Investigating the potential benefit of an online particle size analyser on the feed to a primary milling circuit

C.W. Steyn*, A. Muller*, R.P. Brown, A.L. Haasbroek ****

*Anglo American Platinum, Johannesburg, South Africa (Tel: +2711-3736710, e-mail: chris.steyn@angloamerican.com)
** Stone Three Mining, Somerset West, South Africa (Tel: +2721-8513123, e-mail: robbie@stonethree.com)

Abstract: Tumbling mills are utilised around the world for particle size reduction. Efficient operation of a milling circuit is vital due to its high-power consumption and influence on the downstream beneficiation process.

It is well known that the feed size distribution (FSD) has a significant impact on the performance of a mill. Image processing on the feed material has made it possible to monitor this data in an on-line manner. Several applications have been reported in literature where the FSD was used as a disturbance variable in an advanced controller. Little has been done however, to determine the contribution of the FSD to the performance of the controller.

In order to quantify the benefit of this disturbance variable the controller will be run in a state where the variable alternates between being enabled and disabled. Controller performance will also be assessed by an LQG benchmark that incorporates the effect of a measured disturbance.

1. INTRODUCTION

Grinding mills are energy intensive processing units offering a unique set of challenges due to complex variable and state interactions. Furthermore, milling circuits are sensitive to process input variations, Wills and Napier-Munn (2015), both in ore size and minerology. These features justify, and indeed require, that significant effort be made for optimal operation via advanced control and the tracking thereof through process monitoring.

The aforementioned feed ore characteristics (hardness, particle size distribution, competency, specific gravity, etc.) and internal mill state parameters (power, load, rheology, grinding media, etc.) play a crucial role in the performance of a grinding circuit. Yet, due to the nature of the process it is difficult to measure these variables in a continuous manner. The control system is, therefore, left to react on limited or insufficient information to reject numerous unmeasured disturbances.

Progress in the field of image analysis, as detailed by Raina (2013), has enabled the online measurement of ore particle size distribution (PSD) on a conveyor belt feeding into mills. Morrel & Vallery (2001) rated the importance of feed PSD to be second only to ore competence variation in their influence on AG/SAG mill performance. Image analyses, therefore, provides an opportunity to obtain large efficiency improvements by incorporating the real time feed PSD information into control and monitoring systems.

The use of feed PSD analysers in a milling circuit can broadly be classified into three types of applications, namely:

- online process monitoring and troubleshooting,
- feedback control and
- feedforward control.

The objective of this paper is to investigate the benefit of PSD data in each of these categories.

The paper commences by describing the primary milling circuits under investigation. An investigation into the influence of feed PSD on the mill performance and a brief overview on the image analysis algorithm is then provided. The use of PSD data in a multivariate process monitoring application, and the use of PSD in feedback control is discussed. Arguably the key contribution of this paper is the detail on the use and benefit analysis of utilizing PSD in a feedforward control scheme.

2. PROCESS DESCRIPTION

Primary milling is the first stage of grinding and plays a crucial role in the liberation of the valuable minerals. A typical circuit consists of Autogenous (AG), Semi-Autogenous (SAG), Ball or a combination of aforementioned mills. In an

AG mill no grinding media is added, while in SAG mills the charge is supplemented with steel balls. As more steel balls are added the transition from a SAG to a ball mill occurs.

For the study at hand, two circuits are under investigation, namely: Mototolo and Amandelbult, both of which are briefly discussed below:

Mototolo Circuit

In the primary grinding stage, a Run-of-Mine (ROM) ball mill is used for size reduction. The circuit is preceded by a primary crushing circuit, where the material isn't subjected to any form of size-based classification. Consequently, this renders the circuit susceptible to feed disturbances.

Fresh ore is mixed with water and steel balls at a desired ratio as it enters the mill, Figure 1. The mill then discharges into a sump, where more water is added in order to reduce the pulp density. From here it is pumped to a material classifier, in this case a vibrating screen. Oversized material is sent back to the mill in a recirculating stream, whereas undersized material is sent for flotation beneficiation.

The main controlled variables (CVs) in the circuit are the mill load, mill power, discharge sump level and discharge density. The manipulated variables (MVs) available to control are the fresh ore feedrate, the inlet water (in proportion to the mill feed), the discharge sump dilution water and the discharge flowrate (cascaded to the pump speed).

Amandelbult Circuit

The Amandelbult UG2 number 2 (U2) circuit is similar to the Mototolo lay-out. However, instead of a ball mill the Amandelbult circuit makes use of an AG mill application. Pre-classification of the ore, based on size, occurs and the mill can be fed with a mixture of fine and coarse ore. A graphical representation of the circuit is shown in Figure 2.

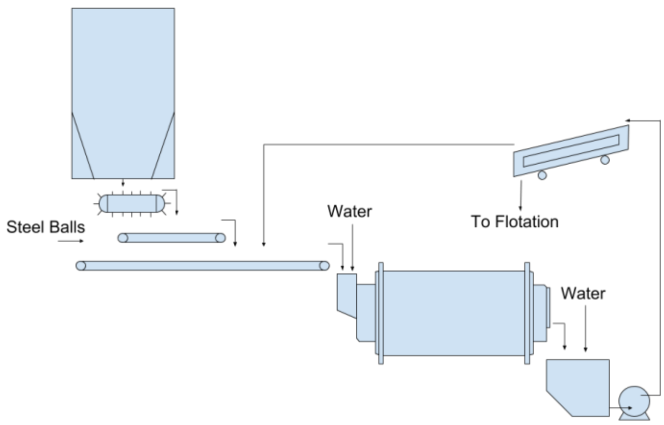


Figure 1: Layout of the milling circuit at the Mototolo JV concentrator.

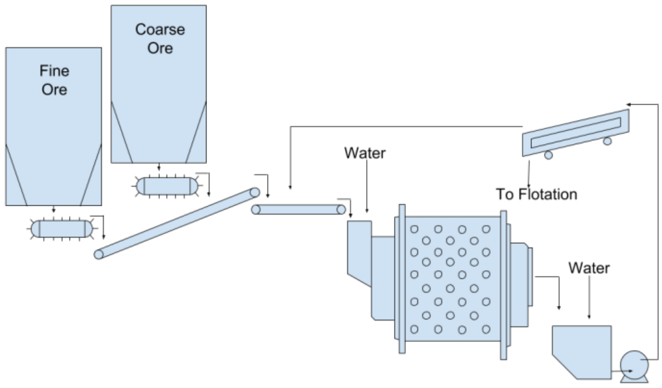


Figure 2: Layout of the milling circuit at Anglo Platinum's Amandelbult concentrator, Steyn and Sandrock (2013).

The CVs and MVs are similar to Mototolo with exception to the variable speed drive (VSD) on the mill as an extra MV. Steyn and Sandrock (2013) regards this additional degree of freedom a major advantage to the optimization of the mill, allowing the water and feed to remain at commercial optimum while the speed controls the load.

3. FEEDSIZE AND MILL PERFORMANCE

Milling circuits require a certain ore feed size distribution to operate efficiently. The feed is usually supplied to the mill by a primary crusher, which only aims to reduce the top size of run of mine ore. The primary crusher is affected by blasting operations and ore body characteristics, Bearman and Briggs (1998). Significant variations of the milling circuit feed size can thus be expected due to the stochastic nature of the breakage events and the subsequent materials handling operation that occur in this environment.

Seeing that the charge in an AG mill consists of only the ore being fed into to mill, it is expected that the feed size will have a significant impact on the operation, Napier-Munn et al (1996): a change in feed size to an AG mill will result in a change in grinding media. Subsequently, this will then affect the breakage characteristics of the ore, which in turn will change the charge level and power draw. Generally, an AG mill operates more effectively in the presence of large rocks due to the increase in kinetic energy to break smaller rocks.

For a SAG mill the ball charge tends to dominate the rock breakage and the contribution of the rock media to grinding will decrease. It follows that, in contrast to AG mills, the coarser rocks mostly constitute a rock burden which increases the overall energy consumption. Therefore, in these circumstances, a reduction in feed size is favourable. Furthermore, as the transition from SAG mill to ball mill occurs, the influence of feed size tends to become less significant.

The influence of feed size on AG/SAG mills was expanded on by Morrel & Vallery (2001). In their work, the authors investigated a SAG mill (treating copper bearing ore) and obtained a correlation between feed size, throughput and specific energy. In particular over the covered range of feed F80 (80% of material passes below this size) a 30% variation in feed rate resulted. Thus, illustrating the importance of feed size on milling circuit performance.

4. FEED SIZE DISTRIBUTION (FSD) VIA IMAGE ANALYSIS

The most common and reliable technique of determining the particle size distribution of a solids stream is by sieving, Napier-Munn et al (1996). However, these measurements are done in a manual ad hoc fashion, preventing it's use in online control. To solve this problem the industry has adopted the use of smart sensors capable of directly measuring PSD in real time. Raina (2013), lists several examples of applications stretching from fragmentation analysis in the mining phase to crusher monitoring and milling circuit optimisation.

Machine vision applications for PSD analysis has been a theme of research and development since the 1980's. Optical methods were first proposed by Carlson and Nyberg (1983) and later expanded by Maerz (1987). Since then several commercial systems have become available, though this paper will focus on the IntelliOre™ Lynxx system developed by Stone Three Mining Solutions.

Two approaches for image acquisition can be followed. In the one approach a camera is used to take photographs of the ore at a high frequency. While the second approach makes use of a line scanning laser to build a height profile of the rocks on the conveyor. Thurley (2013), describes the laser-based methodology of particle size analysis in detail and comments on the accuracy of these systems.

Machine vision sensors are commonly placed in a housing to minimize external interference from the environment. Figure 3 shows a typical installation on a conveyor belt.

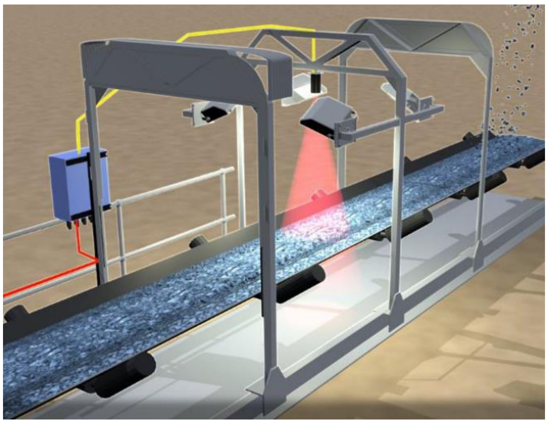


Figure 3: IntelliOre PSA system setup

The delineation algorithm, illustrated in Figure 4, starts with a pre-processing step, where cropping and normalization is performed in order to improve the contrast in the image. Once the pre-processing is completed, marker based watershedding is applied. The extraction of the markers is a crucial step in the algorithm and heavily impacts the segmentation process. The main objective of the marker extraction is to control the watershed algorithm and to avoid over or under segmentation of the image.

A multiscale approach is followed where multiple H-domes are generated for the extraction of hill markers. The hill markers are then sent to a classifier to ensure that only valid markers relating to ore particles are used in the successive steps. Valley markers are also extracted from the image to create boundaries between the individual particles. Given the markers, subsequent segmentation is automatic and requires no configuration. The resulting image is then again sent to a classifier to remove incorrectly segmented objects.

From this final output the mass of the delineated particles is determined. Assuming a constant density a PSD curve, based on a mass distribution per size interval, is constructed.

As an example, Figure 5 (a) shows the result of the segmentation on a camera image, while Figure 5 (b) shows the output of a laser-based system.

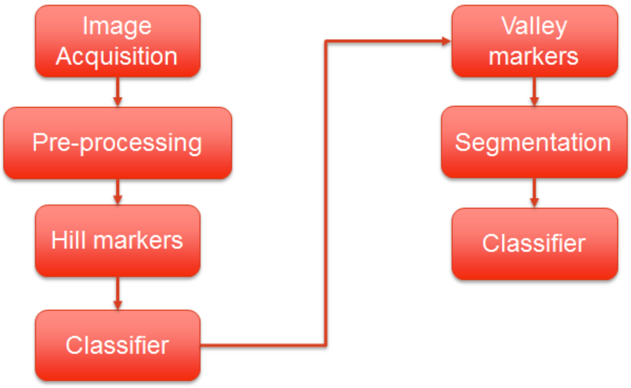
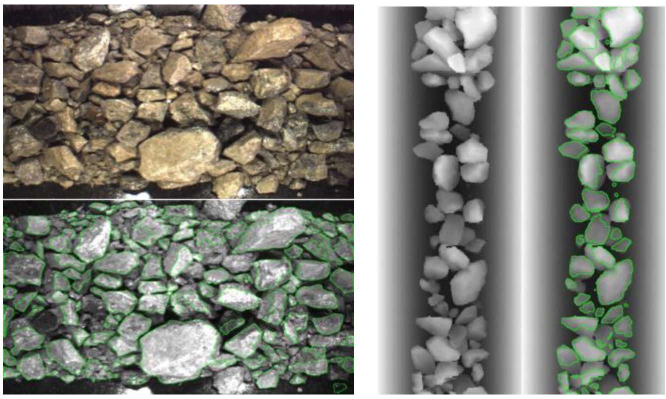


Figure 4: Steps used in the image processing algorithm



(A) (B)

Figure 5: Image segmentation results of a) an optical system and b) a laser based system

5. PROCESS MONITORING AND DAIGNOSIS

An important, often overlooked, benefit of online ore segmentation is the context and information it can visually provide to operators. By implementing live video feed in the process control room, operators may quickly distinguish between known process conditions and confirm the particle size analyser trends.

Such a live video stream has been implemented in the control room at Mototolo. A screenshot from the process analytics platform, IntelliSenzo™, can be seen below where the live feed and important trends are combined. Furthermore, the display in Figure 6 includes sensor health information to aid in sensor troubleshooting.

Complementary to the above mentioned basic visualisation and process context, more advanced analyses may further aid to troubleshoot and manage complex process systems. Increased use of methodologies such Principal Component Analysis (PCA) and Partial Latent Structures (PLS) are starting to surface in literature. As example, Bouajila et al. (2000) studied the use of PLS on milling circuits in order to predict Power and Load. With the use of PLS the contributing factors toward the predicted variables can be captured, which aid in root-cause analysis. Haasbroek et al (2014) further showed how PCA can be used as a monitoring and diagnostic tool during the troubleshooting of a milling circuit operation.

The use of PCA to assess multivariate data was investigated on the Mototolo circuit. Results from this study is presented in the following section.

Mototolo Case Study

The complexity, and especially the connected nature, of most mineral processing processes may obscure the drivers of these processes. As mentioned above, PCA may be used as a diagnostic troubleshooting method to combine and reduce multiple variables, thereby, highlighting a subset of process drivers. This reduction enables the user to quickly sift through a large amount of data and isolate possible issues.

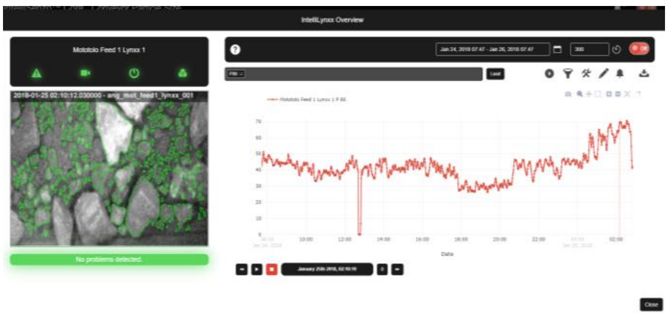


Figure 6: Live visuals and data trends of the particle size analyser at Mototolo

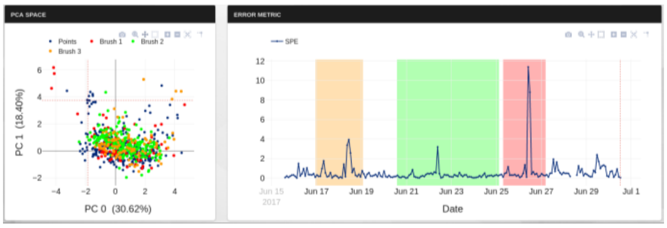


Figure 7: Principal component space and SPE

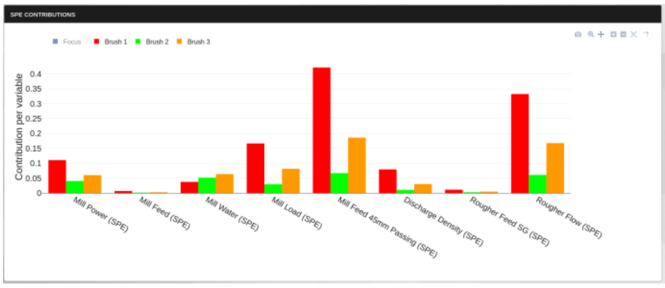


Figure 8: SPE variable error contributions

For this data analysis a one-month period of minute sampled data of the milling circuit, including flotation feed variables, was collected.

In the Figure 7, the reduced PCA space is shown on the left, while the model squared prediction error (SPE) is shown on the right. Outliers on the SPE trend relates to data where the PCA model prediction was poor - the cause of the poor prediction may then be investigated to find which variables contributed to the error.

From Figure 8 it can be seen that the red outlier region is dominated by contributions from mill feed passing 45mm and rougher feed flow. As rougher feed flow will be a result, the error was most likely driven by the mill feed passing 45mm. The green section refers to normal operating conditions (NOC), while the orange section highlights a less significant deviation.

Lastly, the raw data trends need to be investigated to give context to above multivariate error. From the Figure 9 it can be seen that there as a sustained increase in passing 45mm particles (decrease in ore size) after a period of lower passing 45mm ore (larger particles). In an in-depth analysis the above should be compared to mill power and load to substantiate whether the process upset was significant. This brief example does, however, confirm the importance of feed particle size and highlights how an in-depth analysis could be approached.

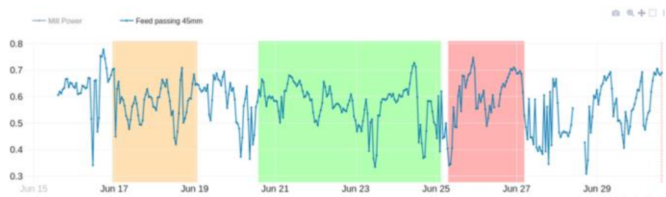


Figure 9: Mill feed passing 45mm

6. CONTROL PHILOSOPHIES INCORPORATING FSD

With the online availability of particle size data, it becomes possible to integrate FSD into a control system. Generally, control is separated into feedback end feedforward strategies. Specific to FSD, feedback control attempts to maintain the PSD at a desired value and reactively adjusts the plant operation if a deviation from setpoint occurs. While under feedforward control, the PSD data is utilised for proactive rejection of FSD disturbances before a setpoint deviation is observed, e.g. on predicted process behaviour.

These strategies are discussed, with specific reference to the Mototolo and Amandelbult circuits during feedforward control, below:

6.1. FSD AS FEEDBACK

Controlling feed size at an optimum to improve the performance of a milling circuit is a well-researched topic. Morrel & Vallery (2001), outlined several options that can be investigated in order to produce a more preferable feed size. However, in order to control the feed size, one should first be able to measure this information. An on-line particle size analyser thus becomes valuable in the following tasks.

It is common to have some form of material storage, stockpile or silo, preceding a primary mill. Segregation occurs naturally in these environments. Morrel and Vallery (2001), illustrated that different feeders can have different size distributions and stated that a desired feed size can be attained by appropriate blending of different feeders. Furthermore, a SAG mill was optimised using similar blending procedures by Felsher et al (2015). Particle size analysers were installed on all the feeders below a stockpile feeding into the mill. These measurements were then incorporated into an advanced control platform that maintained the feed size at a specific setpoint depending on the stockpile level and mill state. As a result, performance improvements in the form of throughput and plant stability were obtained on site.

The blending approach is ultimately subject to the ore size distribution supply and can only target a limited range. For a more direct albeit discrete approach, the activities on the mining stage can be targeted. Morrel and Valery (2001) suggests examining the blasting design to tailor the FSD for mill optimisation. This form of optimisation has been coined by the phrase “mine to mill” which has been successfully implemented in industry. As an example, Lam et al (2001) used to “mine to mill” concept to maximise the throughput of a SAG mill by adjusting the blast fragmentation. In general, the approach entails changing powder factors, drill-hole size and primary crusher operation. By observing the feed size measurements, information can be relayed to mining management who can then adjust the blasting design accordingly. Thus, a feedback loop exists, albeit with in a discrete human-in-the-loop structure. The obvious disadvantage being the extended lag in the response of the system.

6.2. FSD AS FEED FORWARD

Feedback control has an inherent lag action, corrective measures can only be taken once an error has been observed in the controller CVs. Feedforward control attempts to negate the effect proactively by early detection and resultant corrective action.

The disadvantage of feedforward control is that accurate process predictions, relying on process dynamics, need to be available in order to take the correct action. If these dynamics are not understood well, a feedforward controller may in reality aggravate the negative effect on process stability.

Feedforward may be implemented in various manners; one possibility is to incorporate the action into Advanced Process Control (APC). The APC implementation at Mototolo and Amandelbult is model predictive control (MPC). As the name suggests, MPC utilises models of the plant, usually linear, to predict the future evolution of the process and then calculates the optimal moves to achieve the desired operating state.

The subsection below investigates the extraction of the above mentioned dynamic models at Mototolo and Amandelbult.

6.2.1. MILLING SYSTEM DYNAMICS

The process models are extracted during a system identification exercise, as described by Ljung (1999). Firstly, the plant is excited by manipulating the input variables (e.g. feed, inlet water) to generate significant response in the output behaviour. This response is then captured by fitting linear time-invariant process models (LTI) to the data.

The model procedure and results for the investigated circuits are provided below.

I. Mototolo Circuit

Figure 10 shows the linear step response models of the Mototolo circuit. The relative influence of the variables is further shown in Figure 11. The feed size is ranked as having the second highest influence on the power, while the effect on the load is ranked as the lowest when compared to the other MVs. It should however be noted that the models were normalised according to their respective operating ranges.

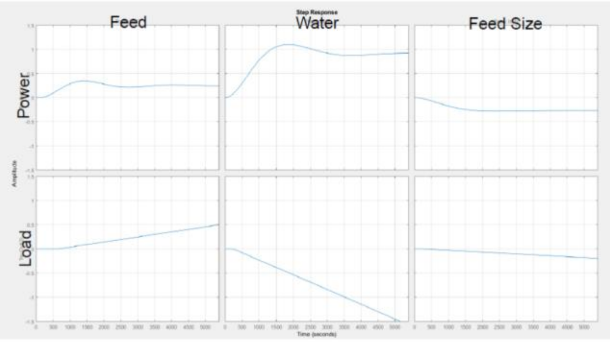


Figure 10: Linear system dynamics for the Mototolo grinding circuit

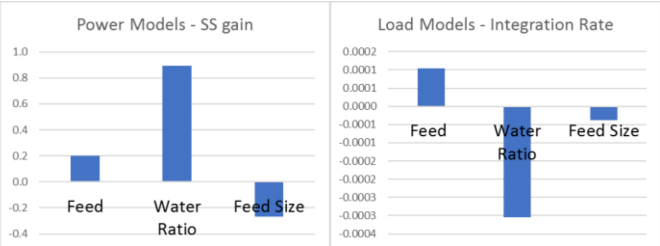


Figure 11: Relative influence of the particle feed size on a steady state basis

II. Amandelbult Circuit

The same approach was followed for the Amandelbult circuit. Step response curves are shown in Figure 12, while the relative influence is shown in Figure 13. The feed size has a considerable impact on the power of the mill, but a low contribution to the load is observed. It is important for this discussion to note that the mill speed not only has a large scaled effect on the load but also exhibits negligible dead time.

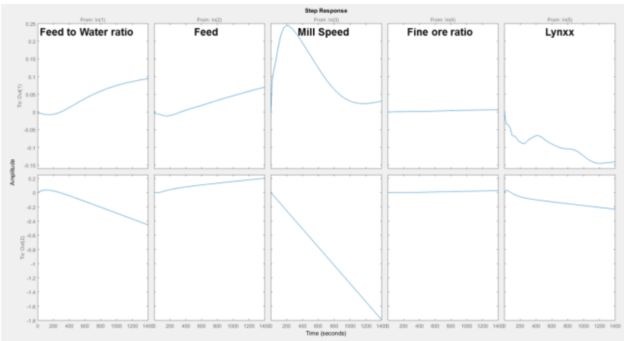


Figure 12: Linear system dynamics for the Amandelbult grinding circuit

Figure 13: Relative influence of the particle feed size on a steady state basis

6.2.2. FEEDFORWARD BENEFIT ESTIMATION

MPC is a control strategy which aims to maintain low variance on the CV's as well as reduce upsets to other processes, conserving energy and decrease equipment wear by lowering MV movement. Therefore, when the performance of an MPC is investigated, both the MV and CV variation should be taken into account.

A possible benchmark, which is suited for MPC, is the Linear Quadratic Gaussian (LQG) benchmark as described by Huang and Kadali (2008). Additionally, the LQG can be used to perform a profit analysis in order to determine whether it is worthwhile to implement feedforward control on a measured disturbance, in our case FSD.

In the section to follow, the theory behind LQG benchmarking is described in context of application to the two milling circuits under investigation.

I. <u>Theory</u>

A brief overview of the LQG calculation is presented here, for a more detailed derivation the reader is referred to Huang and Kadali (2008). LQG benchmarking starts by defining an objective function (J) over a finite horizon.

$$J = \sum_{i=0}^{N-1} (y_i^T y_i \; + \; u_i^T (\lambda I) \; u_i) \qquad \text{...[1]}$$

Where:

- N is the horizon
- y contains the output responses
- u contains the input signals
- λ is the input movement penalty

Using the linear time-invariant models the output over a defined horizon can be calculated by

$$y_{0|N-1} = G_u u_{0|N-1} + G_e d_{0|N-1} \qquad \text{...[2]}$$

In the equation above all the disturbances are lumped to a single disturbance variable, *d,* as they are regarded to be unmeasurable. In the case where there are measurable disturbances, *m*, the equation can be cast into the following form.

$$y_{0|N-1} = G_u u_{0|N-1} + G_d m_{0|N-1} + G_e d_{0|N-1} \qquad \text{...[3]}$$

Minimizing J, considering the aforementioned models and a feedback control law, an optimal *u*, namely u^{opt} can be obtained. If a measurable disturbance, *d*, is included, the effect of *d* on *y* can be taken into account and the input variables can proactively react to reject the disturbance. In this case the optimal u is defined as u_{FFWD}^{opt}.

Substituting u^{opt} and u_{FFWD}^{opt} into the modelling equations and propagating the disturbances then yields the optimal y, aptly named y^{opt} and y_{FFWD}^{opt}. With the availability of the optimal input and output signals the LQG-benchmark trade-off curve, Figure 14, can be constructed by considering the following

$$u_{lqg} = trace\{\, Cov[u^{opt}]\, \} \qquad \text{...[4]}$$

$$y_{lqg} = trace\{\, Cov[y^{opt}]\, \} \qquad \text{...[5]}$$

And for the measured disturbance case

$$u_{lqg}^{FFWD} = trace\left\{\, Cov\left[u_{FFWD}^{opt}\right] \right\} \qquad \text{...[6]}$$

$$y_{lqg}^{FFWD} = trace\left\{\, Cov\left[y_{FFWD}^{opt}\right] \right\} \qquad \text{...[7]}$$

For different values of λ, the values of u_{lqg} and y_{lqg} are obtained. A plot of u_{lqg} vs y_{lqg} represents the LQG performance trade-off curve over the set. By comparing the plots of u_{lqg} vs y_{lqg} and u_{lqg}^{FFWD} vs y_{lqg}^{FFWD} a profit analysis for the inclusion of a disturbance variable into the controller can be obtained. The benefit of feedforward and feedback control versus feedback only can then be calculated for the output variables as:

$$\Delta\text{var}(y) = \frac{(V_y^0)^{fb} - (V_y^0)^{ff\,\&\,FB}}{(V_y^0)^{fb}}\ 100\% \qquad \text{...[8]}$$

And as follows for the input variables:

$$\Delta\text{var}(u) = \frac{(V_u^0)^{fb} - (V_u^0)^{ff\,\&\,FB}}{(V_u^0)^{fb}}\ 100\% \qquad \text{...[9]}$$

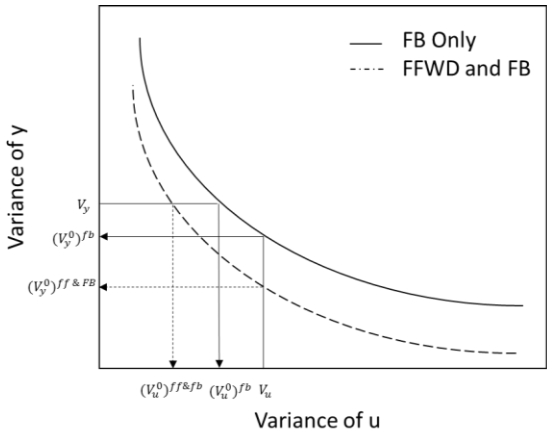


Figure 14: Example LQG trade-off curve used for the profit analysis of implementing feedforward control.

An example of an LQG curve and the aforementioned profit analysis is shown in Figure 14.

II. ***Mototolo Circuit***

At Mototolo, the 45mm passing fraction in the feed to the mill is considered to be a measured disturbance. This signal is included in the MPC which is currently deployed on site. However, the benefit of this inclusion was never assessed. Inspection of the LQG curves for both the feedback and feedforward + feedback curves, thus enable such a benefit estimation.

The analysis presented in section *I* is only valid over a specified disturbance signal. Therefore, to perform the test an excited disturbance signal must be identified. For the Mototolo circuit a period of 24 hours was selected where the feed size varied over a wide range as seen in Figure 15.

The chosen disturbance signal is shown in Figure 15, while the LQG trade of curves for a λ of 1 – 30 are presented in Figure 16.

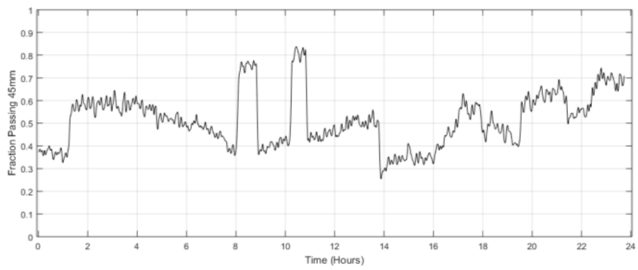


Figure 15: Disturbance signal over which the LQG profit analysis was performed.

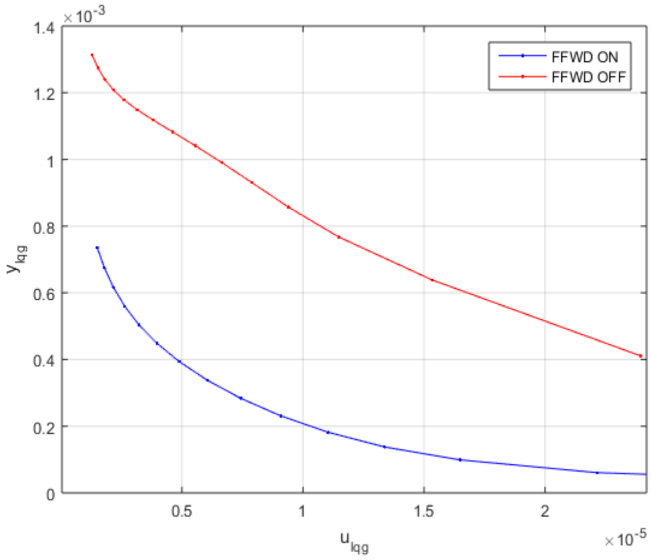


Figure 16: LQG trade-off curves for feedback and feedforward + feedback control at Mototolo.

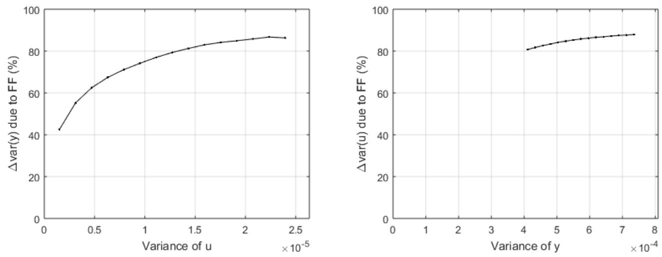


Figure 17: Profit analysis for the implementation of feedforward control on the Mototolo circuit

To further quantify the maximum benefit that is achievable by inclusion of the disturbance signal, the profit analysis in equations 8 and 9 was assessed. Results from this investigation are shown in Figure 17. The LQG analysis indicates that feedforward control has the potential capability of reducing the CV variation up to a maximum extent of approximately 85%.

This is, however, at the lowest move suppression value of λ and unlikely to be implemented on site due to the resulting MV variability. The benefit of feedforward at the maximum tested λ was found to be 45%. A more favourable tuning set will therefore reduce CV variation between 45% and 85% yet allow acceptable movement of the MVs.

Besides the benefit of CV variance reduction, feedforward control can also limit the movement of the MVs. This is due to the fact that the controller is aware of the disturbance and can proactively react if required. For the case of feedback alone the presence of the disturbance is only realised in CV movement. The MVs must then move more aggressively to stabilize the CVs. For the set of λ's tested the variance reduction on the MVs was in the range of 80-88%.

Results obtained by the LQG-type analysis show that the feedforward signal can be used in control to reduce variation on the CVs, power and load, in the presence of feed size upsets. An additional benefit is realised in the fact that the MVs are used less aggressively and a variance reduction can be expected on the feed rate and mill inlet water.

III. Amandelbult Circuit

The same procedure presented in the preceding section was applied to the Amandelbult circuit. Again, a 24hour disturbance signal, Figure 18, was investigated and an LQG profit analysis on the implementation of feedforward control was performed.

The LQG curves, Figure 19, was found to be close to one another, which indicates that the benefit of using feedforward might not be significant. The profit analysis, reiterate this belief as the CVs can only be stabilised to a maximum extent of 25%, over the set of λ's (1-30). Similarly, the MV stability improvement is in the range of 0 to 40%, which is significantly lower than that observed for the Mototolo circuit.

The results obtained on the Amandelbult circuit can be contextualised by inspecting the transfer functions, illustrated in Figure 12. The models between mill speed and power/load have very little deadtime. Therefore, a change in speed will almost instantly affect the power/load and negate a feed size disturbance. Thus, feedback control by observing the power/load behaviour seems to be sufficiently effective and renders the feedforward benefit insignificant.

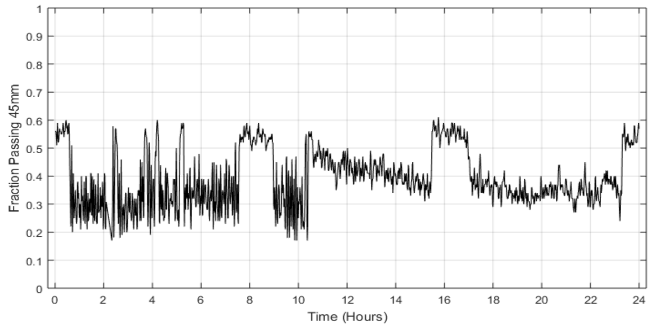


Figure 18: Disturbance signal over which the LQG profit analysis was performed together

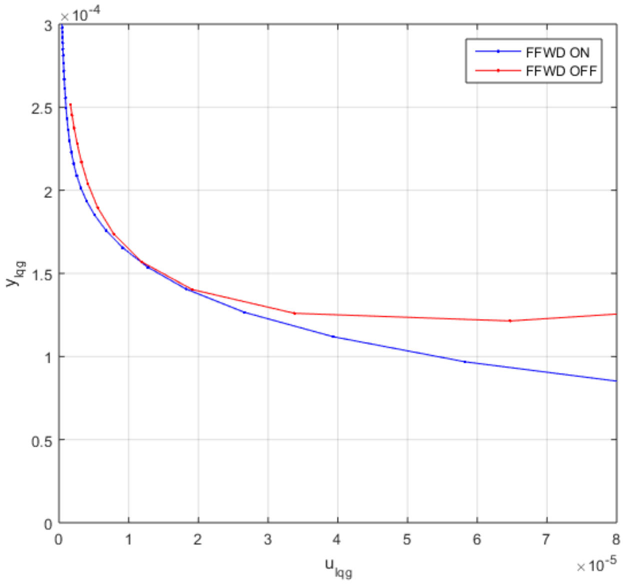


Figure 19: LQG trade-off curves for feedback and feedforward + feedback control at Amandelbult.

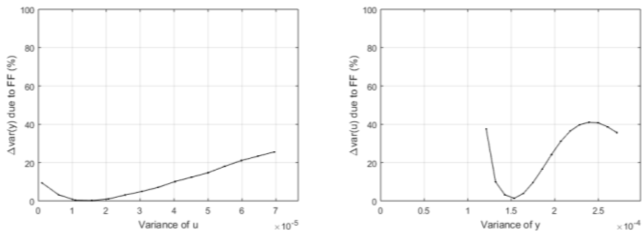


Figure 20: Profit analysis for the implementation of feedforward control on the Amandelbult circuit

IV. Discussion

The results presented in this section relies on linear models, which are only valid over a small operating region. Promising results were obtained for the Mototolo circuit with the LQG indicating significant capacity to stabilize both CVs and MVs with the inclusion of the FSD feedforward. The improvement in stability is a valuable attribute as this can be seen as a form of overload protection in the presence of large FSD variations.

The Amandelbult LQG analysis however, indicates that feedforward control has low potential for improving stability in the circuit. It is therefore recommended to rather investigate how the upstream processes can be manipulated, pursuing the initiatives outlined in 6.1.

6.3. INDUSTRIAL CASE STUDIES

Results in the preceding section were generated via simulation and is dependent on the accuracy of the models. The LTI models applied in the LQG analysis is, by definition, linear approximations, despite it being known that milling circuits exhibit non-linear behaviour. It, therefore, becomes difficult to quantify the actual benefit that will be achieved on site. For this reason, an ON-OFF trial was performed on each of the two sites to investigate real-world benefits.

The trail consisted of enabling and disabling the use of feed size as a disturbance signal to the control system. Each cycle was 8 hours in duration (one shift) and the test stretched over a period of 14 days.

Analysis of the data was performed by calculating the shiftly averages and standard deviations of the controller MV's and CV's over each of the ON-OFF trail categories. A two sample T-test was then used to determine if the difference in the mean and standard deviations over the resulting two populations were significant.

I. Mototolo Circuit

Assessment of the main controller variables are presented in Table 1 and Table 2. Inspection of the feed rate and inlet water ratio (MV's) means show no significant shifts in performance. The variances on the other hand, indicate that the controller used the inlet water more aggressively, while the feed rate remained more stable when the FF was active. Confidence statistics from the T-test are also shown in Table 2, where the change in feed rate standard deviation is accompanied with a confidence level of 79.6%.

During the ON period, an increase in stability (10.68% decrease in variance) was found for the mill load, while an increase in power variance, of 1.0%, was also observed. The confidence level on the load stability improvement is 74.90%, which is a positive indication that the load was indeed more stable with the aid of feedforward control albeit without less than required for statistical significance.

It should be noted that, the feed size (45mm passing fraction) was more stable during ON periods, which makes it difficult to directly compare the two datasets. A larger testbed is therefore recommended for Mototolo to eliminate this external influence.

The results presented indicate that there are observable differences in the operation of the mill with and without the feedforward control component. Yet, unmeasured disturbances occur readily on a milling circuit and complicate the benefit assessment. As such, low confidence levels are observed on some of the statistics.

The reader is referred to Appendix A for the histogram plots for of all the CVs and MVs of the Mototolo primary milling circuit generated during the trial.

II. Amandelbult Circuit

Results from the ON-OFF trails at Amandelbult are given in Table 3 and 4. The disturbance signal for the two periods compare favourably as the 45mm fraction passing data indicate similar variances with a null hypothesis rejection confidence of only 52.7%.

The MV's showed minor differences in operation with respect to their means, while the standard deviations were all lower with the aid of feedforward control. This result supports the conclusions from the earlier LQG analysis. However, the confidence limits, shown in Table 3, are low

Table 1: Means for the Mototolo controller variables

Variable	FFWD & FB - Mean	FB Only - Mean
Feed Ave (TPH)	302.44	300.87
Inlet Water Ratio	0.21	0.20
Load/Bearing Pressure (kPa)	716.70	716.02
Power (kW)	4363.97	4279.43
45mm passing fraction	0.607	0.598

Table 2: Standard deviation for the Mototolo controller variables

Variable	FFWD & FB - STDev	FB Only - STDev	% improvement	Confidence
Feed Ave (TPH)	1.97	3.46	42.97%	79.64%
Inlet Water Ratio	0.0130	0.0125	-3.51%	57.93%
Load/Bearing Pressure (kPa)	6.22	6.96	10.68%	74.90%
Power (kW)	199.49	197.52	-1.00%	52.83%
45mm passing fraction	0.107	0.113	5.39%	66.26%

Table 3: Means for the Amandelbult controller variables

Variable	FFWD & FB - Mean	FB Only - Mean
Feed Ave (TPH)	372.22	373.57
Inlet Water Ratio	0.179	0.174
Mill Speed (%)	85.83	85.27
Load/Bearing Pressure (kPa)	2511.94	2450.97
Power (kW)	208.26	207.47
45mm passing fraction	0.368	0.377

Table 4: Standard deviation for the Amandelbult controller variables

Variable	FFWD & FB - STDev	FB Only - STDev	% improvement	Confidence
Feed Ave (TPH)	8.01	9.43	15.07%	68.94%
Inlet Water Ratio	0.0108	0.0111	2.30%	55.75%
Mill Speed (%)	3.13	3.16	0.72%	51.71%
Load/Bearing Pressure (kPa)	4.97	5.94	16.38%	75.60%
Power (kW)	182.33	164.55	-10.81%	81.37%
45mm passing fraction	0.13	0.13	0.76%	52.72%

and the statistical significance of the changes are inconclusive.

Increased stability was observed on the load (16.38% variance reduction with 75.60% confidence), while power stability declined by 10.81% over the ON period. A high degree of correlation exists between the power and load and it is difficult to control these two CV's independently. It is, therefore, a possibility that the controller opts to stabilise the load, but does so at the expense of power variability.

Appendix B shows the histogram plots of all the CV's and MV's of the Amandelbult UG2-2 primary milling circuit.

III. <u>Discussion</u>

Difficulty was experienced to isolate the influence of the feedforward contribution to the controller. Differences in mill operation are shown by the variances of the main control variables, although the confidence levels were low. It is suspected that unmeasured, external influences play a crucial role in the variability observed on site. This effect will become less pronounced as more data is made available. Therefore, it is recommended to extend the test over a longer duration.

7. CONCLUSIONS

Feed size has a well-documented, significant impact on the performance of a milling circuit. Several initiatives are available to combat fluctuations in feed size and their impact on milling performance. This paper investigated how feed particle size information can be used in monitoring and control applications using simulation and industrial case studies.

As part of a multivariate monitoring system the FSD information shows potential in the troubleshooting of mill operation. It was shown on the Mototolo circuit that FSD data can be used to trace an abnormal operating condition to its root-cause.

Furthermore, a literature study illustrated that FSD can be manipulated by "mine to mill" initiatives, where promising industrial results have been achieved. Measuring the FSD is a vital component in these optimisation approaches, as it provides a means to give feedback to mining operations.

Variability in FSD is, however, inevitable and cannot be removed completely. For this reason, the use of FSD in feedforward control was assessed and the benefit thereof investigated. A LQG benefit estimation was performed using linear process models. The Mototolo circuit indicated that feedforward of the FSD may be a valuable supplement to the feedback control of the mill. For the Amandelbult circuit, it was concluded that the FSD will not significantly improve the control response.

Finally, plant trails were performed to quantify the benefit of feedforward control. Operational differences were observed in terms of stability by comparing the variances in milling performance with and without the feedforward component. Results in favour of the feedforward variable were obtained in both cases where primary variables load and ore feed was stabilised more sufficiently. Due to unmeasured disturbances, that could potentially mask the effect of the controller change, it is recommended to increase the length of the plant trails.

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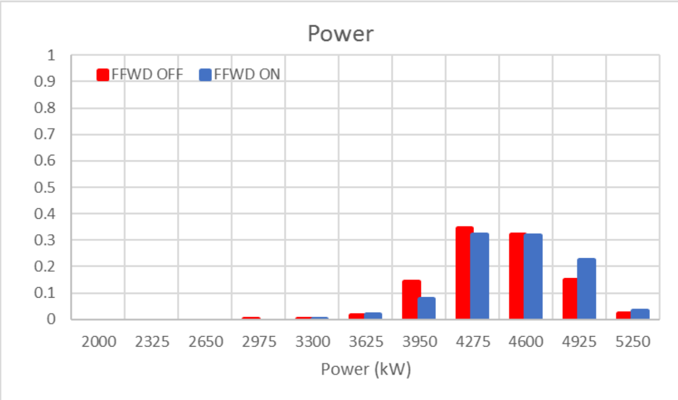
Appendix A – Histograms showing the variability in data at Mototolo



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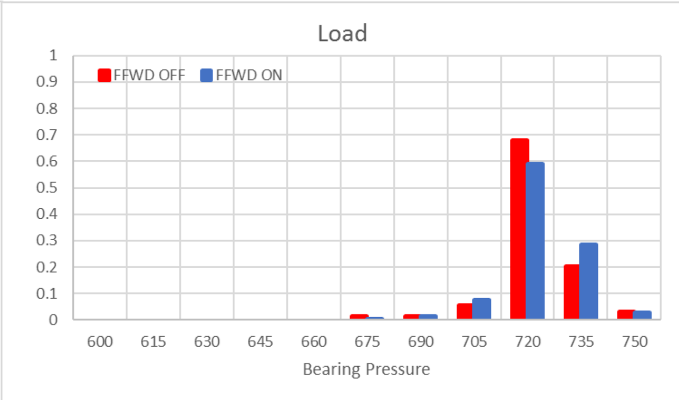
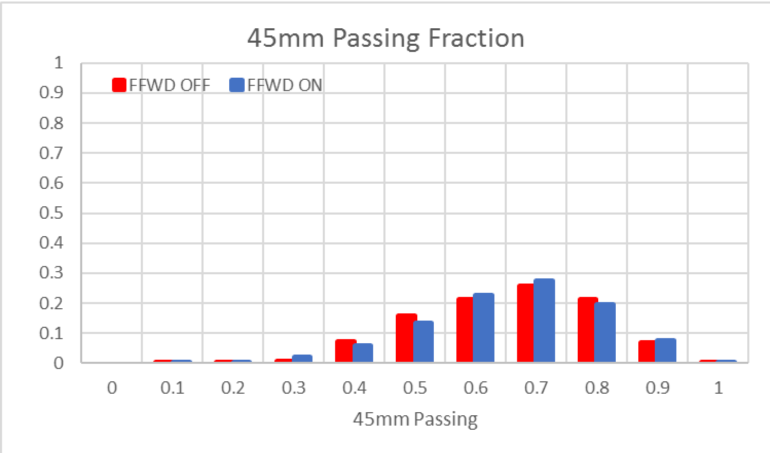
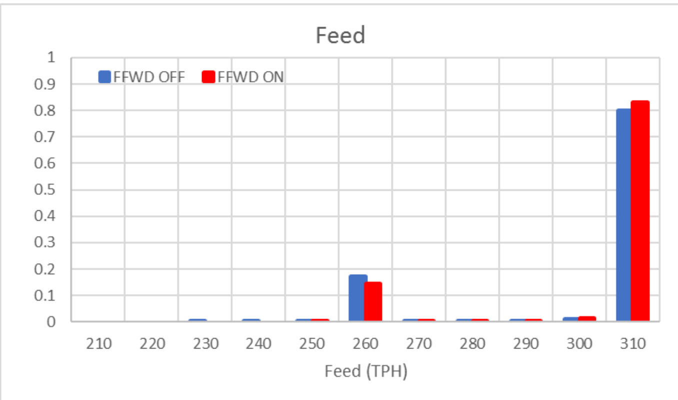


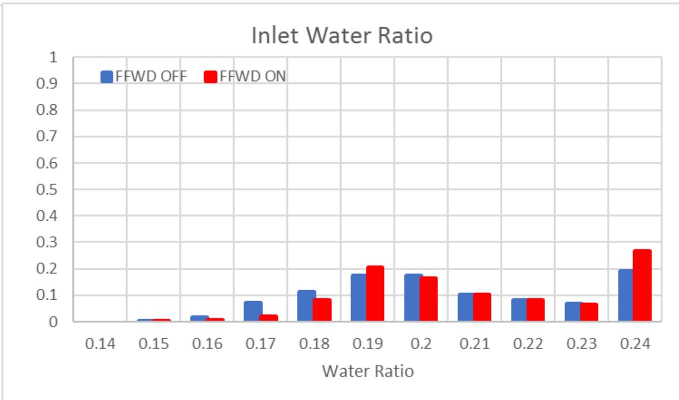
(b)



(c)



(d)



(e)

Figure 21: Histograms of the relevant control variables at Mototolo. (a) Power, (b) load, the disturbance signal (c) 45mm passing, (d) feedrate and (e) inlet ratio

Appendix B – Histograms showing the variability in data at Amandelbult

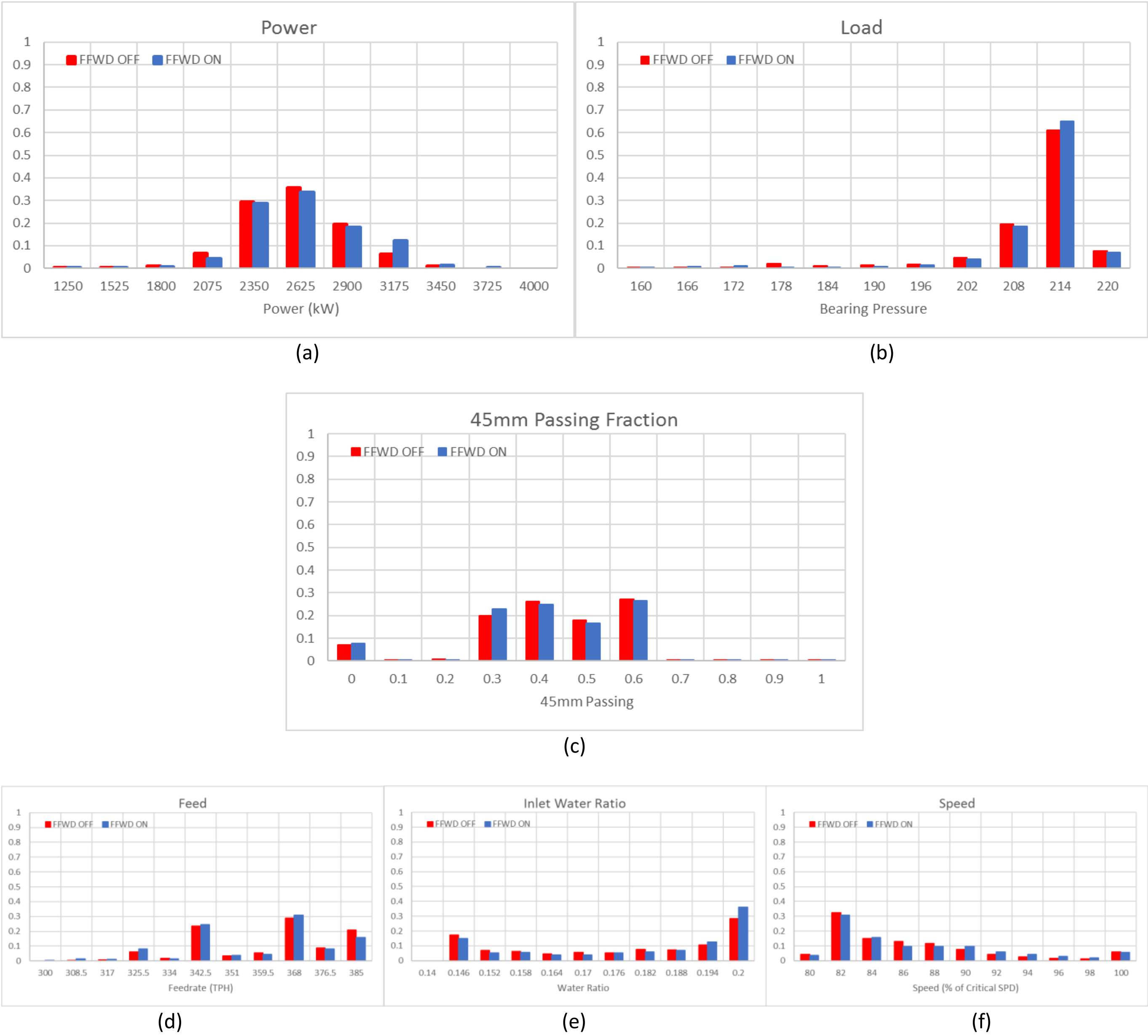


Figure 22: Histograms of the relevant control variables at Amandelbult. (a) Power, (b) load, the disturbance signal (c) 45mm passing, (d) feedrate, (e) inlet ratio and (f) mill speed