the percent solids in the mill at 60 %. The feeders were controlled so that a change in fragmentation from fine to coarse and back to fine was achieved. The fragmentation was indirectly measured using a laser beam to get the object distance and use the value as an indication of the feed size. Photographs of the ore were taken as well, c.f. Figure 4.7. Strain gauge signals and process variables were logged during the whole experiment.

Figure 4.7: Photos and laser measurement showing typical size distributions for the test with coarse (left) and fine (right) ore feed.

4.4 Wavelet transformation

In monitoring of process data, and especially where data from multi-sensor system are available, the frequency of collected data sometimes might reach levels of several thousands every minute. This issue has become critical in many aspects, such as historical data storage capability, speed of computation in on-line applications, and ease of data analysis and interpretation. It is in this context a rapidly emerging technique – the wavelet transform, becomes interesting. Wavelet transformation is a linear transformation, similar to the Fourier transform and its trademarks are good compression and de-noising of complicated signals (Graps, 1995). Important in process monitoring is to preserve the unique features in the original signal also in the compressed one, this is an area where the wavelet technique is superior (Dai et.al., 1994). Wavelets look like small oscillating waves, c.f. Figure 4.8, and they have the ability to analyse a signal according to scale, i.e. inverse frequency. The size of the analysing window in wavelet transform varies with different scales, this together with the property that wavelet functions are local in both time and frequency makes the wavelet transform so useful (Misiti et.al., 1996).
4.4.1 Analysis of process signal features

Signal features, especially the temporal signal features of the process measurements usually carry the most important information of the underlying process behaviours. One of the approaches to understand these behaviours is to analyse the output signal from the sensor directly (Dai et al., 1994). Traditional practice is to do the analysis in the time domain, or apply the Fourier transform to look at the spectrum of the signal in the frequency domain. For a non-stationary signal however, it is better to study the signal features in the two-dimensional time-frequency domain. During the last 10-15 years, wavelet theory, including wavelet transform and its extension wavelet packets theory, provides a new time-frequency signal analysis method. A brief description of the wavelet transform is given below, the interested reader is referred to (Graps, 1995).

The wavelet transform decomposes the signal by projecting it onto pieces of scaled and shifted versions of a so-called mother wavelet. The effect of the shifting and scaling process is the representation of a signal at multiple scales, called multiresolution analysis (Misiti et al., 1996), c.f. Figure 4.8. If the interest is to study high frequency components in the signal a compact version of the wavelet function is used, which appears in the low scale levels. However, interest of low frequency components a more stretched wavelet function is used, which appears at higher scale levels. The discrete wavelet transform and its associated wavelet functions are defined in equation (1) and (2):

\[
\langle f(t) \Psi_{m,n}(t) \rangle = \int_{-\infty}^{\infty} f(t) \Psi_{m,n}(t) \, dt \quad (4-1)
\]

\[
\Psi_{m,n}(t) = 2^{-m/2} \psi(2^{-m} t-n) \quad (4-2)
\]

Where \(f(t)\) is the signal, \(\Psi_{m,n}(t)\) is the wavelet function, \(m\) is the scale and \(n\) is the shift in time and \(\psi\) is the mother wavelet.

In this work, the fast wavelet transform multiresolution analysis (MRA) has been used as a pre-processing method in regression modelling on the sensor signal data [Paper II]. The method used for this is the Mallat Pyramid algorithm (Misiti et al., 1996). Figure 4.9 shows an example of a wavelet transformation, at level 3, of a measurement corresponding to an average mill revolution. The Mallat Pyramid algorithm uses two filters: a low-pass filter (LPF), and a high-pass filter (HPF). The output from the LPF, the approximation is further processed through a new HPF and LPF. This continues until only a wavelet coefficient and the average value of the signal is left. These wavelet coefficients represent both approximations and details from the signal. The wavelet transformation
itself does not produce a compressed version of the original signal. Compression is achieved by eliminating the wavelet coefficients that do not hold valuable information.

![Wavelet decomposition tree](image)

**Figure 4.9:** The wavelet decomposition tree, level 3, according to the Mallat pyramid algorithm. Multiresolution analysis results in a coefficient vector \((cA_j, cD_j, cD_{j-1}, \ldots, cD_1)\) of the same size as the analysed signal.

For regression purposes, we are interested in keeping the systematic information in the data intact, and therefore, the variance spectrum of the data set is a reasonable answer to what coefficients to choose (Trygg et al., 1998). The question of how many coefficients to choose is more difficult to answer. Normally the size of the coefficients, a certain threshold value, is used for this decision. Another practical problem is the selection of an appropriate type of wavelet function. There are different types of wavelet functions that can be applied. Criteria such as orthonormality, regularity, compact support and number of vanishing moments are of importance (Trygg et al., 2001). In the present work the Daubechies wavelet function is chosen mainly because of its overall good properties and capability to capture smooth low-frequency features. Also the computational efficiency is good for the Daubechies wavelets and is of great importance in on-line applications.
4.4.2 Wavelet-PLS regression modelling

The MRA method requires a signal that is of length $2^n$, the dyadic length, where $n$ is an integer. In this work [Paper II], so-called zero-padding is used, no edge effects are assumed to be introduced since the signal is zero outside the original range. The lifter bar is most likely relaxed in the area leaving the charge (position 9) and hit of charge (position 1), c.f. Figure 3.4, which make zero-padding adequate in this application. Based on the characteristics, combination of sharp positive rise and a smooth ending transient of the strain-gauge signal, Daubechies wavelet db4 was selected as the basis of the wavelet transform. Further reason for this selection is to get a simple wavelet function and thereby reduce the number of calculations, which can be of importance in on-line applications.

The next step after applying the wavelet transform as pre-processing is to perform the PLS regression. Figure 4.10 shows the different steps involved in the procedure. Since the focus is monitoring, and PLS is the tool used to analyze the data and for prediction, wavelet coefficients with high variance are selected. The number of selected coefficients is dependent on the problem. This criterion is called variance selection. The PLS model is therefore built on the assumption that selected wavelet coefficients are those ones carrying most of the information about the grinding process.

![Diagram](image)

Figure 4.10: Overview of the different steps taken in the data compression and regression analysis.

4.5 Distinct Element Method

Distinct Element Method (DEM) is a numerical technique developed for granular flow simulation. Unlike continuous numerical approaches such as Finite Element method, Finite Volume method, DEM does not involve the integration of the equation of motion of continuum medium. Instead, the progress in time of every particle in the simulated system is followed by integration the equations of motion of each entity. In this approach, virtually everything is known about every particle in the system at every moment of the simulation. The continuous parameters (particle density, average particle velocity etc.) are obtained by spatial and temporal averaging of the parameters of the motion of DEM particles.

The first paper dealing with DEM was by Cundall (1971) for the analysis of rock mechanics problems and then applied in the area of grinding by Mishra and Rajamani (1992). A thorough description of the method is given in the two-part paper of Cundall (1988) and Hart et al. (1988).

There exist two possible approaches in DEM: a so-called “hard particle” approach and a “soft” particle approach (Campbell, 1997). In the “hard particle” approach the particle contacts are considered to be infinitely rigid, and collisions of the particles are considered to be instantaneous.
The alternative and most widely used approach are the “soft particle” technique. In this type of DEM technique the particle contacts have finite stiffness, and collisions are not considered to be instantaneous. One of the most widely used contact-stiffness laws for simulating comminution devices is the linear viscous damping model for interaction between unbonded particles, the well-known spring-and-dashpot model, c.f. Figure 4.11. Here the collision is modelled by a pair of spring-and-dashpot, one in the normal direction and one in the tangential direction. The actual deformation of a particle that is the result of the particle collision in real life is normally not simulated here. Instead, the particles are allowed to overlap slightly, and a contact force is generated depending on the parameters (distance, approach velocity etc.) of this overlap. This type of numerical model normally has a fixed time step that is determined by the stiffness of the particle contacts and particle mass. Since one has to have at least ten time steps per particle collision, this time step is usually very small even with artificial softening of the contacts used by most DEM simulators. This type of simulation can be inefficient compared to the “hard particle” technique for the low solid fraction particle systems, but this is the only real disadvantage of this approach. The “soft particle” technique is more efficient than the “hard particle” approach for all practical values of solid fractions. Also, one can simulate nearly static and completely static situations with this approach, and non-round particle shapes can be used. All these positive features have led to widespread adoption of “soft particle” DEM.

![Figure 4.11: Schematic representation of the spring-and-dashpot model in the normal and tangential (shear) direction.](image)

The calculation cycle of the “soft particle” DEM simulation is presented in Figure 4.12. The calculation cycle is a time stepping algorithm that requires the repeated application of the law of motion to each particle and a force-displacement law to each contact as well as a constant updating of wall positions. Contacts, which may exist between two balls or between a ball and a wall, are formed and broken automatically during the course of a simulation. At the start of each time step, the set of contacts is updated from the known particle and wall positions. The force-displacement law is then applied to each contact to update the contact forces based on the relative motion between the two entities at the contact and the contact constitutive model. Next, the law of motion is applied to each particle to update its velocity and position based on the resultant force and moment arising from the contact forces and any body force acting on the particle. Also, the wall positions are updated based on the specified wall velocities.
Because most practical applications of DEM for comminution involve a large number of particles and small time steps, the simulation times are long and the amount of data generated is very large. The most advanced three-dimensional DEM simulation involving some 1,000,000 particles in a full-scale mill takes about three weeks on a multi-processor machine. In this work two-dimensional DEM is performed with a substantially smaller amount of particles, about 25,000, resulting in more reasonable simulation times. The 2D approach is also believed to be appropriate enough for the objective in this work, comparison of experimental mill lifter deflection measurements with DEM predictions [Paper V].

In this thesis the DEM simulation of a rotary grinding mill is done with the software Particle Flow Code in 2D (PFC\textsuperscript{2D}) developed by Itasca (2002). PFC\textsuperscript{2D} provides a particle-flow model containing the following assumptions.

- The particles are treated as rigid bodies.
- The contacts occur over a vanishingly small area (i.e. at a point)
- Behaviour at the contacts uses a “soft particle” approach wherein the rigid particles are allowed to overlap one another at contact points.
- The magnitude of the overlap is related to the contact force via the force-displacement law, and all overlaps are small in relation to particle sizes.
- All particles are circular.

4.5.1 Implementation of a flexible lifter

In “classical” DEM simulation forces acting on a wall do not influence its motion. Instead, its motion is specified by the user and remains constant regardless of the contact forces acting upon it. The approach taken in this work is to model one of the lifters in the mill as a flexible lifter with the aim of simulating the behaviour of a real rubber lifter.

The mill itself was modelled by a combination of walls and particles as shown in Figure 4.13. There are two ways of representing a mill with walls in PFC\textsuperscript{2D}: through the basic wall logic, which allows the user to specify and connect multiple line segments into a circular shape, or the general wall logic, which allows the user to define a circle directly. Because the lifters in the pilot ball mill are attached to the inner steel wall, the inner rubber liner is not continuous. As a result, the inner steel wall of the mill was represented with a circular general wall while the inner rubber liner was represented with multiple basic wall segments.
Walls within \textit{PFC}^{2D} act as rigid boundaries so it was necessary to represent the instrumented rubber lifter with bonded particles rather than walls in order to simulate deflection. The remaining lifters were represented with basic wall segments. For the instrumented lifter, a regular assembly of small sized particles in the shape of the lifter was generated at the lifter position and bonded using the parallel bond logic within \textit{PFC}^{2D}. Parallel bonds reproduce the effect of additional material (e.g., cementation) deposited after the balls are in contact and provide for moment, normal and shear resistance at the particle-particle contacts.

Particles at the base of the lifter were fixed relative to one another to represent the rigid base within the actual lifter, as shown in Figure 4.14. The particles representing the rubber part of the lifter were bonded to this rigid base of particles. The deflection of the lifter was tracked by monitoring the positions of two particles at the locations nearest the true base and tip of the lifter. The deflection was calculated by considering the deviation of a line connecting the base and tip particle from a radian passing through the base particle.

Normal and shear stiffness values are assigned to particles rather than contacts within \textit{PFC}^{2D} so that contact behaviour may be derived from the properties of the particular particles comprising it. Two different stiffness models are available in \textit{PFC}^{2D}: a linear model and a simplified Hertz-
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Mindlin model. In the linear model, the forces and relative displacements are linearly related by the constant contact stiffness, which is a function of the intrinsic stiffness of the two contacting entities. In the simplified Hertz-Mindlin model, the forces and relative displacements are nonlinearly related by the non-constant contact stiffness, which is a function of the geometric and material properties of the two contacting entities as well as the current value of the normal force. Work by Cleary (2001) suggests that the linear contact model is appropriate over the range of normal forces typically experienced within a mill and so this model was adopted for the current simulations. In addition, the ratio of normal to shear stiffness was set to 3/2 as proposed by Rajamani et al. (2000).

For the linear contact model, the resulting contact stiffness, $k'$, between two charge particles can be computed assuming that the stiffness of the two contacting particles, $k_A$ and $k_B$, act in series such that

$$ k' = \frac{k_A k_B}{k_A + k_B} $$

(4-3)

The stiffness of the bonds comprising the lifter (input directly by the user) and the contact stiffness (derived from Eq.4-3) act in parallel to control the deformability of the lifter. The results of deflection tests performed on the instrumented lifter in the laboratory were used to calibrate both the particle and bond stiffness by simulating the test in PFC$^{2D}$ and comparing the predicted response to the force-displacement histories [Paper V]. The actual test was performed over a 300mm section of lifter. Since the simulated test would represent deflection of a 1.2-meter long section, the target lifter stiffness for the simulated test was set to four times the actual measured stiffness. It is possible that there is a non-linear relation between lifter stiffness and test length, in which case this assumption may not be valid. The nature of this relation should be examined in future experiments to test the validity of this assumption when representing the mill in two dimensions. The calibrated force displacement relation obtained from the simulated tangential force test is plotted in Figure 4.14 along with the deformed state of the lifter at a displacement of ~ 4mm. The particle and bond stiffness obtained from the calibration is then used as input parameters in the DEM model.

The stiffness of the rubber walls within the simulation (representing the remaining lifters and the rubber liner) were set to achieve the same contact stiffness as the bonded contacts within the particle-based lifter. This is calculated as the sum of the parallel bond stiffness and the contact stiffness provided by Eq.4-3 (since the two stiffnesses act in parallel). Substituting the stiffness of the parallel bonded contact back into Eq.4-3, one can obtain the desired wall stiffness.
5 RESULTS

Only a brief summary of the results is given below. Further results and more comprehensive discussions are given in Papers I to V.

5.1 Effect of operating conditions

A summary of results, expressed as charge positions, from the first experimental campaign performed on the pilot ball mill is presented in Table 5.1. The numbers are average values and standard deviations obtained for each run during the 10 minutes sampling.

Table 5.1. Average and standard deviation, for charge/toe and shoulder angle (CCM) from experimental campaign 1.

<table>
<thead>
<tr>
<th>Exp.</th>
<th>Filling (%)</th>
<th>Mill speed (% n_{critical})</th>
<th>%-solid (%)</th>
<th>Charge angle (degrees)</th>
<th>Toe angle (degrees)</th>
<th>Shoulder angle (degrees)</th>
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</table>

5.1.1 Effect of mill speed

The effect of mill speed was studied on the pilot ball mill. The strain gauge sensor is fitted in such a way that the compression or normal forces perpendicular to the shell are not “observed.” Only the tangential or shear forces parallel to the shell act to deflect the lifter sensor. The tangential force acting on a ball is given by the conceptual Eq. 5-1, (Cleary, 1998). Here μ is a friction coefficient, k, a spring constant and C, a damping constant. When the speed of the mill is increased

\[ F_t = \min\{ \mu F_n, k \int v_t \, dt + C v_t \} \]  \hspace{1cm} (5-1)

the tangential velocity \( v_t \), in this case the angular speed, increases and correspondingly the tangential force \( F_t \). This is also very well reflected in the measurement signal, cf. Figure 5.1. Change in load position also compare adequately with DEM simulations.
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Figure 5.1: Typical signal profiles obtained at different operating conditions of mill speed and charge filling level, measured (solid), DEM predicted (dotted).

The simulation shows a more cataracting charge when mill speed is high and also that the toe moves slightly lower (larger angle), cf. Figure 5.2. Calculated toe angle also shows a statistically significant change, approx. 4 degrees. A low frequency surging, when the charge during a few revolutions climbs the inside of the shell and then looses its grip, that has been reported in some papers (Agrawala, 1997 and Vermeulen et al., 1986) is not visible in our measurements. However, there is some repetitive phenomena in the signal, c.f. Figure 5.2, but it is hard to say if this is a surging phenomena or some noise in the measurement. Toe/shoulder as well as charge angle moves in tandem, c.f. Table 5.1, with respect to change in mill speed, which must be taken as a clear indication of the charge position.

Figure 5.2. Toe angle variations with respect to mill speed, 2D DEM simulations.
5.1.2 Effect of mill load

The effect of mill load was studied on both the pilot ball mill and the full scale ball mill. Figure 5.3 provides an example of the strain gauge signal for three different ball charge load. The profile of the signal shows a significant change. Toe and shoulder positions are clearly identified in all three cases, c.f. Table 5.1. Measurements are also in good agreement with 2D DEM simulations. It is obvious that the dynamic load orientation is well determined by the signal, but of interest is, if the signal carries more information. A closer look at the middle part, or the plateau, of the signal shows a significant change between the different experiments. However, they have one common feature, namely the periodic oscillation which is more pronounced at higher fillings. The frequency of the oscillation correlate almost perfectly to the distance between the lifter bars.

![Figure 5.3: Strain gauge sensor response to varying mill fillings and correspondingly 2D DEM simulations.](image)

This kind of high frequency oscillation has been reported in a number of works (Vermeulen et al., 1988). Koivistonen et al. (1992) measured the mill power during each revolution and found oscillations in the curve. He pointed out that each power peak correlated in time with the lifter bar hitting the charge. Van Nierop et al., (2001) came to the same result using conductivity probes, one of their conclusions were that the oscillation was due to the cataracting load hitting the mill shell. That in turn influences the power draw. From current experiments, a reasonable explanation could be the following. As described earlier this sensor responds to forces acting on the lifter bar and thereby causing a deflection that imply that the force on the lifter varies during its passage in the charge. When the lifter bar next to the sensor lifter bar hits the charge it causes a kind of a shock wave that transfers through the charge and influences the sensor. This action will happen for the next 2-3 lifter bars, for each subsequent lifter bar the distance to travel for the shock wave will be longer and consequently the shock wave will fade-out.

Charge level has the largest effect on calculated angles, it is also statistically significant on both toe and shoulder angle with an effect of almost 10 degrees between low and high charge level, c.f. Figure 5.4. This is an expected result, however, it emphasize the sensors capability to reflect this.
5.1.3 Effect of mill throughput

The effect of feed rate was primarily studied in the industrial AG mill were the main purpose was to investigate the dynamic influence of changes in ore feed rate on the grinding charge. The feed was changed in a number of steps between 300 ton/h and 600 ton/h. Percent solids were kept at 60 %.

The experiment started with a feed of ~ 420 t/h and a power draw of ~5.2 MW. The first change was a decrease of feed to ~300 t/h, c.f. Figure 5.5. This change caused the power to drop slowly, which is also true for the toe-angle. The sensor signal exhibit the lowest amplitude for this low feed, it also shows that it takes somewhat longer time before the lifter hits the charge. Both signal features are typical indications that the volume of the charge has shrunk. Next change was an increase of the feed to ~ 450 t/h. It resulted in a slow response on mill power but a much faster change in toe-angle, both of them increasing and by that displaying a higher mill filling. The corresponding change in the strain gauge signal consists of an increase in amplitude mainly oriented at the shoulder part and a distinct change in time when the lifter bar to hits the charge. The final increase in feed up to ~ 600 t/h causes the power to increase to a level of ~ 4.8 MW where it seems to level out and with a tendency to start decreasing. The toe-angle on the other hand continues to rise until the lifter hits the charge constitutes the main difference in the sensor signal, amplitude however, is in the same range as for the feed of ~ 450 t/h, even somewhat lower.

The result in Figure 5.5 shows that the toe-angle respond faster compared to the power measurement when feed rate is increased. The response time for toe-angle appears to be around 15 min. which also correspond well with the likely residence time for this AG-mill. However, when decreasing the ore feed rate both measurements respond almost in the same way with a long response time indicating the time needed to grind out the charge. Changes made in ore feed rate, especially increase, seem to have been done before the mill reached steady state. Anyhow, the obtained result shows that the strain-gauge sensor responds fast and accurately and thereby is a more appropriate signal for process control purposes.
Figure 5.5: Strain gauge signal profiles for the middle sensor (left), power and toe angle at different ore feed levels (right).

Figure 5.6 shows a typical response from each strain-gauge sensor when the ore feed rate is changed. Here a change in toe-angle is clearly distinguishable and the same signal pattern is received for all sensors, i.e. increase of toe-angle when the ore feed is high. However, the sensors along the mill respond differently regarding amplitude, the sensor in mid and discharge end of the mill shows a modest change in amplitude. Once again indicating what can be understood as various mixing in the mill axial direction.

Feed rate changes was also performed in the pilot ball mill with main purpose of stressing the mill to its limit and create a situation where slurry pooling occur. No significant effect on toe and shoulder angle was obtained however, grinding performance was significantly influenced which is well expected. The result is underlining the fact that a ball charge is quite stable in position.

5.2 Effect of feed particle size and slurry properties

Result from the second experimental campaign performed on the pilot ball mill is presented in Table 5.2. The data table includes in addition to charge position/volume also grinding performance data. In this test campaign the aim was twofold, i) the sensor’s ability to follow changes in slurry properties ii) model strain gauge data for the prediction of grinding performance.
Table 5.2: Experimental design and obtained results from second experimental campaign.

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</tbody>
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5.2.1 Effect of feed particle size

The purpose of these experiments performed on the AG-mill was to investigate the dynamic influence of changes in ore fragmentation on the behavior of the grinding charge. The experiment started with a coarser ore feed, immediately the mill power began to increase at an almost constant rate, c.f. Figure 5.7. Calculated toe-angle was approximately 57° for the whole time period with the coarser feed. The change of feeders gave a direct response on the power measurement, which now continuously dropped with a finer ore feed. The calculated toe-angle also responded very fast, increased to approximately 61° and after further 10 minutes settled at 59°.

![Figure 5.7: Power measurement and calculated toe-angle at different ore size distributions in the ore feed.](image)

A closer look at the CCM signal for the different sensors, c.f. Figure 5.8, reveals differences in the signal profile between coarser and finer ore feed. A deviation in the amplitude is shown quite clearly, whereas difference in the toe region is hardly visible, however calculated toe-angle, by derivation, shows a small but significant difference of approximately 2°, c.f. Figure 5.7.

Interestingly however, is that all sensors show the same change of signal profile, which confirm the sensor capability to detect charge variations. A somewhat more pronounced change of amplitude is shown for the sensor at the discharge end. This could be an indication of a situation where coarser material dams up the flow through the mill. Another interpretation is that coarser feed
takes longer time to grind, and so fills up more at the discharge end compared to a situation with a finer feed.

When changing to a finer ore feed, the power draw of the mill dropped, and the calculated toe-angle increased. By just looking at one or the other of these two measurements it is hard to estimate the effect on the grinding charge. But the combination of them points to a decrease in charge filling and at the same time a change of the angle of repose. This change of angle of repose is most likely caused by a change in slurry viscosity when the amount of fines in the feed increase. In a survey study by Shi et al. (2002) they showed that the amount of fines in the feed influence slurry viscosity and this in turn has a significant effect on grinding performance, positively or negatively depending on the rheology nature of the charge.

Interpretation of the measured signals for coarse feed end up in a probable increase of the filling level and that the expansion of the charge is towards the shoulder region. Supporting this conclusion is, i) mill power is continuously increasing, ii) CCM signal profile shows a time shift mainly oriented to the shoulder region of the charge, iii) no obvious change of toe-angle during time period with a course feed.

5.2.2 Effect of %-solid

There is hardly any visible difference in the sensor signal profile for the levels of %-solid chosen in these experiments performed on the pilot ball mill, cf. Figure 5.8. However, a statistical analysis on the calculated angles gives a statistically significant effect on both toe and shoulder angle. This is a promising result since it shows that the strain gauge sensor is capable of detecting minor variation in charge position.

Figure 5.9. Calculated toe and charge angle as a function of percent solid, upper and lower 95 % confidence limits.
5.2.3 Effect of change in slurry flow properties (viscosity)

Figure 5.10 shows a typical response of the strain gauge sensor for low, 31 vol-\%, and high, 41 vol-\%, solids content and also the change that occurs when a dispersant is added to the pilot ball mill slurry. The signal profile differs significantly for the two solids contents. The main difference constitutes of a wider signal profile for high solids content indicating a larger Charge volume ($J_T$) even though slurry flow through the mill is lower. This can be an indication of increased slurry flow resistance in the mill when solids content gets high.

![Figure 5.10: Typical strain gauge signal response for different slurry conditions.](image)

Running the mill at low solids content, the difference in signal response with respect to dispersant is hardly visually detectable, only a minor decrease of Shoulder angle ($S_D$) is shown. Obviously for low solids content the strain gauge sensor doesn’t show any change in the position of the charge when a dispersant is added despite the significant change in the apparent viscosity obtained. Whereas at high solids content the signal response, with dispersant added, shows both a lower amplitude of deflection and also a significant change of the charge Shoulder angle ($S_D$) region indicating a contracting charge. The results obtained are also in good agreement with a study by Fuerstenau et al. (1990), where they found an effect of charge split between cascading and cataracting regimes when a dispersant aid is added to a dense slurry.

An interaction plot for the grinding performance variables $W_{\text{app}}$ and $G_i$, and the slurry flow resistance expressed as $K_{\text{app}}$ is shown in Figure 5.11. High solids content slightly increase the grinding performance, i.e., lower $W_{\text{app}}$ and higher $G_i$. Whereas the addition of a dispersant give a negative effect on the grinding performance especially when running at low solids content. The effect of a dispersant aid is well reflected in the viscometric measurement, giving a higher $K_{\text{app}}$ in the absence of a dispersant.

![Figure 5.11: Interaction plots for Solids and Dispersant on responses $W_{\text{app}}$, $G_i$, and $K_{\text{app}}$.](image)
6 CONCLUSIONS

This thesis is a contribution to the improvement of methods for continuous monitoring of tumbling mills. A promising method for mill charge measurement has been studied, a strain gauge installed in a rubber lifter bar inside a rotating mill. The sensor in combination with modelling techniques has shown to be capable of establishing the charge position within the mill and bring increased knowledge of charge movement and its influence on grinding performance.

The sensor was found to be sensitive to changes in mill operating conditions in a physically reasonable manner. Data shows that the volumetric mill filling level and charge angles can be predicted with an accuracy better than +/- 1%. It also seems that the sensors do not suffer from any tendency to drift or quickly wear out. Experimental work has demonstrated that the signal pattern generated by the strain gauge sensor varies in a consistent way with changing operating conditions. Detection of charge features has shown good reproducibility independent of type of grinding, AG- or ball mill. The signal profiles obtained for ball mills, independent of mill size, are very much the same. However, amplitude differences are more pronounced in a large ball mill, probably due to higher loads influencing the lifter deflection.

In addition, the signal profile is also demonstrated to contain information of the grinding performance. The work has shown that statistical multivariate regression modelling (PLS) is very useful in modelling the relation between signal profile and grinding parameters. Grinding parameters that are normally measured in the laboratory are readily modelled from the on-line signal. Experience gained from the experiments underscore the importance of signal pre-processing, e.g. signal filtering, feature extraction and signal compression using wavelet analysis, before regressing the signal to grinding performance. The modelling shows that the used wavelet transformation reduces the number of variables considerably. A data set consisting of only 5 % of the original data result in a PLS regression model with almost the same statistical performance. Wavelet transformation of the original strain gauge signal has also clarified the importance of the position of the grinding charge or more correctly how an operating condition implicate the charge movement. The experimental result shows that it is particularly the toe position of the charge that is important to detect since it has a strong correlation with operating performance.

Slurry rheology has been recognised for decades to play an important role in wet grinding, however there are a number of difficulties associated with the measurement of slurry rheological properties. The measurements in this work clearly reveal that an embedded lifter bar sensor is able to pick up flow resistance changes in an operating mill. Signal features influenced by the changed operating conditions were the toe and shoulder angle, where the shoulder angle showed more distinct changes than the toe angle. The resistance to flow here expressed as an apparent viscosity is strongly influenced by solids content and naturally by the addition of a dispersant. Obtained viscometric results clearly show that the slurry flow resistance is changed between the experimental runs. The observed changes in impact force on the lifter bar can mainly be related to the product slurry, because the influence of the load of the charge should not vary much during the various operating conditions investigated here. Independent on the exact location of the slurry at the sensor mill section, the increased load results show how high solids concentrations increased the volume of slurry in the mill which in turn can be related to increased resistance to flow. The corresponding increase in retention time here may also have contributed to increased production of fine material, as shown in a higher grindability index. On the contrary, addition of a dispersant at high solids content showed a lower sensor loading, indicating less resistance to flow, slurry volume and less retention time and thus a decreased grinding performance.

In the AG-mill application a system with 3 sensors mounted at different axial positions (inlet, mid, outlet) along the mill was used. The response in amplitude for these three sensors were quite different, this presumably because of the kind of lifter configuration used in the AG-mill. The lifter configuration was of a high/high type at feed/discharge end, whereas the rows in the middle part of
the mill were of a high/low configuration with the sensor installed in one high lifter. The high/low configuration gives a wider void between the lifters, which filled with grinding charge results in a higher pressure on the lifter and thereby a bigger deflection of it. An implication of the high/high configuration is a probable reduction in mill volume. Furthermore, the grinding work in this section of the mill is also most likely cut back due to a charge that is immobilised between the high lifters. Of course there is a trade-off between having a longer lining lifetime with high lifters compared to the reduced mill volume, and it has to be economically justified. Different charge behavior was identified along the mill when operating conditions were changed, with the most systematic variation at the discharge end. The result indicates that the charge filling along the axial direction of the mill is different, actual variations are more pronounced in a small part at the discharge end of the mill.

To model the charge movement in a physically correct way and compare it to measured data, distinct element modelling (DEM) methods were used. In typical DEM mill modelling, mill walls and lifters are represented as rigid bodies that do not deform during collisions. Here, an attempt is made to improve on the lifter description by the modelling of one bar as a flexible body. A novel method implemented in the DEM model is developed where the instrumented rubber lifter in the pilot mill is represented as a lifter made of an assemblage of parallel bonded particles. Assessment of the predicted deflection profile to experimental data allows us to understand the accuracy of various types of DEM models and the penalties associated with the various assumptions made by these models. An exact match between predicted and measured lifter deflection is difficult to obtain due to simplified assumptions in both the description of the flexible lifter and also in the two-dimensional DEM approach used. However, effects of mill speed as well as charge filling level are well reflected in the simulations and are comparable with pilot mill measurements.

The implemented novel method is an introductory approach and comparisons between real and predicted deflections are on a qualitative basis. The outcome of this part of the work shows a potential to be of use in lifter profile design where flexible material is present. As a consequence the effect on grinding performance can be assessed in a consistent and meaningful manner due to the direct relation to experimental data, obtained by the strain gauge sensor.

The strain-gauge sensor system has shown features such as reproducibility, reliability and fast response time to varied process conditions. Such a system will provide detailed information on the dynamics and grinding characteristics of the charge and detect when the grinding is not performing well. The presented results imply that there are definite possibilities for on-line control and monitoring of a tumbling mill based on the information contained in the strain gauge sensor data.
7 FUTURE WORK

The next step would be to implement the technology for control and optimisation of an AG-mill circuit for iron ore processing. This includes further development in reduced power consumption for the sensor, telemetry system (wireless sensor) and data pre-treatment methods for signal processing as well as data compression.

To reach better accuracy in DEM predictions and enable quantitative comparison to measured data some necessary improvements have been identified. This includes investigation of lifter relaxation in the laboratory, simulation of time-dependent behaviour in the lifter and an extension of the approach to a three-dimensional DEM mill model.
8 ACKNOWLEDGEMENTS

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Gällivare, April 2005
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Continuous monitoring of a tumbling mill

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CONTINUOUS MONITORING OF A TUMBLING MILL

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ABSTRACT

Grinding is one of the most energy consuming unit operations and is also a very inefficient and costly process. Therefore, it is of great importance to run the grinding process as efficiently as possible. The most common way today to control grinding processes is by measuring the power draw of the mill and try to keep it at a maximum level. However, some studies (Kawatra, 1989, Koivistoinen, 1989, Moys, 1989) have shown that this measurement doesn’t reflect everything that takes place inside a mill. Among other parameters like slurry rheology, temperature and charge behaviour, the volumetric filling of a grinding mill seems to have a large influence on the grinding efficiency (Herbst, 1988, Koivistoinen, 1992, Vermeulen, 1988). A problem in attempting to measure those parameters has been to get a sensor that is both robust and sensitive enough for continuous on-line measurement.

This paper presents a method for the measurement of the apparent filling level in a pilot ball mill equipped with the Metso CCM-system. In this technique a strain gauge sensor is mounted on a metal plate which, in turn, is placed under one of the rubber ribs used to lift the charge. In addition, a conductivity probe, the Boliden GMS, is mounted in another lifter bar with the purpose of comparing the two measurements. To visualise the behaviour of the charge aDEMmodelling technique is used.

The results indicate that the system is capable of following the normal variation that occurs in the mill. The signal also very well reflect changes in operating variables such as ball charge level, pulp density and rotational speed. By studying the nature and different features of the signal one can get a better understanding of milling circuit dynamics. Another feature of the technique is the possibility for an operator to continuously follow the grinding process and thereby run the process under optimal conditions.

Keywords: Grinding, Mill monitoring, Measuring techniques, Modelling, Computational methods

INTRODUCTION

Background

Grinding in tumbling mills are inefficient, much of the energy is wasted in impact, that do not break particles. Autogenous (AG) and semi-autogenous (SAG) mills often operate in an unstable state because of the difficulty to balance the rate of replenishment of large ore particles from the feed with the consumption in the charge. This has led to an increased interest in obtaining an accurate and direct measurement of mill load and the behaviour of the mill charge. Several parameters do significantly influence the effectiveness of the grinding operation, however, some of these parameters are either difficult or laborious to measure. Intermittent in-situ measurements of some of the parameters are most often prone to errors and there is often a long time-delay before the acquired data is fed to the control system. Also, an understanding of the charge motion within the mill is of importance in mill optimisation (Agrawala et al., 1997). Both the breakage of ore particles and the wear of liners/ball media are closely linked to the charge motion. Therefore, it is essential to develop a method that can provide a precise, as well as, real time information of the charge to the control system. This paper will present measurements from a pilot mill with a strain gauge sensor, CCM (Persson, 1994-1999) that directly responds to changes in mill load and charge behaviour.
**Previous work**

Work done in the past can be divided into two main categories of methods of load measurement; off-shell and on-shell, cf. Figure 1.

One method of the first category that has been used in many plants is to measure the bearing back-pressure on the mill’s feed and/or discharge end. It gives an idea of the weight of the charge and it can be correlated to the filling level. The great disadvantage is that the pressure is not stable, e.g., shifting temperature causes sensor drift. Moreover, since bearing pressure is related to overall mill weight, changes to the ball charge as well as the wear of the lining will affect the signal. As a consequence, it is hard to develop a robust calibration. Despite these problems, one can still make use of bearing pressure for SAG load control.

In an attempt to circumvent some of the problems associated with bearing pressure, load cells can be used under SAG mills. Proper installation is of great importance, ensuring that the sensors are located beneath all elements bearing weight, including pinions for example, to measure load when the mill is running.

Acoustics have been used in different kinds of setup; single microphones (Watson et al., 1985) correlated sound power with pulp viscosity, arrays of microphones (Jaspan et al., 1986) designed to detect changes in the position of the toe of the mill charge. Koivistoinen et al. (1989) used high frequency sampling of the power draw, and more specifically the amplitude of the power oscillations corresponding to each lifter passing through the pulp, to infer mill loading. In Chile, a CIMM device known as MONSAG also employs the power draw, and through a complex signal processing algorithm estimates torque, which can be correlated with volumetric filling.

The other category of measurements is those involving some device that is resident on the mill shell. These devices are not as well developed yet, largely because of electro-mechanical issues arising from the service demands. This approach certainly holds some appeal, since these systems are capable of inferring the nature of the load more directly. A well-known method (Moys, 1988, Vermeulen, 1988) is to measure the conductivity inside the mill with two probes that are mounted on a lifter. This method has shown some good results but a disadvantage has been the wear of the probes and also the drift that this wear causes. Berggren et al. (2000) has developed a system that is running at one of their operations deducing the toe and shoulder position of the load.

Acoustic or vibration sensitive devices such as ELAC from CIMM Chile provide a non-contact indication of where the toe and shoulder of the load are located. Using geometrical considerations, an estimate of the load is obtained. There is some current research (Pax, 2001) looking at a more sophisticated non-contact acoustical approach.

An approach that is more or less a category in itself is a technique utilizing a soft-sensor for load estimation. In most cases this involves the use of phenomenological models describing the mass balance around the mill, coupled with field measurements. Generally speaking, the more field measurements, the better the soft-sensor, and in such cases it can often be employed to infer more than load and the dynamic angle of repose, for example ore grindability could be estimated on-line.

Techniques that measure the force acting on the lifter or a lifter bolt (Herbst et al., 1988) when it hits the charge inside the mill have got an increased interest recently because of the ability to combine it with DEM modeling. PERI markets a unit called CVM - Continuous Volume Measurement, and this uses the relaxation in strain in an instrumented lifter washer or bolt to infer the normal forces on the lifter. These are negligible.

![Figure 1. Methods of load measurement](image-url)
unless the lifter is in the charge, making it possible to estimate the toe and shoulder positions. The current project uses a strain gauge mounted inside a rubber lifter (Metso CCM).

MEASUREMENT COMPONENTS OF THE SYSTEM

Strain gauge sensor system

The Continuous Charge Monitoring System (CCM) (Persson, 1994-1999) is a quite newly developed electronic measuring system. It is dedicated to continuous measurement of the charge volume and the angle of repose provided that the mill has a rubber or rubber-metal mill lining or that a sensor-equipped rubber lifter bar can be installed in a steel-lined mill. The CCM-system consists of the following basic components; sensor, power supply, signal transmission and signal processing and presentation.

As shown in Figure 2, the lifter bar (1) is equipped with a strain gauge sensor (2) that measures the bending of the lifter bar when it is in contact with the charge. The electrical signal from the sensor is amplified and converted to a HF-signal by the transmitter (3), which is bolted to the shell of the mill. The transmitter is supplied with electrical power from a generator (4) attached to the mill. The HF-signal is transmitted to the receiver (6) via the antenna (5). The receiver also has a trigger-pulse remote sensor, which is activated once every revolution by a metal trigger plate on the mill. The position of the lifter bar (sensor), trigger plate and receiver is very carefully established. The signal from the receiver is sent via an isolated line driver through a screened cable and a line receiver to the system computer (7) where the data are processed to present the charge level and angle of repose.

Principle of the CCM-system

A typical deflection profile of the sensor signal and a corresponding graphical representation of a simulation of a mill are shown in Figure 3. The numbers in Figure 3, indicate important dynamic events during the passage of the sensor-equipped lifter bar under the mill charge.

1. The sensor lifter bar (SL) is still in the air
2. The SL hits the surface of the slurry
3. The SL starts to get submerged in the slurry
4. The SL hits the ball charge and starts to get submerged in the charge (T4)
5. The SL starts to bend forward due to turbulence in the toe area
6. The SL grips the ball charge again
7. The SL is at peak bending
8. The SL has gradually decreased the bending and is at take-off position
9. The SL is leaving the ball charge and starts slowly rise to an upright position (T9)
Figure 3. CCM raw signal showing the bending of a rubber lifter during the passage of the charge.

Calculation of fractional filling $J$ and dynamic angle of repose $\alpha$ (radians) from a CCM system raw signal is quite straightforward since the change in force acting on the lifter relates to both $(J, \alpha)$ of the mill charge. A simple method for estimating those parameters is shown in equation (1) and (2), where $N$ is mill speed (rps) and $T$ is time (s) when lifter enter and leaves the charge.

$$J = (T_9 - T_4)N - (\sin 2\pi (T_9 - T_4)/2\pi)$$  \hspace{1cm} (1)

$$\alpha = \pi (T_9 + T_4)N - (\pi/2)$$  \hspace{1cm} (2)

The toe and shoulder angle can also be calculated from the CCM raw signal. One method is to look at the derivative of the signal and chose the position of $T_4$ as the toe angle and position $T_9$ as the shoulder angle. Metso CCM uses a proprietary algorithm to determine toe and shoulder angles as well as to estimate mill load volume. Reference for all angles are the horizontal plane (9 o’clock = 0°; 6 o’clock = 90°).

Conductivity probe

The Boliden GMS system consists of two electrodes, embedded in a rubber lifter, that measures the conductivity. Figure 4, shows the lifter bar with the two electrodes before assembly. The signal is amplified and transmitted to a computer via a radio modem. In the pilot mill installation, batteries are used for the power supply of the measurement system. However, a plant installation uses a more sophisticated system with a generator placed at the mill end. A typical signal response with the corresponding derivative of the signal, right side of Figure 4, shows the possibility to calculate toe/shoulder angle and fractional filling in the same manner as for the CCM signal.

Figure 4. Lifter bar with two electrodes, and a typical signal response with corresponding derivative.
EXPERIMENTAL SET-UP AND PROCEDURE

The pilot mill is 1.414 m in diameter and 1.22 m in length. It is a grate-discharge mill, equipped with 12 rubber lifters of square size 0.1 m, face angle 45 degrees. Steel balls in the size range 10-30 mm and density 8000 kg/m³, were used in the experiments. The test material, a hematite pellet feed with \(d_{50}\) around 45μm was chosen to get stable grinding conditions with respect to feedsize variations. Feedrate was kept constant at approx. 1.5 t/h. Charge behavior was monitored using both the strain gauge (CCM) and the conductivity sensor (GMS). Figure 5 shows a photo of the pilot mill and the experimental design used.

<table>
<thead>
<tr>
<th>Experimental design</th>
<th>Mill speed (\eta_{\text{crit}})</th>
<th>Charge level</th>
<th>%-solid</th>
<th>Feedrate tph</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>73 78</td>
<td>25 35</td>
<td>70 75</td>
<td>1.5</td>
</tr>
</tbody>
</table>

Figure 5. Pilot mill with the electronics bolted on mill shell, right part shows the experimental domain.

The experiment was ment as a first test of the equipment’s performance, and to study how the sensors responded to changes in some operating variables. To get an understanding of, and distinguish between correlation and causality, the experiments were performed according to a full factorial design with two levels, and in addition two replicates of the experiments at a centerpoint in the charge level setting. Twelve experiments were performed and the variables Ball Charge Level, Mill speed and %-solid were varied according to the table in Figure 5. For every experiment, data were sampled during approx. 10 min., after steady state was reached. At the end of each setting, the feed was stopped and only water was fed to the mill. The purpose of this action was to study the sensor response to a fast dynamic change inside the mill.

With the advent of computer software using DEM simulation codes (Cleary, 1998) it is possible to simulate and animate mass movement of several hundred thousands of balls. In this work the 2D MillSoft, a program developed by Rajamani and coworkers (Rajamani et al., 1990) is used to visualize the effects of the experimental setup.

RESULTS AND DISCUSSION

Variability

Results from this initial test, and experience to date, indicate that the characteristics of both signals vary consistently with mill operating conditions. The signals also show a surprisingly small variation when the mill is running at steady state. Figure 6, shows the average and standard deviation for the CCM raw signal,

![Figure 6. CCM raw signal, solid line = average and dotted line = one sigma, for 2 different settings.](image)

values are calculated from a sampling period of approx. 10 minutes corresponding to 250 revolutions. For monitoring purpose and to avoid noisy curves, it is recommended to study an average signal over a certain time period. Figure 7, shows the spread for the GMS signal, in this case it is ten curves superimposed where each curve represents an average of one minute corresponding to 25 revolutions.

Figure 7. GMS signal, ten curves (one minute average) superimposed.

Comparison of calculated toe and shoulder angles for the two types of sensors, are shown in Figure 8 and further point out the stability in the measurements. However, there are some artifacts for the GMS values, which probably can be handled by filtering techniques. The large differences in derived values can to some extent be explained by the measuring principle. The conductivity probe has to get submerged in the slurry before it gives any signal, therefore, the toe angle will be higher than in the case for the strain gauge. Correspondingly for the shoulder angle, the slurry sticks to the lifter and continues to give a signal after leaving the charge. This can be adjusted for in the algorithm for calculating those values.

Figure 8. Examples of toe and shoulder (minute averages) positions at two mass load conditions.

Table 1. Average and standard deviation, for charge/toe and shoulder angle (CCM) for all twelve experiments.

<table>
<thead>
<tr>
<th>Exp.</th>
<th>Filling (%)</th>
<th>Mill speed (%)</th>
<th>%solid (%)</th>
<th>Charge angle (degrees)</th>
<th>Toe angle (degrees)</th>
<th>Shoulder angle (degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Average α</td>
<td>Average β</td>
</tr>
<tr>
<td>1</td>
<td>25</td>
<td>73</td>
<td>70</td>
<td>45.4</td>
<td>0.5</td>
<td>68.8</td>
</tr>
<tr>
<td>2</td>
<td>25</td>
<td>73</td>
<td>77</td>
<td>44.4</td>
<td>0.4</td>
<td>68.2</td>
</tr>
<tr>
<td>3</td>
<td>25</td>
<td>78</td>
<td>77</td>
<td>48.5</td>
<td>0.5</td>
<td>72.5</td>
</tr>
<tr>
<td>4</td>
<td>25</td>
<td>78</td>
<td>70</td>
<td>47.9</td>
<td>0.4</td>
<td>72.4</td>
</tr>
<tr>
<td>5</td>
<td>35</td>
<td>78</td>
<td>71</td>
<td>47.3</td>
<td>0.3</td>
<td>61.5</td>
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<tr>
<td>6</td>
<td>35</td>
<td>78</td>
<td>76</td>
<td>47.6</td>
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<td>60.6</td>
</tr>
<tr>
<td>7</td>
<td>35</td>
<td>73</td>
<td>76</td>
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<td>0.6</td>
<td>56.6</td>
</tr>
<tr>
<td>8</td>
<td>35</td>
<td>73</td>
<td>71</td>
<td>43.2</td>
<td>0.5</td>
<td>57.3</td>
</tr>
<tr>
<td>9</td>
<td>28</td>
<td>73</td>
<td>70</td>
<td>43.8</td>
<td>0.8</td>
<td>65.5</td>
</tr>
<tr>
<td>10</td>
<td>28</td>
<td>73</td>
<td>75</td>
<td>43.6</td>
<td>0.8</td>
<td>64.1</td>
</tr>
<tr>
<td>11</td>
<td>28</td>
<td>78</td>
<td>75</td>
<td>48.3</td>
<td>0.9</td>
<td>68.9</td>
</tr>
<tr>
<td>12</td>
<td>28</td>
<td>78</td>
<td>70</td>
<td>47.6</td>
<td>0.8</td>
<td>69.4</td>
</tr>
</tbody>
</table>
**Effect of mill speed**

The strain gauge sensor is fitted in such a way that the compression or normal forces perpendicular to the shell are not “observed.” Only the tangential or shear forces parallel to the shell act to deflect the lifter sensor. The tangential force acting on a ball is given by the conceptual Equation 3, (Cleary, 1998). Here $\mu$ is a friction coefficient, $k_t$ a spring constant and $C_t$ a damping constant. When the speed of the mill is increased

$$F_t = \min\{ \mu F_n, \ k_t \int v_t \, dt + C_t v_t \}$$

(3)

the tangential velocity $v_t$, in this case the angular speed, increases and correspondingly the tangential force $F_t$. This is also very well reflected in the measurement signal, cf. Figure 9. Change in load position also compare well with simulated results. The simulation shows a more cataracting charge when mill speed is high and also that the toe moves slightly lower (larger angle), cf. Figure 10. Calculated toe angle also shows a statistically significant change, approx. 4 degrees. A low frequency surging, when the charge during a few revolutions climbs the inside of the shell and then loses its grip, that has been reported in some papers (Agrawala, 1997 and Vermeulen et al., 1986) is not visible in our measurements. However, there is some repetitive phenomena in the signal, cf. Figure 10, but it is hard to say if this is a surging phenomena or some noise in the measurement. Toe/shoulder as well as charge angle moves in tandem, cf. Table 1, with respect to change in mill speed, which must be taken as a clear indication of the charge position.

**Figure 9.** CCM measurements for low and high speed with corresponding Millsoft simulations.

**Figure 10.** Toe angle variations with respect to mill speed
Effect of charge level

Figure 11 provides an example of the strain gauge signal for three different ball charges. The profile of the signal shows a significant change. Toe and shoulder positions are clearly identified in all three cases, cf. Table 1. Measurements are also in good agreement with Millsoft simulations. It is obvious that the dynamic load orientation is well determined by the signal but it probably carries more information. A closer look at the mid part, or the plateau, of the signal shows a significant change between the different experiments. However, they have one common feature, namely the periodic oscillation which is more pronounced at higher fillings. The frequency of the oscillation correlate almost perfectly to the distance between the lifter bars.

This kind of high frequency oscillation has been reported in a number of works (Vermeulen et al., (1988). Koivistonen et al., (1992) measured the mill power during each revolution and found oscillations in the curve. He pointed out that each power peak correlated in time with the lifter bar hitting the charge. Van Nierop et al., (2001) came to the same result using conductivity probes, one of their conclusions were that the oscillation was due to the cataracting load hitting the mill shell. That in turn influences the power draw. From current experiments, a reasonable explanation could be the following. As described earlier this sensor responds to forces acting on the lifter bar and thereby causing a deflection that imply that the force on the lifter varies during its passage in the charge. When the lifter bar next to the sensor lifter bar hits the charge it causes a kind of a shock wave that transfers through the charge and influences the sensor. This action will happen for the next 2-3 lifter bars, for each subsequent lifter bar the distance to travel for the shock wave will be longer and consequently the shock wave will fade-out. The given interpretation will be further investigated in future work in this project.

Charge level has the largest effect on calculated angles, it is also statistically significant on both toe and shoulder angle with an effect of almost 10 degrees between low and high charge level, cf. Figure 12.

Figure 11. CCM signal response to varying mill fillings and correspondingly Millsoft simulations.

![Figure 11. CCM signal response to varying mill fillings and correspondingly Millsoft simulations.]

Figure 12. Calculated toe and charge angles as a function of charge level, upper and lower 95 % confidence limits.
Effect of % solid

There is hardly any visible difference in the sensor signal profile for the levels of % solid chosen in these experiments, cf. Figure 9. However, a statistical analysis on the calculated angles gives a statistically significant effect on both toe and shoulder angle. This is a promising result since it shows that the strain gauge sensor is capable of detecting minor variation in charge position. The other change, made to study the sensitivity of the sensor, was the action of stopping the ore feed and only feed water to the mill. The signal response is shown in Figure 14; the first peak is with normal feed, the second is after 10 minutes with water only. There is a clear difference in the signal profile which indicate the sensors ability to pick up changes in the slurry and not only to changes in mill speed and ball charge.

CONCLUSIONS

The experimental data from both the CCM- and GMS-system points to their capability to detect charge position changes within a pilot ball mill with relatively good precision. Experimental results also compare well with Millsoft simulations, which gives an indirect possibility to confirm media motion. The measurements have also shown that there seems to be an oscillation phenomenon that takes place during a mill revolution. Reasons for this are not quite clear but it seems to correlate with lifter bars hitting the charge.

The sensors were found to be sensitive to changes in mill operating conditions in a physically reasonable manner. Data shows that the volumetric mill filling level and charge angles can be predicted with an accuracy better than +/- 1%. It also seems that the sensors do not suffer from any tendency to drift or quickly wear out. Thereby they should have the possibility to be used in a monitoring system for continuously follow...
the grinding operation. Such a system will provide detailed information on the dynamics and grinding characteristics of the charge and detect when the grinding is not performing well.

Next phase in this project will emphasize on the development of essential elements in a monitoring system that can be suitable for the possible use as an on-line process-monitoring tool and to help the operator run the mill at optimal conditions.

ACKNOWLEDGEMENT

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REFERENCES


Monitoring of a tumbling mill using PLS-regression on a wavelet transformed strain-gauge signal

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Monitoring of a tumbling mill using PLS-regression on a wavelet transformed strain-gauge signal

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ABSTRACT

A strain gauge sensor that measure the deflection of a lifter bar when it hits the charge inside a tumbling mill is studied for different operating conditions in a pilot scale ball mill. The deflection of the lifter bar during every mill revolution gives rise to a characteristic signal profile that is shown to contain information on both the charge position and grinding performance. As a signal pre-processing method the discrete wavelet transform is used. It distinctly shows a capability of signal feature extraction where both time and frequency are of interest. Its well-known ability to achieve good data compression without loss of information is also demonstrated, here a data reduction ratio of 20:1 is obtained. The results presented for prediction of grinding performance suggest that the strain gauge signal in combination with wavelet transformation and multivariate data analysis provide a promising means for monitoring and control of process fluctuations. The low prediction error obtained for grinding performance clearly highlights the importance of well-planned experimental design, signal pre-processing, multivariate modelling and validation. Results demonstrate that different operating conditions is well distinguishable from each other and by that the finding of proper operating regimes is highly feasible. Grinding parameters that are normally measured in the laboratory are now readily modelled from the on-line signal. As a consequence this opens new possibilities for real time monitoring and control of the grinding process.

Keywords: Strain gauge, Process monitoring, Measuring practice, Regression modelling, Wavelet transform, Grinding

1 INTRODUCTION

The properties of raw material entering a grinding mill are strongly affecting the grinding performance and thereby determining the performance and quality of downstream processes. Owing to large fluctuations in the raw material properties (size, hardness and mineral composition), the fineness of the ground product
varies to a significant extent. Without extensive control of the raw material fed, efficient regulation of the grinding process is difficult to accomplish. Unfortunately, most methods for the characterisation of the raw material are tedious and done off-line in a laboratory. However, monitoring of the grinding mill performance and especially the behaviour of the grinding charge provide possibilities for efficient process control [9]. A source of difficulty in monitoring the grinding process is to get sensors with adequate availability, due to the fact that grinding of ores normally is done in a very harsh and wearing environment. To overcome this, technical development has led to sensors that preferably measure indirect properties of the grinding process, such as sound, vibration etc., [17, 18, 28]. The drawback of such methods is the inevitable demand for finding good statistical relations with real-world operational data and manually sampled responses. Other workers [7, 9, 13] addressing the problem of measuring load dynamics has made significant contributions using direct sensing techniques. Many of them have focused on finding important mill load variables such as toe and shoulder position of the charge, angle of repose, load filling level and then introduced them into a control scheme.

The present work has focused on a sensor that in a more mechanistic sense reacts to different operating conditions. The sensor, a strain gauge, measures the deflection of a rubber lifter bar inside a tumbling mill [3]. Its magnitude of deflection is a direct response to the volume of grinding charge inside the mill and also to some extent the behaviour of the grinding charge. Charge volume and its movements strongly affect grinding efficiency and wear of the mill lining. The strain-gauge signal accordingly contains information and features of the grinding process, and the scope of this work is to show how the measured signal can be used for monitoring the grinding process.

In monitoring of process data, and especially where data from multi-sensor system are available, the frequency of collected data sometimes might reach levels of several thousands every minute. This issue has become critical in many aspects, such as historical data storage capability, speed of computation in on-line applications, and ease of data analysis and interpretation. It is in this context a rapidly emerging technique – the wavelet transform, becomes interesting. Wavelet transformation is a linear transformation, similar to the Fourier transform and its trademarks are good compression and de-noising of a complicated signal [6]. In this work, we have examined how pre-processing of data from a strain gauge sensor can be done using the wavelet transform to obtain a lower number of parameters.

An important issue to address when measuring different features on-line in a process is to find the relation, a model, to significant quality variables. Here the generated strain gauge signal were subjected to multivariate calibration modelling using partial least squares regression (PLS) [5] for prediction of the grindability. Combining data pre-processing by wavelet transformation with multivariate statistics provides opportunities for generating useful insights into process monitoring, data analysis, and data interpretation [1].

2 SENSOR SYSTEM

The Continuous Charge Monitoring (CCM) system [12] is a rather newly developed electronic measuring system. It is dedicated to continuous measurement of the charge volume provided that the mill has a rubber or rubber-metal mill lining installed in the mill. As shown in Figure 1, the lifter bar (1) is equipped with a strain gauge sensor (2) that measures the bending of the lifter bar when it is in contact with the charge. The electrical signal from the sensor is amplified and transmitted to a receiver. The receiver also has a trigger-pulse remote sensor, which is activated once every revolution by a metal trigger plate on the mill. The position of the lifter bar (sensor), trigger plate and receiver is carefully established. The signal from the receiver is sent to a system computer where the data are processed to present the charge level and angle of repose.
A typical deflection profile of the sensor signal and an attempt to divide it into seven segments is shown, together with a corresponding graphical cross-section of a mill, in Figure 2. The boundaries and size of the partitions are determined by engineering knowledge of the grinding process. Each segment in Figure 2 illustrates an important dynamic event during the passage of the sensor-equipped lifter bar under the mill charge. The ordinate in Figure 2 shows the deflection of the lifter bar, which indirectly correspond to the force acting on it and the abscissa is the mill rotation angle with a resolution of $1^\circ$.

The sensor signature reflects different process features such as mill load and behaviour of the mill charge. Both segment $S_2$ (hit of charge) and $S_6$ (leaving charge) are well known, and can be used to calculate the volumetric mill load and the angle of repose, collectively these data give a good measure of the location of the charge. The other segments are less known but expected to carry information of the grinding efficiency, which is the purpose of this work to show. Thus, features can be extracted from the sensor signal for the purpose of process monitoring and diagnosis of process performance. Table 1 provides the summary of the stages during one mill revolution. Lifter bar angles given in Table 1 correspond to the positions marked in the left part of Figure 2, as a reference is the nine o’clock position, which corresponds to 0 degrees.

The frequency band of each scale (see sec.3.2) can be estimated. Given a signal of length $N$, sampled during 1s, results in frequency band given by

\[ \frac{N}{2^{(\text{scale} + 1)}} : \frac{N}{2^{\text{scale}}} \]

For example in our case the frequency bands of scales 1-4 are 37.5-75, 18.75-37.5, 9.375-18.75 and 4.6875-9.375 Hz respectively. Frequencies of interest are relative to size and speed of the mill and therefore will vary accordingly.
Table I. Sensor lifter bar signal segmentation and process features

<table>
<thead>
<tr>
<th>Segment</th>
<th>Lifter bar angle</th>
<th>Process feature</th>
<th>Frequency band of interest</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$: the sensor lifter bar (SL) is still in the air</td>
<td>$&lt; 50^\circ$</td>
<td>indicates the toe position of the charge, and if present, the slurry pool</td>
<td>$d_1: 37.5 – 75$ Hz $d_2: 18.75 – 37.5$ Hz $d_4: 4.6875 – 9.375$ Hz</td>
</tr>
<tr>
<td>$S_2$: the SL hits the ball charge and starts to get submerged in the charge</td>
<td>$50^\circ – 75^\circ$</td>
<td>Rate of change varies with mill speed</td>
<td>$d_1: 37.5 – 75$ Hz $d_2: 18.75 – 37.5$ Hz</td>
</tr>
<tr>
<td>$S_3$: the SL starts to bend forward due to turbulence in the toe area</td>
<td>$70^\circ – 85^\circ$</td>
<td>Both speed and charge level has an influence, wear of lifter</td>
<td>$d_1: 37.5 – 75$ Hz</td>
</tr>
<tr>
<td>$S_4$: the SL is at peak bending</td>
<td>$75^\circ – 90^\circ$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$S_5$: the SL is moving through the charge</td>
<td>$80^\circ – 190^\circ$</td>
<td>Indication of every lifter bar hitting the charge</td>
<td>$d_4: 4.6875 – 9.375$ Hz</td>
</tr>
<tr>
<td>$S_6$: the SL has gradually decreased the bending and is at take-off position</td>
<td>$190^\circ – 215^\circ$</td>
<td>Indicates the shoulder position of the charge</td>
<td>$d_4: 4.6875 – 9.375$ Hz $d_6: 1.1718 – 2.3437$ Hz</td>
</tr>
<tr>
<td>$S_7$: the SL is leaving the ball charge and starts slowly to rise to an upright position</td>
<td>$&gt; 215^\circ$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3 MATERIAL AND METHODS

3.1 Design of experiments

The statistically planned experiment was performed on a pilot ball mill, diam. 1.4 m, instrumented with the CCM measurement system, c.f. Figure 1. The objective was to study the performance and monitoring capability of the strain-gauge sensor for different operating conditions. Also of interest was to investigate if compressing of the sensor signal using wavelets maintain the predictive ability of a PLS model. Statistical experimental design was used to form sets of samples introducing different types of variation occurring in a ‘real’ process.

The test material, a hematite pellet feed with median size ($d_{50}$) around 35μm was chosen to get stable grinding conditions with respect to feedsize variations. Feedrate was kept constant at approx. 1.5 t/h. Table 2 shows the experimental design used, which resulted in twelve runs with different levels on mill speed, charge level and percent solid by weight, all levels in accordance with table 2. Every individual run was initiated with a run-in time of approx. 30 min. to reach steady state. When steady state was reached data acquisition and manual sampling started and lasted for approx. 10 min. The CCM system gives for every mill revolution a measurement vector of 360 elements, i.e. 1 deflection value/degree. The mill rotate with 1 revolution per 2.2 s, this time resolution is good enough for the monitoring of a grinding process.

Table II: Experimental design

<table>
<thead>
<tr>
<th>Experiment number</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charge level (%)</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>35</td>
<td>35</td>
<td>35</td>
<td>35</td>
<td>28</td>
<td>28</td>
<td>28</td>
<td>28</td>
</tr>
<tr>
<td>Mill speed (%)</td>
<td>73</td>
<td>73</td>
<td>78</td>
<td>78</td>
<td>78</td>
<td>73</td>
<td>73</td>
<td>73</td>
<td>73</td>
<td>78</td>
<td>78</td>
<td>78</td>
</tr>
<tr>
<td>Solid content (%)</td>
<td>70</td>
<td>77</td>
<td>77</td>
<td>70</td>
<td>71</td>
<td>76</td>
<td>76</td>
<td>71</td>
<td>70</td>
<td>75</td>
<td>76</td>
<td>71</td>
</tr>
</tbody>
</table>

The responses used for regression was: (1) Grindability index, $G_i$, the fineness of the ground material, expressed as the produced amount of material less than 45μm pro kWh net. (2) An apparent work index, $W_{app}$, expressed as energy per treated tonnage (kWh/t).
3.2 Wavelet transformation

Signal features, especially the temporal signal features, e.g. toe and shoulder angles of the process measurements, usually carry the most important information of the underlying process behaviours. One of the approaches to understand these behaviours is to analyse the output signal from the sensor directly [2]. Traditional practice is to do the analysis in the time domain, or apply the Fourier transform to look at the spectrum of the signal in the frequency domain. For a non-stationary signal however, it is better to study the signal features in the two-dimensional time-frequency domain. It is in this context a rapidly emerging technique – the wavelet transform, becomes interesting. Wavelet transformation is a linear transformation, similar to the Fourier transform and its trademarks are good compression and de-noising of a complicated signal [6].

The wavelet transform decomposes the signal by projecting it onto pieces of scaled and shifted versions of a so-called mother wavelet. The effect of the shifting and scaling process is the representation of a signal at multiple scales, called multiresolution analysis [8]. The discrete wavelet transform and its associated wavelet functions are defined in equation (1) and (2):

\[
\langle f(t) | \psi_{m,n}(t) \rangle = \int_{-\infty}^{\infty} f(t) \psi_{m,n}(t) \, dt
\]  

\[
\psi_{m,n}(t) = 2^{m/2} \psi(2^m t-n)
\]

Where \( f(t) \) is the signal, \( \psi_{m,n}(t) \) is the wavelet function, \( m \) is the scale and \( n \) is the shift in time and \( \psi \) is the mother wavelet. The wavelet transformation itself does not produce a compressed version of the original signal. Compression is achieved by eliminating the wavelet coefficients that do not hold valuable information. In this work the wavelet transform is used to reduce the number of parameters from the measurements. The interested reader is referred to Graps [6] for further details.

Based on the characteristics, a combination of sharp positive rise and a smooth ending transient of the strain-gauge signal (c.f. Figure 3), the Daubechies wavelet db4 was selected as the basis of the wavelet transform. Further reason for this selection is to get a simple wavelet function and thereby reduce the number of calculations, which can be of importance in on-line applications.

3.3 Multivariate analysis

Partial least squares (PLS), is a multivariate projection method that models the relationship between the responses \( Y \) and the predictors \( X \). PLS maximises the covariance between process variables and responses. In PLS the matrix \( X \) (process variables) is decomposed and modelled in such a way that the information in \( Y \) (responses) can be predicted as well as possible. In addition, PLS uses only the significant variation in the \( X \) matrix to predict the variation in the \( Y \) matrix. Therefore, noise and insignificant variations are not used in modelling [15]. Interested readers can get detailed theory in reference [5].

The decomposition results in a much lower dimensional space compared to the original variable space, it also results in vectors that are orthogonal. Together, these features make it possible to compress information in the presence of collinearity and redundancy. To make the PLS calculation and the interpretation easier, pre-processing is often necessary [16].

Since the focus is monitoring, and PLS is the tool used to analyze the data and for prediction, wavelet coefficients with high variance are selected, this selection criterion is called variance selection [16]. In this work the number of selected coefficients were based on the criterion to keep approx. 90 % of signal variation retained by those coefficients. With this choice the strain gauge signal is compressed to less than 5 % of original size which is of importance considering data storage capacity. The PLS model is therefore built on
the assumption that selected wavelet coefficients are the ones carrying most of the information about the grinding process.

The data set used was split into two parts where the first part, 48 spectra, is used for model calibration and the rest, 87 spectra, make up the test set. An obvious risk with this procedure is that the test set is too similar to the training set and therefore results in predictions with lower root mean square error of prediction (RMSEP), which describes the standard deviation of the prediction error. Anyhow, in comparison of the different models they will be equally influenced. To get an apprehension of the sampling error, run nos. 9 to 12 were run for longer time, so it was possible to get three additional manual samples. These samples give us an estimate of the "normal" spread.

Software used for the wavelet transformation is the Wavelet Toolbox, which is run on the MATLAB v.6.5 platform, Mathworks Inc. Both ordinary PLS modelling and WT-PLS modelling is performed with SIMCA P+ 10.0.2 software developed by Umetrics Inc.

4 RESULTS

4.1 Signal feature extraction

A key objective of the pilot mill trial was to establish that different process features are possible to detect and in some part quantifiable by a proper analysis of the strain-gauge signal. Results obtained in these aspects are very promising and confirm that the sensor system accurately manage to monitor different operating conditions. In our case, changes of the signal due to different process conditions are reflected in the waveform profile (signal segment 2, 3, 4), Figure 3 shows typical signal profiles obtained at different operating conditions of mill speed and charge filling level.

![Figure 3: Typical signal profiles obtained at different operating conditions of mill speed and charge filling level.](image)

A typical signal profile for the case of low filling, low mill speed and low %-solid (run no.1) and its corresponding wavelet coefficients for scale level d1 (highest frequency band) and d4, is shown in Figure 4. Both scale levels are reconstructed to original signal length in order to facilitate interpretation. The high frequency level d1 shows high wavelet coefficient in the region where the lifter is supposed to hit the charge, signal segment S2 and S3, c.f. Figure 2 and Table 1. In this region the rate of change of deflection is at its maximum, which well agree with the fact that force on the lifter is at maximum when it is introduced into the steel ball charge. By choosing an appropriate threshold value on the wavelet coefficient and then finding the corresponding time or in our case the angle of rotation, it is possible to determine the actual toe position of the charge. In our case the threshold value is based on an engineering assessment of the signal profile.
combined with the demand of a stable detection of the toe angle. The maximum coefficient value in itself is in some situations influenced by high frequency components in signal segment S4, which cover a greater angular range and therefore finding the position of the toe from the maximum coefficient value will result in a larger spread.

![Image](image.png)

**Figure 4**: Strain-gauge signal (left) with wavelet coefficients for level d1 (middle) and d4 (right) with operating variables at low filling, low mill speed and low %-solid.

Toe position of the charge is also quite well marked by the high negative peak at level d4, c. f. right most part of Figure 4. Figure 5 shows the toe angle for the runs, obtained from wavelet scale levels d1 and d4. Load orientation calculated from d1 is more sensitive to change in operating conditions, filling level and mill speed, while d4 especially for the case high filling, run 5-8, doesn’t reflect the change in mill speed. The obtained spread in the measurements is sufficiently low, since we consider detection accuracy less than 2 degrees good enough for milling purposes.

![Image](image.png)

**Figure 5**: Location of the Toe of the charge obtained from wavelet scales d1 and d4 at different operating conditions.

The level d4, frequency band 4-9 Hz, shows an interesting oscillation of the wavelet coefficient values, c. f. right part of Figure 4. The frequency of this oscillation corresponds well with the number of lifters in the mill, 12 lifter and 2.4 sec/rev, giving a frequency of 5 Hz. Similar oscillation phenomena has been observed in other work [17], especially when analysing the motor power signal.

There is another interesting signal feature, indicated at level d4, corresponding to signal segment S2. Here a somewhat smaller change of the wavelet coefficient values occur, which is interpreted as a detection of what is called the slurry pool, marked by circles in Figure 6. Indication of process situations where slurry pooling occur is of great importance since it will influence the slurry transport within the mill and consequently the grinding efficiency. In run number 3 and 4 this phenomena is more pronounced, most likely due to higher
mill speed which cause the ball charge to move higher up on the mill shell but the interstitial slurry doesn’t. In the original signal this can be seen at the very beginning of the deflection, rotating angles between $56^\circ - 68^\circ$, a closer look at $d_4$ shows that the first positive peak is at angle $56^\circ$.

![Signal](image)

**Figure 6:** Strain-gauge signal (left) and wavelet coefficients for level $d_4$ (right) for the case of high mill speed and low filling, run no.3. The circles mark what most probably is slurry pooling.

One of the main advantages with wavelet transformation, and the main purpose in this work, is that the original signal can be represented in terms of a wavelet expansion, using coefficients in a linear combination of the chosen wavelet function. Data operations can then be performed using just the corresponding wavelet coefficients. In addition, truncating the coefficients below an appropriate threshold value the data can be sparsely represented. Figure 7 shows an example of only using the 16 largest coefficients, i.e., a compression ratio higher than 20:1, but still preserving the interesting features in the original signal such as toe and shoulder region. Pre-processing of process data in this manner can considerably enhance on-line performance, especially in applications like this where the measured data has spectra-like properties, i.e. a large number of variables.

![Signal](image)

**Figure 7:** Comparison of the original signal (left) with the wavelet compressed signal (right) using the 16 largest wavelet coefficients.

### 4.2 Modelling

For comparison of the predictive ability and the advantage of using the complete signal profile instead of only some key signal variables, three different PLS models was calculated. Predictor variables for each PLS model is given below, responses for all of them are the Apparent workindex ($W_{app}$) and Grindability index ($G_i$).

i) **PLS model 1**: Power, Design variables and from the strain gauge signal derived variables (toe angle, Shoulder angle and Angle of Repose).

ii) **PLS model 2**: Amplitude of deflection for all 360°.

iii) **PLS model 3**: Wavelet coefficients, 16 largest.
Prior to the wavelet transformation a standard normal variate (SNV) correction was done on the strain gauge signal. SNV signal correction is performed on every individual measurement. The main purpose is to correct for base line and variance differences and by that focus on the signal profile instead of absolute values.

Table 3 displays the modelling results, all models based on the original design including 48 samples. Included model principal components (4) are all considered significant by cross-validation [19]. For the predictions of \(W_{\text{app}}\) and \(G_i\), the calculated PLS model 1 described 99.6 % of the variation in predictor variables (R\(^2\)X=0.996) and 58.3 % of the variation in response variables (R\(^2\)Y=0.583). The predictive ability according to cross-validation was 50.8 % (Q\(^2\)=0.508). Prediction of the test set, consisting of 87 samples not used in the calibration calculation set, gave an RMSEP value of 11.3 kWh/ton for the Apparent Workindex and 1.6 kg <45\(\mu\)m for the Grinding Index. Corresponding values for PLS model 2 and 3 are provided in Table 3. Model 2 and 3 gave in comparison with model 1, almost a 50 % increase in explained variance of responses and halving the standard deviation of the prediction error. One may notice the very small difference between the PLS models 2 and 3 in terms of statistical performance and the overall predictive ability despite the large difference in number of predictor variables. For all models the explained variance of the predictor variables is high, showing that the experimental design had the intended effect and that achieved variation is reflected by the process variables and especially by the strain gauge sensor.

![Table III: Summary of modelling results for the original model, and the data compressed WT-PLS models.](image)

A plot of observed and predicted values for the response \(G_i\) is shown in Figure 8. Here, every predicted data point is an average value of individual predictions per run in the test set, producing totally 12 samples per PLS model. Predictions by PLS model 1 shows a spread that is too high which rejects the model 1’s possibility for monitoring and process control. PLS model 2 and 3 however, presents prediction performance that is believed accurate enough and therefore an input of importance in grinding control.

5 DISCUSSION

In grinding of ores a major problem is varying properties of the feed material, such as grindability and size variations, and its consequences on end product quality. These ore feed properties are very difficult to measure directly and thereby render the control complicated. A feasible solution is to find other measurable variables that carry information of the performance of the grinding process. Other workers addressing this matter [10, 11, 13, 18] have contributed with valuable knowledge of the grinding process but many of them facing the problem of finding clear relations to grinding performance due to lack of robustness, accuracy and reliability for the sensor used. In this work a strain gauge sensor embedded in a lifter bar inside the grinding mill has been employed. The strain gauge sensor has shown to be capable of establishing the charge position within the rotating mill with an accuracy equivalent to other work [7, 9, 14]. The uniqueness of this sensor is that in addition to charge position the signal profile also is shown to contain information about grinding performance.

The results presented here for prediction of grinding performance suggest that the strain gauge signal in combination with wavelet transformation and multivariate data analysis provide promising means for monitoring and control of process fluctuations. The low prediction error clearly highlight the importance of well-planned experimental strategy including experimental design, signal pre-processing, multivariate modelling and validation. The calculated PLS regression model 1, where predictor variables constituted of process variables and derived variables from the strain gauge signal, shows weak predicting performance. The explained variation in predictor variables (R\(^2\)X = 0.996) are extremely high indicating that the experimental design resulted in a desired systematic variation. However, despite these prerequisites the explained variation in response
variables ($R^2_Y = 0.583$) is insufficient for process control. The obtained result for model 1 very well reflects a typical situation in a production plant. Grinding control based on traditional variables rather often face problems even if advanced model-based control is applied. This clearly indicates that some kind of measurement, e.g. particle size, of the ground product is needed to obtain a proper grinding control.

![Observed vs predicted values for the different PLS models](image)

Figure 8: Observed vs predicted values for the different PLS models. Correlation coefficients between observed and predicted values of $W_{app}$ and $G_i$ are, $R^2 = 0.23$ (model 1), $R^2 = 0.88$ (model 2), $R^2 = 0.87$ (model 3) and $R^2 = 0.20$ (model 1), $R^2 = 0.90$ (model 2) and $R^2 = 0.87$ (model 3) respectively.

However, it is not easily achieved on a continuous basis. Instead, a direct measurement on the charge has merits in the derived signal quality. For the obtained PLS regression models 2 and 3 where the complete strain gauge signal formed the predictor variables, the achieved results are really promising. Also in these models the variation in the X data are well explained ($R^2X_{model2} = 0.951, R^2X_{model3} = 0.967$), demonstrating that the strain gauge sensor has the capability to capture the charge variations caused by the experimental design. Both models generate almost the same result regarding predicting performance ($R^2Y_{model2} = 0.848, R^2Y_{model3} = 0.797$). It is to be noted that PLS model 3, which only use the wavelet compressed data, consisting of 16 wavelet coefficients as predictor variables, produce comparable results. The achieved result is of great value and preferable in real time operations since both data storage and floating point operations will be reduced while still preserving all information retained from the original data. The obtained model predictions are well acceptable for process control and feasible operating regimes should be possible to detect.
Further studies will focus on increasing the discriminating power of certain process states. One approach will be to separately model process conditions where charge filling and mill speed are at fixed levels and study the effect of change in slurry flow conditions in the charge. Moreover, future work will emphasize on methods to enhance the ability to detect undesired or exceptional process states. In particular it has been of great interest in the past to detect a certain condition called slurry pooling. This phenomenon seems to have possibilities to be detectable with the sensor used, and together with wavelet analysis it should be possible to quantify and position the slurry pool inside the mill.

6 CONCLUSION

The measurement system, a strain gauge installed in a lifter bar inside a rotating mill, has in an unprecedented way shown to be capable of unambiguously establish the charge position within the rotating mill. In addition the signal profile also demonstrate to contain information of the grinding performance. Grinding parameters that are normally measured in the laboratory are now readily modelled from the on-line signal. As a consequence this opens unique new possibilities for real time monitoring and control of the grinding process.

The modelling shows that the used wavelet transformation reduces the number of variables considerably. A data set consisting of only 5 % of the original data result in a PLS regression model with almost the same statistical performance. Wavelet transformation of the original strain gauge signal has clarified the importance of the position of the grinding charge or more correctly how an operating condition implicate the charge movement. The experimental result has also shown that it is particularly the toe position of the charge that is important to detect since it has a strong correlation with operating performance.

7 ACKNOWLEDGEMENTS

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8 REFERENCES

On-line Measurement of Charge Position and Filling Level in Industrial Scale Mills

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ABSTRACT: Pilot scale experiments, presented here, show good results in detecting charge movement when using the Metso Continuous Charge Measurement system (CCM). In this technique a strain gauge sensor is mounted on a steel plate that, in turn, is placed under one of the rubber lifters used to lift the charge. A deflection profile is registered and the signal pattern is correlated to charge position and filling level. Charge measurements in industrial scale mills: a ball mill at the LKAB iron ore beneficiation plant in Malmberget, and an AG-mill at the Boliden Aitik copper mine plant as well as a comparison with a pilot scale ball mill, are presented.

The results indicate that the system is very capable of following the normal variations, which occur in the mills. Determination of different charge parameters such as volume and toe position is shown to be both robust and accurate. A prediction error less than +/- 1 % in mill filling level has been achieved and this ought to be adequate for process control purposes. By studying the nature of the signal it is possible to get a better understanding of the dynamics of grinding circuits. Influence of ore feed size on the dynamic charge behavior in an AG-mill has been studied with interesting indications of change in slurry rheology. Another feature of the sensor is its ability to respond quickly to various operating conditions. This facilitates for an operator to continuously follow the grinding process and also to incorporate the signal into a control strategy for real-time actions and thereby run at optimal operating conditions.

Keywords: Strain gauge, measurement technique, industry automation, process monitoring

1. INTRODUCTION

Grinding is one of the most energy and money consuming unit operations in ore beneficiation. Therefore, it is of great importance to run the grinding process as efficiently as possible. The most common way today to control a grinding process is by measuring the power draw of the mill and try to keep it at a maximum level (Krogh, 1979). On the other hand some studies (Kawatra et.al., 1989, Koivistoinen et. al., 1989, Moys, 1988) have shown that power measurement doesn’t reflect everything that takes place inside a mill. Other parameters like slurry rheology, temperature and load behavior, the volumetric filling of a grinding mill also seems to have a large influence on the grinding efficiency (Herbst, 1988, Koivistoinen et.al., 1992, Moys, 1989, Vermeulen et.al., 1988).

There exist a number of methods to measure the mill filling. One that has been used in many plants is to measure the bearing backpressure on the mill’s feed and/or discharge end. This
method gives an idea of the weight of the charge and it can be correlated to the filling level. The great disadvantage is that the pressure is not stable, for instance the temperature causes a drift. Another well-known method (Moys, 1988, Vermeulen, 1988) is to measure the conductivity inside the mill with two probes, which are mounted on a lifter. This method has shown some good results but a disadvantage has been the wear of the probes and also the drift that this wear causes. Here, we report on a technique that measures the force acting on the lifter when it hits the charge inside the mill. A similar method, using a strain gauge in a lifter bolt was reported by Herbst (1988).

The purpose of the reported project was to evaluate a measurement system for industrial scale mills. The measurement system, originally developed by SKEGA AB and Swedish Aerospace Research Institute (Persson, 1994-1999), today further developed and marketed by Metso Minerals (Dupont et.al., 2001), uses a strain gauge mounted inside a rubber lifter. Section 2 gives a short description of the equipment used. The system has been tested on different mills, in a small pilot ball mill (Ø1.4m×1.2m) where the feed was composed of a fine ground (dₘ₀~50μm) hematite ore, with a density of 5.2 g/cm² (Tano et.al. 2003). In an industrial tertiary ball mill (Ø4.9m×5.7m) where the feed was a magnetite ore, density of 5.0 g/cm² and a size distribution having a dₘ₀~80μm. For the case with a primary AG mill (Ø6.7m×12.2m), three (3) sensors were installed: at the inlet, middle and outlet end of the mill. In that case the feed was a porphyry copper sulfide ore with a feed top size of approximately 200mm and density ~2.8 g/cm².

2. MEASUREMENT SYSTEM

2.1 Strain gauge sensor system

The equipment consists of three main parts; the sensor, the telemetry system and the computer for data analysis and presentation. The most exposed component is the sensor, since the mechanical environment is very stressful due to the number of deflections of the sensor spring is far above the normal fatigue limit, usually in the order of 10 million. Furthermore, the sensor is exposed to moisture/water with temperatures between 30-60°C and also to high stress during parts of every revolution. Consequently, the system is constructed and built with great attention placed on the included components.

Figure 1: To the left a cross section of a mill with a horizontal reference line, used in the ball mill case, the right part shows the lifter (1) with a strain gauge (2).

A simplified view of the sensor is shown in Figure 1. The mill has a number of lifters on the inside of the mill shell. One of these lifters (marked 1) is equipped with a spring plate whose deflection is measured by the strain gauge (marked 2). As the mill rotates and the lifter with
the sensor dips into the charge, the force acting on the lifter increases, which in turn, causes a deflection. The strain gauge mounted on the spring plate converts this deflection to an electronic signal. The signal is then amplified, filtered and transformed to a pulse with a modulated HF-signal in the transceiver and by the antenna wired around the mill transmitted to the receiver placed close to the mill, c.f. Figure 2. A pendulum driven generator placed on the mill end produces the power to the transceiver. The receiver has also a trigger pulse that is activated once every revolution. This is for the system to know when a new revolution occurs. Finally the signal is transmitted by cable to the measurement computer where the calculation, analysis and presentation of the signal is done. Data acquisition by the A/D-converter in the computer is done at a frequency of 100 Hz. Since the large ball mill rotates at 14.7 revolutions per minute, this results in 408 measurements every revolution. All the data are stored in the computer for further processing.

![Figure 2: Overview of the mill with its mounted CCM components, to the right a cross section of a mill with a vertical reference line, used in the AG-mill case.](image)

The Aitik experiments were conducted with three strain gauge sensors mounted in lifters at different locations along the shell of a primary AG mill. One was mounted at the feed, one in the middle and one at the discharge end, c.f. Figure 2. The system used for transmitting the data is slightly different from the one described earlier. Instead of using a modulated HF-signal, the Boliden system has a radio modem with a baudrate of 4800 kBit/s. For each revolution the signal shape from the previous revolution is sent by a radio modem to the receiver beside the mill. From the radio modem, data is transmitted with short distance modems to a computer in the control room where it is received by the serial port. Since only one signal, i.e. from one analog input channel, can be transmitted at a time for one mill the system scans the three input channels consecutively. Each signal is sampled with 125 Hz for 246 degrees of the total revolution. With a mill speed of 12.8 rpm this corresponds to 400 measurements each revolution. A LabView™ application filters the signal and calculates the toe-angle of the grinding charge. In this case the toe-angle is defined as the angle between a vertical line and the point where the lifter hits the charge, c.f. right part of Figure 2. A higher value corresponds to either a higher mill filling or a charge that is more horizontally positioned due to mill speed, slurry rheology etc.

### 2.2 Signal features

To get a better understanding of the phenomena that take place in the mill, the initial signal from the sensor was analyzed. The left part of Figure 3 shows typical average curve shapes delivered by the sensor for every revolution of the different mills. Curves in the figure are
normalized and displaced in time to simplify comparison. To avoid noisy curves it is recommended to study an average signal value over a certain time period. This time period is subject to the purpose of application, i.e., pure monitoring or process control. The right part of Figure 3 shows typical curves for the Aitik installation with three (3) sensors. The difference in amplitude between the middle sensor and the other two at the feed/discharge end is most likely caused by the lifter configuration. At the feed/discharge end the lifter configuration is high/high, whereas the rows in the middle part of the mill are a high/low configuration with the sensor installed in one high lifter.

![Figure 3: Time signal showing the behavior of the load during one mill revolution for the different mills (left) and for the AG-mill with sensor placement at three different mill positions (right).](image)

The curves can be divided into a number of phases, where every phase corresponds to different phenomena that the lifter encounters during a revolution. The division into phases is done with respect to the changes in signal level that occurs during the revolution, and which is more clearly seen in ball milling. In current work the focus is on the phase where the lifter hits the grinding charge, the toe-angle region. This phase of the signal also comprises an interesting part in the curve, marked in left part of Figure 3, an indication of a possible slurry pool.

2.3 Signal pre-processing and regression methodology

Pre-processing of the CCM signal comprises both filtering and other mathematical manipulations with the purpose to extract signal features. The toe-angle of the charge has in this work been determined by either numerical derivation of the original signal (AG-mill) or by a wavelet transformation of the original signal (pilot ball mill). Wavelet transformation of the CCM signal has shown good properties in e.g. discrimination between toe-angle detection and the indication of slurry pooling (Tano et.al.,2004). Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelet algorithms process data at different scales or resolutions. The interested reader is referred to Graps (1995).

To improve the calibration of the equipment a multivariate statistical technique, partial least squares (PLS) regression was used for the ball mill case. PLS is useful when the purpose of the analysis is to build a model that is able to predict some of the process variables that cannot be directly measured (Wold, 1984). As opposed to an ordinary regression technique, i.e. multiple linear regression, PLS is suitable even if the data are highly correlated, if the predictor variables (X) are far more than the number of experiments and situations with
missing data due to sensor failure, which is not unusual in industrial applications. A tutorial to PLS is given in reference Geladi et.al. (1986).

3. RESULT AT THE LKAB MALMBERGET MINE

3.1 The overflow ball mill

Figure 4 shows a typical flowsheet for concentrating iron ore. The coarse materials at 10-15 mm in size are fed to a primary wet magnetic cobbing separator (M1). The magnetic concentrate is discharged into a primary ball mill (#1), and the ground product (pulp) is transferred to a secondary magnetic separator (M2). The resultant magnetic concentrate is then pumped into a secondary ball mill (#2). The ground product is finally upgraded by a tertiary magnetic separation unit (M3) and the concentrate is used as feed for the tertiary grinding stage (#3). The strain-gauge sensor was installed in the tertiary-grinding mill (#3).

![Flowsheet of multi-stage grinding and magnetic separations.](image)

The overflow ball mill used in the tertiary grinding stage has an outside diameter of 4.9 m and a length of 5.7 m, and is run in open circuit. The grinding charge consists of approximately 400 tons of 25 mm diameter chromium steel balls corresponding to 40 % in charge volume. The height of the new rubber liner lifters is about 70 mm. The mill is driven by two 1800 kW AC motors. The mill speed is set at 14.7 rpm giving a fraction of critical speed \( \eta_c \approx 0.78 \). Under normal grinding condition, the rated power draw, the pulp density and the feed rate are 2550 kW, 72 weight-% solids and 250 t/h respectively.

3.2 Calibration result and discussion

This experiment was the first full-scale test of the equipment’s performance. Until then the development had concentrated on work with sensor accuracy and tuning of the data acquisition system. The equipment had been installed 1.5 months before the test period started, in order to ensure reliability.

To get an understanding of, and distinguish between correlation and causality, the experiments were performed according to a statistical design. The fact that the variables are changed between fixed levels and chosen so the whole interesting area is examined makes it possible to build predictive models. Nine experiments were performed and the variables Ball Charge and Feed were varied according to Table 1.

To accomplish the different fillings the mill was stopped and emptied of balls, in the first case 25 ton of the charge and in the next case additional 25 tons. In each case when the mill was...
stopped the height of the charge was manually measured. With these measurements it was possible to calculate the percent volumetric mill filling level, see Table 1.

<table>
<thead>
<tr>
<th>Table 1: Experimental plan at the LKAB Malmberget plant.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manually meas. filling level</td>
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<tr>
<td>-----------------------------</td>
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<tr>
<td></td>
</tr>
<tr>
<td>Feed levels</td>
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<td></td>
</tr>
</tbody>
</table>

Calibration of the model was done using the manually observed values of the mill filling level. Two model components were found to form the PLS model with the best predictive power. The total explained variance in the filling level is around 99%, which is a very high value. As shown in left part of Figure 5, the agreement between observed and predicted values in the modeling data are very good with a prediction error that is less than +/- 1 %. This is satisfying enough to fulfill the goal of this model.

Another interesting feature of the initial signal is the differences in the curve shape at varying charge levels. As shown in right part of Figure 5, it is clear that there exists a large difference between the curve shapes. First of all, the amplitude of the signal differs significantly, about 100 units. If integrated for the whole revolution a significant difference in the area under every curve will arise, increasing area with higher filling level. Physically this could be connected to the energy expended in the grinding. The correlation between the area and the power draw by the mill is very high (corr. coeff. = 0.98). The differences in amplitude are with high probability, caused by the heavier load in the mill resulting in a larger deflection of the lifter.

Secondly, there is a time shift between each curve indicating a change of both the toe and the shoulder angles that well correspond to change in filling level. Time differences that appear are firstly at the plateau that occurs after ~0.2 sec. The width of the plateau decreases with increased filling. This could be an indication of the increased amount of balls in the toe region that starts to occupy the area where normally the slurry pool is present. It is also logical that the amount of slurry pooling becomes lower at a higher ball charge filling. Next difference in time appears at the shoulder region indicating that the ball charge travels higher on the mill shell, obviously it’s not a large growth of the mid part of the charge. Similar results have been shown in DEM simulations of mill charge behavior (Dong et. al., 2003, Cleary et. al., 2003).
To sum up, the experiment has shown that it is possible to get a signal that can be used to predict the volumetric filling level in a tumbling mill. Furthermore, the information contained in the signal also gives some physical insight into the phenomena that take place in the mill.

4. RESULT AT THE BOLIDEN AITIK MINE

4.1 The primary AG-mill

The flowsheet for the grinding line at Aitik where the experiments was conducted is shown in Figure 6. The ROM material is fed to the primary autogenous grinding mill, $\varnothing 6.7 \text{m} \times 12.2 \text{ m}$ with installed power of 6000 kW. From the primary mill, 40 to 80 mm pebbles are extracted to the secondary pebble mill, $\varnothing 5.2 \text{m} \times 6.8 \text{ m}$, motor power of 3000 kW. The primary and secondary mill is running in closed circuit with a spiral classifier where the coarse material goes back to the primary mill. During normal operation, the primary mill is controlled using a simple and effective optimizing control strategy implemented in the DCS. The objective for the optimizing control is to maximize the throughput. This is done by always keeping the mill at one of two constraints limiting the throughput. The two constraints are maximum allowed mill filling or maximum allowed power draw. Which of the constraints that is active depends on the ore type and fragmentation. The strain-gauge sensor is installed in the primary AG-mill.

![Flowsheet of a grinding line at the Aitik plant.](image)

4.2 Experimental conditions

This part of the work had a focus on studying the ability of the sensor to detect how changes in operating conditions and variables influence the grinding charge, this with respect to both position and filling level of the charge. The changes were aimed to be within what could be seen as a normal operating range during production. The final goal with these experiments was to find out if the charge measurement could be used in a control strategy where throughput is maximized. A number of different step changes were made, summarized in Table 2.

<table>
<thead>
<tr>
<th>Exp. nr</th>
<th>Operating condition/variable changed</th>
<th>Water addition</th>
<th>Ore type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Feed 400 [t/h]</td>
<td>60 [wt-% solid]</td>
<td>Coarse ⇒ Fine</td>
</tr>
<tr>
<td>2</td>
<td>Feed 300 ↑ 600 [t/h]</td>
<td>60 [wt-% solid]</td>
<td>Normal</td>
</tr>
</tbody>
</table>
4.3 Results and discussion

4.3.1 Influence of ore fragmentation

The purpose of the experiments was to investigate the dynamic influence of changes in ore fragmentation on the behavior of the grinding charge. Changing feeders under the stockpile made it possible to use the natural segregation in the stockpile for changing the fragmentation. During the experiment the ore feed was kept constant at a level of 400 ton/h and the percent solids in the mill at 60%. The feeders were controlled so that a change in fragmentation from fine to coarse and back to fine was achieved. The fragmentation was indirectly measured using a laser beam to get the object distance and use the value as an indication of the feed size. Photographs of the ore were taken as well, c.f. Figure 7. Strain gauge signals and process variables were logged during the whole experiment.

![Figure 7: Photos and laser measurement showing typical size distributions for the test with coarse (left) and fine (right) ore feed.](image)

The experiment started with a coarser ore feed, immediately the mill power began to increase at an almost constant rate, c.f. Figure 8. Calculated toe-angle was approximately 57° for the whole time period with the coarser feed. The change of feeders gave a direct response on the power measurement, which now continuously dropped with a finer ore feed. The calculated toe-angle also responded very fast, increased to approximately 61° and after further 10 minutes settled at 59°.

A closer look at the CCM signal for the different sensors, c.f. Figure 9, reveals differences in the signal profile between coarser and finer ore feed. A deviation in the amplitude is shown quite clearly, whereas difference in the toe region is hardly visible, however calculated toe-angle, by derivation, shows a small but significant difference of approximately 2 – 4°, c.f. Figure 8.

![Figure 8: Power measurement and calculated toe-angle at different ore size distributions in the ore feed.](image)
Interestingly however, is that all sensors show the same change of signal profile, which confirm the sensor capability to detect charge variations. A somewhat more pronounced change of amplitude is shown for the sensor at the discharge end. This could be an indication of a situation where coarser material dams up the flow through the mill. Another interpretation is that coarser feed takes longer time to grind, and so fills up more at the discharge end compared to a situation with a finer feed.

When changing to a finer ore feed, the power draw of the mill dropped, and the calculated toe-angle increased. By just looking at one or the other of these two measurements it is hard to estimate the effect on the grinding charge. But the combination of them points to a decrease in charge filling and at the same time a change of the angle of repose. This change of angle of repose is most likely caused by a change in slurry viscosity when the amount of fines in the feed increase. In a survey study by Shi et.al. (2002) they showed that the amount of fines in the feed influence slurry viscosity and this in turn has a significant effect on grinding performance, positively or negatively depending on the rheology nature of the charge.

![Figure 9: CCM signal profile exhibited by all sensors at different size distributions in the ore feed.](image)

Interpretation of the measured signals for coarse feed end up in a probable increase of the filling level and that the expansion of the charge is towards the shoulder region. Supporting this conclusion is, i) mill power is continuously increasing, ii) CCM signal profile shows a time shift mainly oriented to the shoulder region of the charge, iii) no obvious change of toe-angle during time period with a course feed.

4.3.2 Influence of ore feed rate
The purpose of this experiment was, similar to Experiment 1, to investigate the dynamic influence of changes in ore feed rate on the grinding charge. The feed was changed in a number of steps between 300 ton/h and 600 ton/h. Percent solids were kept at 60 %. Also in this experiment strain gauge signals and process variables were logged.

The experiment started with a feed of ~ 420 t/h and a power draw of ~5.2 MW. The first change was a decrease of feed to ~300 t/h, c.f. Figure 10. This change caused the power to drop slowly, which is also true for the toe-angle. The sensor signal exhibit the lowest amplitude for this low feed, it also shows that it takes somewhat longer time before the lifter hits the charge. Both signal features are typical indications that the volume of the charge has shrunk. Next change was an increase of the feed to ~ 450 t/h. It resulted in a slow response on mill power but a much faster change in toe-angle, both of them increasing and by that displaying a higher milling filling. The corresponding change in the strain gauge signal consists of an increase in amplitude mainly oriented at the shoulder part and a distinct change in time when the lifter bar to hits the charge. The final increase in feed up to ~ 600 t/h causes the power to increase to a level of ~ 4.8 MW where it seems to level out and with a tendency to start decreasing. The toe-angle on the other hand continues to rise until the feed is dropped.
back to normal level. Both responses indicate a probable commenced over filling. The time until the lifter hits the charge constitutes the main difference in the sensor signal, amplitude however, is in the same range as for the feed of ~ 450 t/h, even somewhat lower.

![Diagram](image)

**Figure 10:** CCM signal profile for the middle sensor (left), power and toe_angle at different ore feed levels (right).

The result in Figure 10 shows that the toe-angle respond faster compared to the power measurement when feed rate is increased. The response time for toe-angle appears to be around 15 min. which also correspond well with the likely residence time for this AG-mill. However, when decreasing the ore feed rate both measurements respond almost in the same way with a long response time indicating the time needed to grind out the charge. Changes made in ore feed rate, especially increase, seem to have been done before the mill reached steady state. Anyhow, the obtained result shows that the strain-gauge sensor responds fast and properly and thereby ought to be of great use in a control system.

Figure 11 shows a typical response from each strain-gauge sensor when the ore feed rate is changed. Here a change in toe-angle is clearly distinguishable and the same signal pattern is received for all sensors, i.e. increase of toe-angle when the ore feed is high. However, the sensors along the mill respond differently regarding amplitude, the sensor in mid and discharge end of the mill shows a modest change in amplitude. Once again indicating what can be understood as various mixing in the mill axial direction.

![Diagram](image)

**Figure 11:** CCM signal profile exhibited by all sensors at different ore feed rate.

In Figure 12 the dynamic capability of the strain-gauge sensor, here as averaged minute values of the sensor signal, is shown, i) immediately after a step change of the feed from 300 t/h up to 600 t/h, ii) 10 minutes later and iii) 20 minutes after the change. It is well marked by the sensor that the lifter bar hits the charge earlier and earlier during its passage in the charge after an increase of the ore feed, indicating a continuous increase of the filling level. There is also a change of the CCM signal at the shoulder part further showing that the charge is...
growing at both ends. The maximum amplitude of deflection shows small differences and are mainly oriented to the shoulder region.

![AG-mill middle sensor](image)

**Figure 12:** Strain gauge signal profile exhibited by the middle sensor at different times after a change in the ore feed.

### 5. CONCLUSIONS

A promising method for mill charge measurement has been studied in industrial ball and AG-mill applications. The measurement system produces a signal whose profile contains information about the charge position, filling level and its behavior during different conditions. Testwork has demonstrated that the signal pattern varies in a consistent way with changing operating conditions. Detection of charge features such as filling level and toe-angle has shown good reproducibility independent of type of grinding, AG- or ball mill, and is also independent of mill size for ball milling. The change in curve shape for the large ball mill corresponds well with changes achieved in the pilot mill at different charge levels. The profile of the curves for ball mills, independent of mill size, are pretty much the same. However, amplitude differences is more pronounced in a large ball mill, probably due to higher loads influencing the lifter deflection.

For the ball mill application a partial least squares calibration model, derived from experimental data was found to be accurate and robust both from statistical and technical points of view. There is no doubt that the volumetric mill filling level can be predicted with an accuracy of +/- 1%. It also seems that the system does not suffer from any tendency to drift or quickly wear out. This may enable the equipment to be used as an on-line measurement of the filling level.

In the AG-mill application a system with 3 sensors mounted at different axial positions (inlet, mid, outlet) along the mill was used. The response in amplitude for these three sensors were quite different, this presumably because of the kind of lifter configuration used in the AG-mill. The lifter configuration was of a high/high type at feed/discharge end, whereas the rows in the middle part of the mill were of a high/low configuration with the sensor installed in one high lifter. The high/low configuration gives a wider void between the lifters, which filled with grinding charge results in a higher pressure on the lifter and thereby a bigger deflection of it. An implication of the high/high configuration is a probable reduction in mill volume. Furthermore, the grinding work in this section of the mill is also most likely cut back due to a charge that is immobilised between the high lifters. Of course there is a trade-off between having a longer lining lifetime with high lifters compared to the reduced mill volume, and it has to be economically justified.
Different charge behavior was identified along the mill when operating conditions were changed, with the most systematic variation at the discharge end. The result indicates that the charge filling along the axial direction of the mill is different, and an implication is that the mixing in an industrial grinding mill varies along the mill. This observation is in line with those of Van Nierop et al. (2002) using conductivity and temperature probes.

The sensor responded well when the amount of fines in the ore feed was increased. Interpretation of the signal profile points to a change in the angle of repose for the grinding charge, this conclusion could hardly have been done by just measuring the power of the mill. The obtained result is most likely due to an alteration in slurry viscosity, and this also conforms to conclusions by Shi et al. (2002) from a survey conducted on full-scale mills. How well the strain-gauge sensor will capture variations in slurry viscosity and its influence on grinding performance will be further investigated in a pilot mill.

If the power is the only available indicator of a mill’s performance there is a large risk that the mill is run at less than optimum condition. The strain-gauge sensor has shown features such as reproducibility, reliability and fast response time to varied process conditions. The latter is of great importance to achieve satisfying control of the grinding process. The experiments have shown that the strain-gauge sensor respond in the same time range as the residence time for the mill. This is a huge advantage since mill power has more than double response time.

A characteristic property of this system is the possibility for an operator to continuously follow the grinding process. This could be done by a proper display showing the charge toe angle, angle of repose and/or the volumetric filling of the mill. However, experience gained from these experiments underscore the importance of signal pre-processing, e.g. signal filtering, feature extraction using wavelet analysis, before regressing the signal to grinding performance. Then the opportunity to enhance the control of grinding is widely opened.

6. ACKNOWLEDGEMENT

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On-line monitoring of rheological effects in grinding mills using lifter deflection measurements

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On-line lifter deflection measurements showing flow resistance effects in grinding mills

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Abstract

The deflection that a lifter bar is subjected to when passing through a grinding charge was measured using an embedded strain gauge sensor. The obtained signal profile is analysed and interpreted in relation to charge properties such as toe and charge angle for the grinding charge. The current work has focused on the charge and slurry flow behaviour when solids content is changed and how well the sensor reflects this. Bench scale measurements with a vane type viscometer, roughly evaluated in terms of apparent viscosity is used as a character for the resistance to motion of the slurry.

The slurry flow resistance is strongly influenced by solids content and obviously by the addition of a dispersant. The strain gauge sensor reflected this change well, showing that toe and shoulder region of the charge varied in a systematic way. Results obtained also shows that change of slurry flow resistance exert an influence on grinding performance.

A multivariate statistical method, partial least squares regression, is applied to the sensor data producing a model that can predict the change in slurry flow resistance. The output from the model also shows good properties to be used as a process-monitoring tool. The predictive capability of the model is believed to be of such quality that it can be used for process control.

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Keywords: Grinding; Deflection sensor; Mill monitoring; Flow resistance; Slurry viscosity

1. Introduction

Size reduction is an inevitable unit operation in mineral processing. Comminution is also by far the most energy consuming part in mineral concentrators and at the same time extremely inefficient, less than 10% of supplied power produce new mineral surfaces. The economical potential is substantial if efficiency can be increased just a couple of percent. In general, the only grinding control is to maximize the power drawn by the mill. Unfortunately, the relation between power and grinding performance is a complex and non-linear function.

Development of advanced control systems has helped the situation considerably (Herbst and Rajamani, 1982). However, these systems still are lacking relevant information such as mill load, charge position or slurry properties. Sensors capable of delivering this information are therefore of great value.

The difficulty for a sensor is that the complex motion of a grinding charge is determined by both mill design variables such as liners, lifter profile, discharge mechanism, etc. and process operating variables such as solids content, size distribution and slurry viscosity. It does not make it simpler that e.g. viscosity itself is a function of several variables in addition to volume percent solids, such as solids size distribution, particle shape distribution, slurry temperature, etc. This illustrates how complicated it is for a single sensor to detect changes in...
grinding performance in such a multivariate process system. Moys (1985) and Herbst and Gabardi (1988) have done pioneering work in the development of dynamic sensors, conductivity probes, and also in its application to the control of grinding mills. Moys and Montini (1987) showed that conductivity measurements well describe the load behavior and that it is strongly influenced by e.g. slurry rheology. Moys (1989) stated that the interactions between the slurry, charge and the mill are mainly governed by the slurry viscosity. In an extensive contribution, Shi and Napier-Munn (2002) investigated effects of slurry rheology on industrial grinding performance. The results were focused on the overall breakage behaviour with a grinding index used as a criterion. It was concluded that slurry viscosity affected grinding performance and that this influence depends on the rheological nature of the slurry.

Furthermore, the development of sophisticated data analysis software has opened new possibilities to measure mill properties such as sound and vibration (Pax, 2001) and then correlate them with grinding performance calculated from variables measured in the laboratory. It is in this context the current research project is to be placed.

The project aim is to study how a sensor that is influenced by the grinding charge and its motion has the ability to collect relevant information and to use it for process control. The sensor uses a strain gauge mounted inside a rubber lifter (Persson, 1994–1999). The sensor picks up the deflection of the lifter when it moves through the grinding charge, with a resolution of 1/176, and a characteristic signal profile is obtained. A typical deflection profile of the sensor signal and an attempt to divide it into six segments is shown, together with a corresponding graphical cross-section of a mill, in Fig. 1. The boundaries and size of the partition are determined by engineering knowledge of a grinding process. Each segment in Fig. 1 illustrates an important dynamic event during the passage of the sensor-equipped lifter bar under the mill charge.

The sensor has been further developed and integrated into a complete measurement system (Dupont and Vien, 2001a). It is at present marketed by Metso Minerals under the name CCM. The sensor system has been tested on both pilot and full scale grinding mills under different operating conditions (Tano et al., 2003; Dupont and Vien, 2001b). Results obtained show that there exist a clear correlation between the signal profile and different charge properties such as load volume, angle of repose and charge position expressed as toe and shoulder angle.

The objective of the current contribution is to further study how well the strain-gauge sensor detect changes in product slurry resistance, here evaluated in terms of bench scale viscosity measurement, and its influence on grinding performance. The term flow resistance is used here to reflect that rheological (viscous) properties are mainly characterized by a medium formed by water and particles with sizes less than 20–30 microns. The resistance to flow is then a combination of viscous influence and effects of two-component hydrodynamic and mechanical behavior of larger particles.

In the current work we have deliberately stressed the pilot mill to its maximum with respect to slurry flow rate and flow resistance, aiming to test the sensors ability to detect such possible process states. To assess the joint influence of the variables (feed, solids content, dispersant) an experimental method, design of experiments (DOE), is used (Eriksson et al., 2001). A multivariate regression model for the flow resistance and grinding performance is derived. An approach to use this regression model for continuous monitoring is also presented.

2. Experimental

2.1. Material

The test material for the pilot ball mill was a hematite pellet feed with $d_{50}$ around 35 µm and a solids density of 5200 kg/m$^3$. A relatively fine ground material was chosen to get stable grinding conditions and also to minimise the effect of variations in the amount of fines in the feed.

Particle size distributions from which the grinding performance indices were calculated are given in Fig. 2.

![Fig. 1. Strain-gauge sensor response with segmentation based on important dynamic events during one passage in the charge.](image-url)
2.2. Grinding performance indices

The performance indices used is a Grindability index 
\((G_i)\) showing the produced amount of material finer than 
45 \(\mu\)m calculated as in Eq. (1).

\[
G_i = 10^8 \frac{(S_{D_i}^{45\mu m} - S_{F_i}^{45\mu m}) \times F}{P} \quad [\text{kg < 45 \(\mu\)m/kWh]}
\]

where \(S_{D_i}^{45\mu m}\) and \(S_{F_i}^{45\mu m}\) is the percentage of material finer 
than 45 \(\mu\)m for discharge and feed, respectively. \(F\) is the 
amount of feed [tonne/h] and \(P\) is the mill power [kW].

The other performance index, an Apparent-Workindex 
\((W_{app})\), is calculated as following

\[
W_{app} = \left(\frac{P}{F}\right) \left(\frac{10}{\left(1/\sqrt{d_{80}^{\text{Out}}} - 1/\sqrt{d_{80}^{\text{In}}}ight)}\right) \quad [\text{kWh/ton}]
\]

where \(P\) is mill power [kW], \(F\) is the amount of feed 
[tonne/h] and \(d_{80}\) is the 80\% passing size [\(\mu\)m] for 
discharge and feed, respectively.

2.3. Dispersant

Dispex N40 provided by AB CDM was the disper-
sant used. It is a mixture of 40\% sodium polyacrylate 
and 60\% water, having a pH value of 7–7.5 and a density 
of 1.3 according to specifications.

2.4. Viscometer

Overall assessment of flow resistance is done by mea-
surement with a vane-type viscometer of type Bohlin 
CS10 Rheometer. It has a measurement cylinder, a 
Bob of \(\varnothing\) 25 mm and the vane tool is of type V14 (4 
blades), \(\varnothing\) 14 mm and 30 mm high. Details about rheo-
logical measurements and evaluations are well described 
by for example Zaman (1998). When values of shear 
stress, \(\tau\), and shear rate, \(\dot{\gamma}\), are available, they can be 
plotted in a diagram, rheogram, where the apparent vis-
cosity is defined as

\[
\eta_{app} = \frac{\tau_k}{\dot{\gamma}} \quad \text{[Pas]}
\]

In this work the relative resistance to flow was expressed 
by an apparent viscosity, c.f. Eq. (3), at a shear rate of 
100 [s\(^{-1}\)], which is a reasonable average order of magni-
tude in a mill following analyses and discussions by Shi 
and Napier-Munn (1999).

2.5. Pilot ball mill and experimental conditions

The pilot mill at the LKAB R&D facilities is \(\varnothing\) 1.414 m \(\times\) 1.22 m in length. It is a grate-discharge mill, 
equipped with 12 rubber lifters of square size 0.1 m, face 
angle 45\^o. The mill was run at 24.4 RPM corresponding 
to 73\% of critical speed. Steel balls in the size range 10– 
30 mm and density 7800 kg/m\(^3\), were used in the exper-
iments. The ball mill charge filling was approximately 
28\% of total mill volume. A frequency converter and a 
conveyor scale controlled the mill feed. The feed rate 
and solid content in the mill were varied according to 
Table 1. Addition of the dispersant to the mill feed 
was achieved using a peristaltic pump with a rate of 
approximately 90 ml/min. Fig. 3 shows the design region 
spanned by all 10 experiments.

Table 1

<table>
<thead>
<tr>
<th>Exp. (#)</th>
<th>Feed [t/h]</th>
<th>Solids [vol.%]</th>
<th>Disp. [ml/min]</th>
<th>Power [kW]</th>
<th>Weight [ton]</th>
<th>Toe angle [(^\circ)]</th>
<th>Shoulder angle [(^\circ)]</th>
<th>Dynamic charge volume [%]</th>
<th>(G_i) [kg&lt;45 (\mu)m/kWh]</th>
<th>(W_{app}) [kWh/ton]</th>
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<td>36</td>
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<td>32.5</td>
<td>1.64</td>
<td>65.0</td>
<td>203.1</td>
<td>18.8</td>
<td>11.7</td>
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</table>
Mill Power is measured in the switch gear room giving total power, i.e., mill, transmission and gearbox. Load cells are used to measure the mill weight and slurry temperature is measured by a handheld IR-sensor on the mill discharge sample. Design variables and measured responses are listed in Tables 1 and 2.

Charge behavior was monitored using the strain gauge and an average of the signal profile was stored every minute. After steady state was reached in each experiment, data were logged and the mill discharge was sampled. Analyses of the particle size were done with a laser diffraction instrument, Malvern Mastersize S (optical mode-polydisperse, dry), and slurry viscosity using the Bohlin CS10 cylinder viscometer.

2.6. Methods of analysis

The statistical tool used in this work is partial least squares projections to latent structures or PLS. PLS is a regression extension of principal component analysis, which is used to connect the information in two blocks of variables, \( X \) and \( Y \), to each other by a linear multivariate model. The reference Wold et al. (1984) is recommended for the interested reader.

PLS can be seen as a biased regression method and can as such be expressed in terms of a set of polynomials (one for each \( Y \)-variable) according to Eq. (4).

\[
Y = X \times B_{PLS} + F
\]

\( F \) is a matrix of residuals. The matrix of biased regression coefficients, \( B_{PLS} \), can be calculated in many ways, see Höskuldsson (1988) for details. If the data in matrix \( X \) is scaled properly, i.e. centered and scaled to unit variance, then the obtained regression coefficient can be interpreted and compared to each other.

Latent variables, scores, derived from PLS computations of process data can be displayed graphically, c.f. Fig. 9 (Kourti et al., 1996). The objective of these graphs is to monitor the performance of a process over time in order to understand whether the process behaves as it is expected to do. And if it does not, the analysis should first detect the occurrence of an event and secondly provide clues to the problem, which enable corrections to be made. In this work the score plot is used to distinguish different operating conditions (Tano, 1996).

3. Results and discussion

Tables 1 and 2 summarises the responses obtained from the strain gauge sensor recordings and the samples taken on the mill feed/discharge. Toe and Shoulder angles, \( T_a \) and \( S_a \), respectively, are determined from the strain gauge signal, which in turn are used to calculate the dynamic volume of the grinding charge, \( J_T \) (Herbst et al., 1990). For the first PLS model, these sensor variables (\( T_a, S_a, J_T \)) are considered as response variables to analyse the effect of design variables on charge behaviour. When the objective is to monitor slurry flow properties and predict grinding performance the complete strain gauge signal will be regarded as predictor variables in the PLS regression.

Grinding index in Table 1, calculated according to Eq. (1), is lower compared to industrial mills, which is most probably a scale effect. Nevertheless, in these experiments the relative change is of interest and therefore the variations in grinding performance is considered to be adequate for the evaluation of the experiments.

<table>
<thead>
<tr>
<th>Exp. (#)</th>
<th>Feed to mill [tonne/h]</th>
<th>Solids conc. by volume [%]</th>
<th>Dispersant [mL/min]</th>
<th>Temperature (degree C)</th>
<th>Apparent viscosity [mPas]</th>
<th>Yield value [Pa]</th>
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<td>24.7</td>
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</table>

Fig. 3. Design region for all 10 experiments.
3.1. Viscometric measurements

To demonstrate that different conditions regarding slurry flow resistance was achieved in the ball mill simple viscometric measurements were done on the pilot mill discharge. From the obtained rheograms apparent viscosity and yield stress are derived, see Table 2. At high slurry concentration, 41 vol.% solids, the slurries exhibit a time-independent non-Newtonian behaviour of pseudoplastic type with a yield stress. When slurry concentration is lowered a transition of flow character appears, indicating a slurry fluid of a pseudoplastic type but without or a very low yield stress, c.f. Table 2.

3.2. Strain gauge sensor response

Fig. 4 shows a typical response of the strain gauge sensor for low, 31 vol.%, and high, 41 vol.%, solids content and also the change that occurs when a dispersant is added to the mill slurry. The signal profile differs significantly for the two solids contents. The main difference constitutes of a wider signal profile for high solids content indicating a larger Charge volume \( J_T \) even though slurry flow through the mill is lower. This can be an indication of increased slurry flow resistance in the mill when solids content gets high.

Running the mill at low solids content, the difference in signal response with respect to dispersant is hardly visually detectable, only a minor decrease of Shoulder angle \( S_a \) is shown. Obviously for low solids content the strain gauge sensor does not show any change in the position of the charge when a dispersant is added despite the significant change in the apparent viscosity obtained. Whereas at high solids content the signal response, with dispersant added, shows both a lower amplitude of deflection and also a significant change of the charge Shoulder angle \( S_a \) region indicating a contracting charge. The results obtained are also in good agreement with a study by Fuerstenau et al. (1990), where they found an effect of charge split between cascading and cataracting regimes when a dispersant aid is added to a dense slurry.

3.3. Evaluation of the statistical design

Firstly a PLS regression model, conceptual model given in Eq. (5), was calculated. In addition to the main design variables (feed, solids, dispersant), is also one interaction term included in the model (solids * dispersant). Other interactions (feed * dispersant) and (feed * solids) are excluded in the model since they did not contribute to better modelling statistics, i.e., no significant increase of explained variance, \( R^2_Y \). The model were calculated for all ten experiments, process variables are average values (10 min) for each experimental setting, see Table 1 for values. The main purpose with
the first model is to study the effect of design variables on some response variables.

\[ Y = f(\text{feed, solids, dispersant, solids} \times \text{dispersant}) + F \]  

(5)

\( F \) is the residual matrix. The calculated model gave five significant PLS components with explained variance, \( R^2 \), and predictive capability, \( Q^2 \), for the different responses shown in Fig. 5. A comparable measure for bivariate data is the correlation coefficient. The result shows that the variables Weight, Grindability, Shoulder angle and Charge volume are reasonably well modelled, with high \( R^2 \) and \( Q^2 \), whereas the variables Power and Temperature shows low predictive ability, low \( Q^2 \). Mill torque is presumably a more adequate power measurement, since losses and inaccuracies in the mill drive system will then be excluded from the power figure. The low \( Q^2 \) for the Temperature can unfortunately be a result from the handheld measurement, an indication of a low accuracy for the instrument. For the variable Apparent Viscosity, the result demonstrates the difficulty to model rheological properties using standard mill variables.

However, the obtained model is statistically acceptable and can be used for studying the different effects. The following interaction plots displays the predicted change in the response variables when one design variable varies, and the second variable is set at both its low and high level, all other variables being set on their centre value.

Of primary interest is to study the effect on the traditionally monitored mill variables, Power, Weight and Temperature. All of them are positively affected when solids content increase. When a dispersant is added to the slurry, the effect on Power and Weight is almost negligible at low solids content. The lower mill Power when dispersant is present is probably due to a change of charge position and thereby a different centre of gravity for the charge. The Temperature shows an inconsistent response when dispersant is present, which is difficult to interpret, once again, can be an inaccuracy in the measurement (Fig. 6).

Next to study is the effects found from the strain gauge sensor, expressed as \( T_a \) and \( S_a \), together with the derived Charge volume, \( J_T \). At low solids content, the calculated variables are influenced by the presence of a dispersant aid only to a minor degree. On the other hand, at high solids content both \( T_a \) and \( S_a \) angles are affected, with the largest change, taking place at the shoulder of the charge. High solids content seems to expand the charge and with the addition of dispersant it falls back to a volume corresponding more or less to the situation at low solids content. The change for the variable Charge volume is analogous since it is calculated from \( T_a \) and \( S_a \) angles (Fig. 7).

The last interaction plot is for the grinding performance variables \( W_{app} \) and \( G_i \), and the slurry flow resistance expressed as \( \eta_{app} \). High solids content slightly increase the grinding performance, i.e., lower \( W_{app} \) and higher \( G_i \). Whereas the addition of a dispersant give a negative effect on the grinding performance especially when running at low solids content. The effect of a dispersant aid is well reflected in the viscometric measurement, giving a higher \( \eta_{app} \) in the absence of a dispersant (Fig. 8).
3.4. Process monitoring approach

The result from the first analysed PLS model shows that the strain gauge sensor with the variables, $T_a$ and $S_a$, determined from the sensor signal, well reflects changes in slurry properties that can be related to rheological conditions. By that opens the possibility to use the sensor to detect those changes for continuous monitoring of the grinding operation and in the end also to improve grinding control.

When dealing with a large number of variables, multivariate statistical methods such as principal component analysis (PCA) or partial least squares regression (PLS) is of great help (Eriksson et al., 2001). The strain gauge sensor in the pilot ball mill produces 360 variables one for each degree of revolution and together with traditional process variables gives a total data vector of ~370 variables. As mentioned before, some signal features, such as $T_a$ and $S_a$, are possible to detect by various univariate methods. However, interpretations of the sensor signal in earlier sections have also shown that for some operating conditions it is the combination of several signal features that brings the information about the charge behavior not only $T_a$ and $S_a$. Fig. 4 shows a typical response from the strain-gauge sensor, where a change in $S_a$ is clearly distinguishable, i.e. decrease of $S_a$ when a dispersant is present. At the same time there is also a change in the sensor signal amplitude at different positions during a mill revolution. Therefore a multivariate method is necessary when analyzing what part of the signal profile that bears information about the charge behavior. A conceivable monitoring system can take use of the output data from a PLS model, especially the score plot, c.f. Fig. 9. These score plots can be seen as a multivariate window into the process variable space. The units on the abscissa and ordinate do not have any direct physical meaning other than observations close to each other have similar properties, whereas those far from each other are dissimilar. Often different directions, principal components, can be interpreted and given a physical or chemical meaning.

A comparison between two PLS regression models is done, where the first model include the ordinary process variables together with the calculated $T_a$, $S_a$, and $J_T$, a total of 8 predictor variables, c.f. Table 3. A new second model uses all 360-sensor variables corresponding to a complete mill revolution with a resolution of $1^\circ$. As a quality measure of the obtained PLS models the amount of explained variance in the predictor variables, $R^2_X$, and response variables, $R^2_Y$, is used. Both models have totally 50 observations, i.e. 5 observations per run, which correspond to 5 min of data recording.

The explained variance, $R^2_X$, indicates a high systematic variation among the predictor variables for both

![Fig. 8. Interaction plots for solids and dispersant on responses W_app, G_i and g_app.](image8)

![Fig. 9. Score plot for PLS model 1 and 2 showing 5 observations per run, totally 10 experiments. Black box indicate runs with dispersant present (run #8–10), black crosses for the rest (run #1–7).](image9)
models. For model 1 this is expected since \%-solids is a part of the experimental design. However, model 1 cannot fully use the high \( X \)-variation to model the response variables, only half of the variation for \( W_{\text{app}} \), \( G_i \) and \( g_{\text{app}} \) is explained. Scaled and centered regression coefficients for PLS model 1 are listed in Table 4.

The score plot for model 1, c.f. Fig. 9, also demonstrate the difficulty to discriminate the runs where dispersant is present, from the other runs. The experiments with dispersant (run # 8–10) are mixed up with runs at low solids content (run # 1–3) in the upper right quadrant. The distribution of the scores for model 1 is mainly governed by the solids content and the amount of feed. Best grinding performance is achieved for observations in the upper left quadrant in the score plot, meaning high solids content and to some extent high feed.

For model 2 the value of \( R^2 \) is also notably high, indicating that the strain gauge sensor picks up the systematic and relevant information about the charge behavior. The ability to discriminate the different runs for model 2 is shown in the score plot, c.f. Fig. 9b. Experimental runs (run # 8–10) where dispersant is added to the slurry is distinctly marked and separated from other runs in the upper right quadrant. Runs at high solids content are placed to the left, whereas runs at both low and mid solids content are spread from the lower center and to lower right quadrant in the score plot indicating an unwanted operating regime since grinding performance is low for these runs.

Grinding performance is not well modelled in PLS model 2, as shown by the low values of \( R^2 \) for \( W_{\text{app}} \) and \( G_i \). The result emphasizes the fact that size reduction is energy dependent and therefore information of applied mill power and throughput is necessary in a regression model. This is also confirmed in the analysis of model 1 where highest regression coefficients was obtained for the process variables \( \text{Feed} \) and mill \( \text{Power} \), c.f. Table 4.

For model 2 however, the obtained result points out that the \( X \)-variation is strongly related to the flow resistance in the mill, expressed as the Apparent Viscosity, \( \eta_{\text{app}} \). Fig. 10 shows the predicted vs measured viscosity, where \( \text{exp}_1 \) and \( \text{exp}_3 \) deviate from the regression line. Analysis of the residual observation variance do not show any specific high value for these experiments, which is an indication that the correlation structure is unchanged and the most probable cause for the deviation is the total measurement error, i.e., sampling and instrument error. The obtained prediction accuracy is of course not acceptable as an absolute value for slurry viscosity but as an on-line indicator of slurry flow character it is believed to be usable for process monitoring.

4. Conclusions

The measurements clearly reveal that an embedded lifter bar sensor is able to pick up flow resistance changes in an operating mill. Signal features influenced by the changed operating conditions were the \( \text{Toe} \) and \( \text{Shoulder angle} \), where the \( \text{Shoulder angle} \) showed more

| Table 3 | Explained variance for predictor and response variables |
|----------------|----------------|----------------|----------------|----------------|
| PLS model | Predictor variables \([R^2 X]\) | Response variables \([R^2 Y]\) |
| 1 | Power, weight, \%solids, temp, \( T_a \), \( \phi_o \) \( J_T \) | \( W_{\text{app}} \) | \( G_i \) | \( g_{\text{app}} \) |
| 1 | 0.713 | 0.503 | 0.598 | 0.498 |
| 2 | \( \theta_{\phi_o} \)–360\(^\circ\) | 0.82 | 0.373 | 0.194 | 0.809 |

| Table 4 | Scaled and centered regression coefficients for PLS model 1 |
|----------------|----------------|----------------|----------------|----------------|
| Response variables | Predictor variables | Power | Weight | \%solids | Temp | Feed | \( T_a \) | \( \phi_o \) | \( J_T \) |
| \( W_{\text{app}} \) | 0.24 | 0.08 | –0.18 | –0.08 | –0.35 | 0.14 | –0.23 | –0.23 |
| \( G_i \) | –0.36 | –0.16 | 0.20 | 0.05 | 0.50 | –0.11 | 0.23 | 0.24 |
| \( g_{\text{app}} \) | 0.06 | 0.09 | 0.10 | 0.15 | –0.03 | –0.16 | 0.19 | 0.17 |

Fig. 10. Measured vs. predicted apparent viscosity, \( \eta_{\text{app}} \) for PLS Model 2.
distinct changes than the *Toe angle*. Addition of disper- 
sant at low solids content gave hardly any response on 
the signal profile. However, at high solids the dispersant 
influenced the whole signal profile, and gave a generally 
lower signal amplitude. This is interpreted as a more 
movable slurry and thereby producing a lower impact 
force on the lifter bar.

The resistance to flow here expressed as an *Apparent 
Viscosity* is strongly influenced by solids content and 
naturally by the addition of a dispersant. Obtained vis-
cometric results clearly show that the slurry flow resis-
tance is changed between the experimental runs. The 
observed changes in impact force on the lifter bar can 
mainly be related to the product slurry, because the 
influence of the load of the charge should not vary much 
during the various operating conditions investigated 
here. In addition to interstitial slurry flow within the 
charge, slurry may show up as a free surface on top, 
as schematically shown in Fig. 1. Independent on the ex-
act location of the slurry at the sensor mill section, the 
increased load results show how high solids concentra-
tions increased the volume of slurry in the mill which 
in turn can be related to increased resistance to flow. 
The corresponding increase in retention time here may 
also have contributed to increased production of fine 
material, as shown in a higher *Grindability index*. On 
the contrary, addition of a dispersant at high solids con-
tent showed a lower sensor loading, indicating less resis-
tance to flow, slurry volume and less retention time and 
thus a decreased grinding performance.

The presented results imply that there are definite 
possibilities for on-line control and monitoring of a tum-
bling mill based on the information contained in the 
strain gauge sensor data. The presented method should 
also be seen as a suggestion of how to handle and ana-
lyse large amounts of multivariate data directly applied 
in a real process situation.

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Comparison of experimental mill lifter deflection measurements with DEM predictions

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ABSTRACT

Computational demands and the lack of detailed experimental verification have limited the value of Distinct Element Method (DEM) modelling approaches in mill simulation studies. This paper presents the results of a study in which the deflection of a lifter bar in a pilot ball mill was measured by an embedded strain gauge sensor and compared to deflections predicted from DEM simulations.

An assembly of bonded particles represents a flexible rubber lifter in the DEM model. The deflection is tracked by monitoring the displacement of particles near the actual strain gauge base and tip.

The deflection profile obtained from the DEM simulation shows a reasonably good correspondence to the pilot mill measurements. The difference is attributed to the fact that time-dependent behaviour of the rubber lifter is ignored, resulting in rapid relaxation of the lifter when the exerted force is released. Mill charge features such as toe and shoulder position of the charge are well marked. However, DEM prediction shows lower values compared to measurements which is most likely an effect of the two dimensional (2D) model used and the inability to model the effect of slurry present in the mill.

The approach presented here is a contribution to the validation of DEM simulations and an introduction to the description of a bendable rubber lifter implemented in a DEM mill model.

Keywords: Strain gauge sensor, Distinct element modelling, Simulation, Grinding

1 INTRODUCTION

Distinct element methods (DEM) may be used as simulation tools to gain insight into particulate flow processes. When applied to grinding it affords us an opportunity to study many aspects of grinding in greater detail than has been possible to date. DEM can be used to describe and visualise the motion of the grinding charge and how it is influenced by both design and operating conditions. Furthermore DEM predictions provide useful information on collision forces, energy loss spectra and power consumption. Computer simulations can in many cases replace long-term and complicated field experiments (Dennis and Rajamani, 2001).
In harmony with increased computer performance, DEM has evolved substantially lately. The distinct element method proposed by Cundall and Strack (1979) was first applied to grinding problems by Mishra and Rajamani (1992). Other researchers who have contributed to the progress of DEM in milling are Cleary (1998, 2001), Radziszewski (1999), Inoue and Okay (1996), Herbst and Nordell (2001), Agrawala et al. (1996), Datta et al. (1998), Bwalya and Moys (2001), Djordjevic (2003), and Govender et al. (2001a).

The input parameters to a DEM model have a significant impact on the output (Cleary, 1998; Dong and Moys, 2002). The contact stiffness, coefficient of restitution and friction control the interaction between particles. To obtain reasonable accuracy the choice of material properties should be guided by the results of experiments that mimic the conditions within a mill. This is a complicated task and the methods used are often simplified to the point where they might cause significant errors in the simulation results. When it comes to the use of DEM for predicting breakage rate the mentioned input parameters are probably of less importance, it is of greater importance in this case to model the behaviour of the fluid and its interaction with ore particles (Cleary, 2001).

Höfler and Herbst (1990) proposed that the normal contact stiffness could be decided using the Ultra Fast Load Cell, developed at University of Utah. A computational limitation for the choice of contact stiffness is that too high values will result in an extremely small calculation time-step, resulting in excessive simulation times. An early method for determining the coefficient of restitution (Mishra and Rajamani, 1992) showed that it is independent of material type. A later method using a high-speed digital camera (Dong and Moys, 2003) showed that it is insensitive to collision velocity and can be given a constant value. Powell (1991) performed experiments where he showed that vibration frequency influenced static and dynamic friction, the latter to a minor extent. Cleary (1998) showed that power prediction from DEM is insensitive to the value of the coefficient of friction, while Mishra and Rajamani (1992) and Van Nierop et al. (2001) found a definite effect, especially at high mill speed. The above clearly illustrates that it is possible to draw different conclusions regarding parameter values from experiments and as long as there is a lack of detailed experimental verification, DEM techniques will have a limited value in the milling field.

Validation of DEM has been the subject of recent research (Govender et al., 2001, McBride et al., 2004, Powell and McBride, 2004, Dong and Moys, 2002). Focus has been on comparison of power prediction, toe and shoulder estimations, centre of circulation location and energy distributions. In work by Cleary (2001) and Rajamani et al. (2000) they showed that prediction accuracy in three-dimensional DEM simulation is superior to that obtained in two-dimensional simulations. In work by Moys et al. (2000) the force exerted on a lifter bar was calculated from DEM simulations and compared with data obtained from a laboratory mill. Good agreement of charge motion in general was achieved at low mill speed, however on a detailed level there was a discrepancy because of random interaction between particles and the mill lifter bar. The study presented here aims to expand upon this work.

The objective of this work is to link computational results to experimental data obtained from an instrumented pilot ball mill. The approach taken is to emulate the behaviour of a rubber lifter when it is exposed to forces from the grinding load in a 2D DEM mill model using the particle flow code PFC2D. Traditionally walls in a DEM model are made up of rigid bodies where the equations of motion are not satisfied for each individual wall - i.e., forces acting on a wall do not influence its motion. Here the instrumented rubber lifter is represented as an assemblage of bonded particles rather than walls in order to simulate deflection. The measured data is the response from a strain gauge sensor embedded in one of the rubber lifter bars in the pilot mill. This paper provides an overview of the work being done to provide the experimental data against which DEM predictions can be verified and also some background of the method for implementing a flexible lifter in a DEM model is given as well.

2 EXPERIMENTAL SET-UP

2.1 Strain gauge sensor

A simplified view of the sensor is shown in Figure 1. The mill has several lifters one of them (marked 1) is equipped with a leaf spring whose deflection is measured by the strain gauge (marked 2). As the mill rotates
and the lifter with the sensor dips into the charge, the force acting on the lifter increases, which in turn, causes a deflection. The strain gauge mounted on the leaf spring converts this deflection to an electric signal. The signal is then amplified, filtered and transmitted to a computer. The sensor system is marketed by Metso Minerals under the name Continuous Charge Measurement system (CCM).

![Figure 1: To the right a cross section of a mill with a horizontal reference line, the left part shows the lifter bar (1) with a strain gauge sensor embedded (2).](image)

A typical deflection profile of the sensor signal and an attempt to divide it into different segments is shown in Figure 2. The boundaries and size of the partitions are determined by engineering knowledge of the grinding process. Each segment in Figure 2 illustrates an important dynamic event during the passage of the sensor-equipped lifter bar under the mill charge. The ordinate in Figure 2 shows the deflection of the lifter bar, which indirectly corresponds to the force acting on it and the abscissa is the mill rotation angle with a resolution of 1°.

![Figure 2: Segmentation of a typical sensor signal during its passage in the charge.](image)

The sensor signature reflects different charge features such as mill volume, position and behaviour of the mill charge. Both toe region (S2) and shoulder region (S6) are well known, and can be used to calculate the volumetric mill load and the angle of repose, collectively these data give a good measure of the location of the charge. The other segments are less known but are expected to provide information about grinding efficiency. Such features can be extracted from the sensor signal for the purpose of process monitoring and diagnosis of process performance. Table 1 provides a summary of the stages during one mill revolution. The lifter bar angles given in Table 1 correspond to the positions marked in Figure 2, as a reference in these measurements is the horizontal line, which corresponds to 0 degrees at the 9 o’clock position, c.f. Figure 1.

In this work an attempt is made to identify the corresponding segments in a predicted deflection profile obtained from DEM simulation. The toe/shoulder position in particular will be compared for validation purposes.
Table 1. Sensor lifter bar signal segmentation and grinding load features

<table>
<thead>
<tr>
<th>Segment</th>
<th>Lifter bar angle</th>
<th>Process feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&lt;sub&gt;1&lt;/sub&gt;: the sensor lifter bar (SL) is still in the air</td>
<td>&lt; 50°</td>
<td></td>
</tr>
<tr>
<td>S&lt;sub&gt;2&lt;/sub&gt;: the SL hits the ball charge and starts to get submerged in the charge</td>
<td>50° – 75°</td>
<td>Indicates the toe position of the charge, and if present, the slurry pool</td>
</tr>
<tr>
<td>S&lt;sub&gt;3&lt;/sub&gt;: the SL starts to bend forward due to turbulence in the toe area</td>
<td>70° – 85°</td>
<td>Rate of change varies with mill speed</td>
</tr>
<tr>
<td>S&lt;sub&gt;4&lt;/sub&gt;: the SL is at peak bending</td>
<td>75° – 90°</td>
<td>Both speed and charge level has an influence, wear of lifter</td>
</tr>
<tr>
<td>S&lt;sub&gt;5&lt;/sub&gt;: the SL is moving through the charge</td>
<td>80° – 90°</td>
<td></td>
</tr>
<tr>
<td>S&lt;sub&gt;6&lt;/sub&gt;: the SL has gradually decreased the bending and is at take-off position</td>
<td>190° – 215°</td>
<td>Indicates the shoulder position of the charge</td>
</tr>
<tr>
<td>S&lt;sub&gt;7&lt;/sub&gt;: the SL is leaving the ball charge and starts slowly to rise to an upright position</td>
<td>&gt; 215°</td>
<td></td>
</tr>
</tbody>
</table>

2.2 Force-Displacement calibration

The force exerted by the grinding load on a rubber lifter will cause it to deflect. To establish the relation between applied force and the obtained deflection a mechanical calibration procedure was carried out. The tangential and oblique (45°) force-displacement characteristics of the lifter bar were measured using the set-up shown in Figure 3. A 300 mm long piece of the lifter bar was bent with a tube-shaped load applicator which also was 300 mm long and had a diameter of 50 mm. The lifter bar was firmly bolted to the foundation of a tensile test machine. The displacement of the load applicator, which was equal to the movement of the crossbeam of the tensile test machine, was measured using a dial indicator. The “Force F1” test sequence, involving a stepwise increase of applied force and recording of resulting displacement, was carried out first followed by the “Force F2” test sequence.

![Figure 3: Arrangement for the calibration of lifter modulus of elasticity.](image)

The results of the mechanical calibration are presented in Figure 4. A linear relation is obtained within the test range investigated. The slope of the curve, 0.54 kN/mm was used to calibrate the particle contact and bond stiffness in a simulation of the “Force F1” test. It is believed that the rubber lifter may exhibit some time-dependent behaviour upon sudden release of the applied force, however the tensile test machine is not capable of measuring these effects. Introduction of a time-dependent contact behaviour into PFC<sup>2D</sup> might permit modelling of such behaviour if it also can be measured directly in the lab.
The pilot mill is 1.414 m in diameter and 1.22 m in length. It is a grate-discharge mill, equipped with 12 rubber lifters of square size 0.1 m and a face angle of 45 degrees. Steel balls with a diameter ranging between 10-30 mm and a density of 7800 kg/m\(^3\) were used in the experiments. The test material, a hematite pellet feed with \(d_{50}\) around 35\(\mu\)m and a solids density of 5200 kg/m\(^3\), was chosen to get stable grinding conditions with respect to feedsize variations. Feedrate was kept constant at approx. 1.5 t/h. Four experiments were run with the mill speed operated at 73% and 78% of critical speed (\(n_{crit}\)) for two levels of mill filling (\(J = 25\% \) and 35\% by volume). The embedded strain gauge sensor measures the load position (toe and shoulder) using the CCM algorithm, proprietary of Metso Minerals.

3 FLEXIBLE LIFTER IMPLEMENTATION IN A 2 D DEM MODEL

The mill itself was modelled in PFC\(^2\)D by a combination of walls and particles as shown in Figure 5. There are two ways of representing a mill with walls in PFC\(^2\)D: through the basic wall logic, which allows the user to specify and connect multiple line segments into a circular shape, or the general wall logic, which allows the user to define a circle directly. Because the lifters in the pilot ball mill are attached to the inner steel wall, the inner rubber liner is not continuous. As a result, the inner steel wall of the mill was represented with a circular general wall while the inner rubber liner was represented with multiple basic wall segments.

Walls within PFC\(^2\)D act as rigid boundaries so it was necessary to represent the instrumented rubber lifter with bonded particles rather than walls in order to simulate deflection. The remaining lifters were
represented with basic wall segments. For the instrumented lifter, a regular assembly of small sized particles in the shape of the lifter was generated at the lifter position and bonded using the parallel bond logic within PFC\textsuperscript{2D}. Parallel bonds reproduce the effect of additional material (e.g., cementation) deposited after the balls are in contact and provide for moment, normal and shear resistance at the particle-particle contacts. Particles at the base of the lifter were fixed relative to one another to represent the rigid base within the actual lifter, as shown in Figure 6. The particles representing the rubber part of the lifter were bonded to this rigid base of particles. The deflection of the lifter was tracked by monitoring the positions of two particles at the locations nearest the true base and tip of the lifter. The deflection was calculated by considering the deviation of a line connecting the base and tip particle from a radian passing through the base particle.

![Simulated load applicator](Image)

Figure 6: Plot of force-displacement history from calibrated lifter test and the deformed state of the lifter. The particles representing the rigid base as well as the tip and base of the strain gauge used for deflection measurement are indicated.

### 3.1 Microproperties

The particle and parallel bond properties used to represent the lifter and charge within the PFC\textsuperscript{2D} model are outlined in Table 2. The methodology for choosing these properties is outlined in the following sections.

<table>
<thead>
<tr>
<th></th>
<th>Charge (Particles)</th>
<th>Instrumented Lifter (Bonded Particles)</th>
<th>Rubber Liner (Walls)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Particle Radius</td>
<td>5mm-15mm (uniform distribution)</td>
<td>2mm</td>
<td></td>
</tr>
<tr>
<td>Particle Density</td>
<td>5333 kg/m(^3) (downward adjusted from true steel density of 8000 kg/m(^3) to compensate for 2D representation)</td>
<td>1274 kg/m(^3) (upward-adjusted from true rubber density of 1130 kg/m(^3) to compensate for pore space in lifter)</td>
<td></td>
</tr>
<tr>
<td>Normal stiffness, (k_n) (N/m)</td>
<td>(4.0\times10^4)</td>
<td>(1.1\times10^4)</td>
<td>(2.2\times10^4)</td>
</tr>
<tr>
<td>Ratio of normal to shear stiffness, (k_s/k_n)</td>
<td>3/2</td>
<td>3/2</td>
<td>3/2</td>
</tr>
<tr>
<td>Bond stiffness, (k_b) (N/m)</td>
<td>(6.4\times10^6)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bond radius (multiple of particle radius)</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Friction coefficient</td>
<td>0.5</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Damping</td>
<td>Viscous; critical damping ratio=0.15 (normal); zero shear damping</td>
<td>Local; critical damping ratio=0.22</td>
<td>Viscous; critical damping ratio=0.15 (normal); zero shear damping</td>
</tr>
</tbody>
</table>
3.1.1 Particle Density

The mass and inertial properties of the particles representing the charge and lifter are automatically calculated in PFC2D as a function of a user specified global disk thickness, \( t \). In this case, the disk thickness was set equal to the length of the pilot mill, 1.2 meters. This results in correct mass and inertial properties for the instrumented lifter when the density of the rubber particles is increased to account for the pore space present in the bonded assembly. Because of the two-dimensional representation, the particles in the PFC2D mill represent rods rather than spheres. In order to mimic the mass and inertia of a string of charge balls rather than a solid rod, the density of the particles representing the charge was lowered accordingly. The consequence of this two-dimensional representation is that any single particle impacting the lifter within the two-dimensional model is actually simulating the simultaneous impact of a string of charge balls running the full length of the mill. Such simultaneous impact is not likely happening in reality and so this should be considered when interpreting deflection results from the 2D model.

3.1.2 Particle and Bond Stiffness

Normal and shear stiffness values are assigned to particles rather than contacts within PFC2D so that contact behaviour may be derived from the properties of the particular particles comprising it. Two different stiffness models are available in PFC2D: a linear model and a simplified Hertz-Mindlin model. In the linear model, the forces and relative displacements are linearly related by the constant contact stiffness, which is a function of the intrinsic stiffness of the two contacting entities. In the simplified Hertz-Mindlin model, the forces and relative displacements are nonlinearly related by the non-constant contact stiffness, which is a function of the geometric and material properties of the two contacting entities as well as the current value of the normal force. Work by Cleary (2001) suggests that the linear contact model is appropriate over the range of normal forces typically experienced within a mill and so this model was adopted for the current simulations. In addition, the ratio of normal to shear stiffness was set to 3/2 as proposed by Rajamani et al. (2000).

The particle stiffness assigned to the charge particles is outlined in Table 2. For the linear contact model, the resulting contact stiffness, \( k_c \), between two charge particles can be computed assuming that the stiffness of the two contacting particles, \( k_x \) and \( k_y \), act in series such that

\[
\frac{k_c}{k_x + k_y} = \frac{k_x k_y}{k_x + k_y}
\]  

(1)

The stiffness of the bonds comprising the lifter (input directly by the user) and the contact stiffness (derived from Eqn.1) act in parallel to control the deformability of the lifter. The results of deflection tests performed on the instrumented lifter in the laboratory were used to calibrate both the particle and bond stiffness by simulating the test in PFC2D and comparing the predicted response to the force-displacement histories shown in Figure 4. The actual test was performed over a 300mm section of lifter. Since the simulated test would represent deflection of a 1.2-meter long section, the target lifter stiffness for the simulated test was set to four times the actual measured stiffness of 0.54 kN/mm. It is possible that there is a non-linear relation between lifter stiffness and test length, in which case this assumption may not be valid. The nature of this relation should be examined in future experiments to test the validity of this assumption when representing the mill in two dimensions. The calibrated force displacement relation obtained from the simulated tangential force test is plotted in Figure 6 along with the deformed state of the lifter at a displacement of ~ 4mm. The particle and bond stiffness obtained from the calibration is outlined in Table 2.

The stiffness of the rubber walls within the simulation (representing the remaining lifters and the rubber liner) were set to achieve the same contact stiffness as the bonded contacts within the particle-based lifter. This is calculated as the sum of the parallel bond stiffness and the contact stiffness provided by Eqn.1 (since the two stiffnesses act in parallel). Substituting the stiffness of the parallel bonded contact back into Eqn.1, one can obtain the desired wall stiffness.

3.1.3 Friction Coefficient

The friction coefficients of the steel and rubber were set to 0.5 and 0.9, respectively based on values published by Rajamani et al. (2000).
3.1.4 Damping

Damping is employed in PFC2D to simulate dissipation of kinetic energy in the mill. The default damping within PFC is local damping, which applies a force to particles in proportion to acceleration and a damping coefficient. Gravitational acceleration during free fall is damped in this case, resulting in incorrect free-fall velocities. As a result, local damping cannot be used for the charge balls. In the simulations reported here, local damping was used only to damp energy within the instrumented lifter. Viscous damping was used to damp energy at the contact between charge balls and between charge balls and the rubber lifter and walls. In this damping formulation, viscous dashpots (in the normal and shear directions) are used to damp energy at contacts between impacting particles. Damping constants are specified as a fraction of the critical damping ratios in the normal and shear directions. Critical damping results in a system response that decays to zero at the most rapid rate. The damping constants used in the simulation were chosen based on published relations to the coefficient of restitution (Figure 7).

![Figure 7: Relation between restitution coefficient and critical damping ratio used to obtain the critical damping ratios for the mill simulation. The curve for the notension on case was used for the simulations reported here. (Itasca, 2002).](image)

3.2 Simulation

Assigning a rotational velocity to all of the wall elements simulated mill rotation. Due to the fact that particles cannot be attached to walls in PFC, another scheme had to be developed to rotate the particle-based lifter at the exact same rate with the same centre of rotation. This was accomplished by using the clump logic within PFC2D, which provides a means to create and modify groups of slaved particles or clumps. By creating a mirror duplicate of the rigid lifter base on the opposite side of the mill and combining the two bases to form a clump, the centre of rotation shifted to the exact centre of the mill and the rigid base could be rotated synchronously with the mill walls.

4 RESULTS

A DEM prediction of lifter deflection for the case high filling ($J = 35\%$) and high speed ($\eta_{crit} = 78\%$) is shown in Figure 8. The overall agreement of the predicted and measured deflection profile is acceptable, however some differences can be noted. Key features of the grinding charge, such as toe and shoulder positions are comparable. Definitions of toe and shoulder are not always consistent in the literature; here we try to follow the concept described by Powell and McBride (2004). In all run cases the simulated mill speed is fairly low resulting in purely cascading charge movement where impact toe and bulk toe coincide. Shoulder position is taken as the point where the charge leaves the mill shell.

The signal segment $S_2$ and $S_3$ exhibits the same behaviour for DEM prediction and pilot mill measurement, high impact during short time. Predicted toe position is lower, c.f. Table 3, indicating a charge that is more horizontally positioned or in this case showing a more distinct bi-plane shape. Some of the differences in toe angle can be explained by limitations of the 2D representation when compared to 3D DEM simulations.
(Cleary, 2001). Furthermore the combined time constant for the measurement system and the rubber lifter itself will give rise to a delay (low pass filtering) that contributes to higher values for toe position in mill measurements, c.f. Figure 8. The latter is of importance when setting up the algorithm for finding toe and shoulder position from the signal profile.

Figure 8: Comparison of DEM predicted (dotted) deflection with a low pass filtered (solid). Run case $J = 35\%$ and $\eta_{\text{crit}} = 78\%$.

Signal segment $S_4$ and $S_5$ is different with respect to both peak value and the lifter relaxation. The peak value of the deflection from the PFC$^{2D}$ model is approximately $1/3$ of the measured value. This difference may be reduced by decreasing the stiffness of the simulated lifter, however the fundamental cause is likely related to the limitations of a 2D model, which produce approximately 15% less contact events compared to 3D (McBride et al., 2004). The deflection within the DEM model decays fast, almost linearly, after reaching peak bending while the experimental deflection remains at a plateau level. A possible cause is the neglect of the time-dependent behaviour. A low pass filtering of the DEM predicted value, solid curve in Figure 8, result in a signal profile that is in a better accordance with mill measurement for signal segment $S_4$. By incorporation of a relaxation function in the DEM calculations a response similar to mill measurements should be possible to achieve for signal segment $S_5$. Shoulder region, segment $S_6$, is more distinct in prediction and a low pass filtering will smooth the signal and thereby make it more difficult to find the shoulder position.

Figure 9: DEM prediction of lifter deflection for different contact stiffness of the rubber liner, $K_n=2.2\times10^6$ (dotted) and $K_n=2.2\times10^7$ (solid). Run case $J = 25\%$ and $\eta_{\text{crit}} = 78\%$.

The two curves in Figure 9 show the effect of varying the stiffness of the rubber liner (walls). Differences are not significant, however the impact behaviour shows better correspondence to mill measurements at the higher contact stiffness. The predicted deflection profile obtained for the lower contact stiffness indicates a
behaviour at the toe position that in a real grinding mill could be interpreted as an effect of slurry pooling, which is not possible to achieve in a DEM model as slurry is not involved.

In Figure 10, DEM predictions (low pass filtered) and mill measurements is shown for all run cases. To facilitate comparison of the signal profiles a normalisation of the magnitude of deflection is done. The 2D DEM predictions match the experimental values reasonably well with aforementioned exceptions. The main effect of mill speed is reflected in the signal profile in segment S2. As shown high mill speed results in higher toe angle and higher peak value in the lifter deflection, which is comparable in both DEM prediction and measured value. The effect of filling level is mainly reflected as a broader signal, i.e. lower toe angle and higher shoulder angle.

![Figure 10: Comparison between DEM predicted, low pass filtered (solid) and measured (dotted) lifter deflection profiles obtained at different operating conditions of mill speed and charge filling level.](image)

Table 3 shows predicted and measured toe and shoulder position for all run cases. DEM prediction is visually evaluated from snapshots of predicted charge profile whereas measured values are calculated using the Metso Minerals proprietary algorithm. Toe position is easily found from mill measurements due to a distinct change in signal profile. Furthermore, at relatively low mill speed as is the case with these experiments there should not be any misinterpretation between impact toe and bulk toe. Decay and shoulder position however, are difficult to assess due to the slow relaxation of the real-life rubber lifter bar. Measurement value is therefore dependent on the search algorithm used.

<table>
<thead>
<tr>
<th>DEM prediction</th>
<th>Low speed ((\eta_{\text{crit}} = 73%)</th>
<th>High speed ((\eta_{\text{crit}} = 78%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low filling ((J = 25%)</td>
<td><img src="image" alt="image" /></td>
<td><img src="image" alt="image" /></td>
</tr>
<tr>
<td>High filling ((J = 35%)</td>
<td><img src="image" alt="image" /></td>
<td><img src="image" alt="image" /></td>
</tr>
</tbody>
</table>

Table 3: DEM predicted and mill measured toe and shoulder position expressed in rotation angle where the horizontal line at 9 o’clock represents the reference point.

<table>
<thead>
<tr>
<th>J=25% / (\eta_{\text{crit}}=73%)</th>
<th>J=25% / (\eta_{\text{crit}}=78%)</th>
<th>J=35% / (\eta_{\text{crit}}=73%)</th>
<th>J=35% / (\eta_{\text{crit}}=78%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>toe</td>
<td>shoulder</td>
<td>toe</td>
<td>shoulder</td>
</tr>
<tr>
<td>DEM prediction</td>
<td>45</td>
<td>210</td>
<td>50</td>
</tr>
<tr>
<td>CCM measured</td>
<td>69</td>
<td>202</td>
<td>72</td>
</tr>
</tbody>
</table>
Figure 11 shows typical PFC$^2$D snapshots of charge shapes obtained for the different conditions studied. The DEM model predicts very few balls to exhibit a parabolic trajectory of cataracting motion for low as well as high mill speed. The overall charge shape changes from a bi-plane profile, for the case of low filling, to a typical linear profile at high filling level. The result is in a good agreement with a thorough study by Dong and Moys (2003), where charge shapes were photographed at a number of different mill speed and charge levels. The obtained result is taken as a demonstration that the developed 2D DEM model can be used for comparison with measurements despite limitations of 2D compared to 3D.

<table>
<thead>
<tr>
<th>Low speed ($t_{\text{crit}} = 73%$)</th>
<th>High speed ($t_{\text{crit}} = 78%$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low filling ($J = 25%$)</td>
<td></td>
</tr>
<tr>
<td>High filling ($J = 35%$)</td>
<td></td>
</tr>
</tbody>
</table>

Figure 11: Typical snapshots of charge shapes obtained at different operating conditions of mill speed and charge filling level. Instrumented lifter marked in black.

5 CONCLUSIONS

In typical DEM mill modelling, mill walls and lifters are represented as rigid bodies that do not deform during collisions. Here, an attempt is made to improve the description of one of the lifter bars as a flexible body. A novel method implemented in the DEM model is developed where the instrumented rubber lifter in the pilot mill is represented as a lifter made of an assemblage of parallel bonded particles. Parallel bonds reproduce the effect of additional material deposited after the balls are in contact and provide for moment, normal and shear resistance at the particle-particle contacts. Assessment of the deflection profile presents new possibilities to compare DEM outputs to experimental data especially when the slurry fluid is taken into account.

A force-displacement calibration procedure was performed to find the microproperties to be used in representing the rubber lifter and walls within the mill simulation. Simulation result shows that the model describes the motion of the charge adequately. An exact match between predicted and measured lifter deflection is difficult to obtain due to simplified assumptions in both the description of the flexible lifter and also in the two-dimensional DEM approach. However, effects of mill speed as well as charge filling level are well reflected in the simulations and are comparable with pilot mill measurements.
The implemented novel method is an introductory approach and comparisons between real and predicted deflections are on a qualitative basis. The outcome of this work shows a potential to be of use in lifter profile design where flexible material is present. As a consequence the effect on grinding performance can be assessed in a consistent and meaningful manner due to the direct relation to experimental data, obtained by the strain gauge sensor.

To reach better accuracy in predictions and enable quantitative comparison some necessary improvements have been identified and will be investigated in future work. This includes investigation of lifter relaxation in the laboratory, simulation of time-dependent behaviour in the lifter and an extension of the approach to 3D.

6 ACKNOWLEDGEMENTS

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7 REFERENCES
