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# The Use of a Semi-Rigorous SAG Mill Model for a Hands-On Workshop

**Margret Bauer** [**] **Kevin Brooks** [*] **John Burchell** [†]
**Loutjie Coetzee** [***] **Derik le Roux** [**] **John McCoy** [****]
**Jason Miskin** [‡] **Danielle Winter** [‡]

[*] *Department of Chemical and Metallurgical Engineering, University of the Witwatersrand Johannesburg, South Africa (e-mail: kevin.brooks@bluesp.co.za)*
[**] *Department of Electrical, Electronic and Computer Engineering, University of Pretoria, Pretoria, South Africa (e-mail: margret.bauer@up.ac.za; derik.leroux@up.ac.za)*
[***] *Mintek, Johannesburg, South Africa (email: loutjiec@mintek.co.za)*
[****] *Stone Three Digital, Somerset West, South Africa (e-mail: john.mccoy@stonethree.com)*
[†] *Sibanye-Stillwater, Johannesburg, South Africa (e-mail: john.burchell@sibanyestillwater.com)*
[‡] *Opti-Num Solutions, Johannesburg, South Africa (e-mail: jason.miskin@optinum.co.za; danielle.winter@optinum.co.za)*

**Abstract:** This paper describes the extension of a grinding mill model that is publicly available for educational and training purposes. This industrially derived model of a mill is used to explain complex concepts of advanced process control (APC) such as model predictive control and soft sensing. The resulting concepts were developed in a hands-on workshop in the wake of the IFAC MMM 2019 conference entitled “Modern Data Analytics for Control in Minerals Processing”. The workshop and the material presented here are aimed at control engineers to explain the use of APC methods to improve process performance. Both academic and industrial control engineers attended the workshop, highlighting the relevance of the application of real-life process control problems.

*Keywords:* Control engineering education, system identification, advanced process control, soft sensing, multivariate statistics, university-industry collaboration

## 1. INTRODUCTION

Teaching automatic control concepts requires specific applications such as an inverted pendulum or automotive or robotic challenges. Remote laboratories, also called virtual labs, are usually based on simulation of simple problems that can be described easily. A successful example of a remote lab is a mobile robot and ball-plate problem presented by Ionescu et al. (2013).

Process control is an important branch of control engineering with complex models and problems. Goodwin et al. (2010) give several excellent examples of process control problems such as rolling mill processes, paper machines and continuous casting plants that can be used to teach the impact of model uncertainty, the use of soft sensors, and the impact of multivariable interactions, highlighting the value of simulation as an alternative to physical experiments. Martin-Villalba et al. (2008) had earlier described a heat exchanger, an industrial boiler, and a batch chemical reactor to explain chemical process control in a virtual laboratory environment.

Advanced process control (APC) is a cumulative description of state-of-the-art aspects of control in the process industries such as model predictive control (MPC) and soft sensing but also auto-tuning, control loop performance monitoring and much more. The application of APC is difficult to convey because all depends on the underlying, complex process. It is therefore necessary to first understand the process and then to explain the concepts such modern data analytics.

In 2019, The South African Council of Automation and Control (SACAC) arranged a workshop prior to the 18th IFAC Symposium on Control, Optimization and Automation in Mining, Mineral and Metal Processing (MMM 2019) held in Stellenbosch, South Africa. The workshop entitled “Modern Data Analytics for Control in Mineral Processing” was aimed at providing delegates with an introduction to modern tools used in soft-sensor, dynamic modelling, and model predictive control development. Seven speakers from two universities and four consulting organisations delivered the workshop. In South Africa, control engineers are generally well versed in minerals applications due to the country’s wealth of natural resources.

To explain APC visually and understandably, the presenters decided at an early stage of the development of the workshop to utilise a public domain model of a semi-autogenous grinding (SAG) mill (Le Roux et al., 2013; Wakefield et al., 2018) as the "plant" on which all applications would be built. This model should serve as the golden thread for all the hands-on workshops through the two days of workshop exercises.

This paper discusses the extension of the model for the purpose of conveying the APC concepts MPC and soft sensing, as well as the results achieved from this hands-on approach. The remainder of this paper is organised as follows: Section 2 gives the background to the SAG grinding mill model, while Section 4 discusses its implementation in MATLAB and Simulink. Section 5 presents the use of the model to develop data to develop a soft sensor for the particle size estimate. Section 6 outlines model predictive control design and development, and Section 7 discusses the technical experiences of the workshop.

## 2. MILL MODEL BACKGROUND

The grinding mill circuit grinds the incoming ore into smaller particles. The resulting slurry is processed further in following stages. This section describes the milling process as well as the model used here.

### *2.1 Process Description*

Fig. 1 shows the closed single-stage SAG mill circuit used for the workshops. The main elements of the circuit are a SAG mill, a sump and a hydrocyclone. Table 1 lists the manipulated and control variables considered. The mill receives three streams: mined ore ($MFO$) (t/h), water ($MIW$) (m$^3$/h), steel balls ($MFB$) (t/h) and underflow from the hydrocyclone. The mill charge is a mixture of grinding media and slurry. Grinding media refers to the steel balls and rocks which break the ore, and slurry refers to the mixture of solids and water.

Table 1. Nomenclature

| Manipulated Variables | | |
|---|---|---|
| Variable | Units | Description |
| $MIW$ | m$^3$/h | Mill inlet water |
| $MFO$ | t/h | Mill feed ore |
| $MFB$ | t/h | Mill feed balls |
| $SFW$ | m$^3$/h | Sump feed water |
| $CFF$ | m$^3$/h | Cyclone feed flow |
| Controlled Variables | | |
| Variable | Units | Description |
| $LOAD$ | m$^3$ | Volume of charge in mill |
| $SVOL$ | m$^3$ | Volume of slurry in sump |
| $PSE$ | % | Product particle size |

The mill is rotated along its longitudinal axis by a motor. Liners on the inside of the mill lift the charge and create a cascading motion of the charge. This motion causes the ore to break through impact breakage and abrasion. The power draw ($Pmill$) (kW) of the motor turning the mill indicates the kinetic and potential energy imparted to the charge. The volume of charge in the mill is given by $LOAD$ (m$^3$).

The ground ore in the mill mixes with water to create a slurry. The slurry is discharged through an end-discharge grate where the aperture size of the end-discharge grate limits the particle size of the discharged slurry. Ore too large to pass through the end-discharge grate are referred to as rocks and must be broken further. All ore small enough to pass through the end-discharge grate are referred to as solids. The aim of the circuit is to grind the ore to below a specification size, e.g. 75 $\mu$m. The broken ore below the specification size are referred to as fines. Solids are a combination of fine ore and coarse ore, where coarse ore refers to the portion of solids larger than the specification size.

The slurry discharged from the mill is collected in a sump. The slurry is diluted with water ($SFW$) (m$^3$/h) before it is pumped to the hydrocyclone ($CFF$) (m$^3$/h) via a variable speed-pump. The volume of slurry in the mill is given by $SVOL$ (m$^3$). The hydrocyclone classifies the material discharged from the sump. The coarse particles return to the mill for further grinding via the underflow, and the fine particles exit the circuit via the overflow. The percentage of particles in the product smaller than the specification size is referred to as the product particle size estimate ($PSE$) (%).

## 3. MODEL DESCRIPTION AND DISCUSSION

Le Roux et al. (2013) provide a continuous time semi-mechanistic dynamic model of the closed single-stage SAG mill circuit in Fig. 1. The aim of the model is not for circuit design, but rather to provide a simulation platform to evaluate the performance of controllers (Coetzee et al., 2010; Aguila-Camacho et al., 2017) and observers (Le Roux et al., 2017; Wakefield et al., 2018) as applied to the circuit. Each process unit within the circuit is modelled separately so that various circuit configurations can be simulated. The approach in the derivation of each unit model was to use as few states and parameters as possible to produce qualitatively accurate model responses. The aim of the small parameter set is to improve model invertibility to simplify parameter fitting to data.

The model divides ore into three size classes: rocks, solids and fines. Given the size class distribution, only five states are used to model constituents in the mill (water, solids, fines, rocks, balls), and only three states are used to model constituents in the sump (water, solids, fines). A volume balance is defined for each state at the mill and sump respectively.

For the ore feed to the mill, two parameters are used to model the fraction of rocks and fines in the feed ore respectively. These parameters can be varied to simulate disturbances to the feed ore disturbances. The consumption and production terms in the volume balance of the states in the mill are similar to the cumulative breakage rate expressions of Hinde and Kalala (2009). The energy per tonne of rocks consumed, balls consumed, and fines produced are represented by three separate parameters. These parameters can be varied to simulate ore hardness disturbances on the mill.

The mill model introduces an empirical term, called the rheology factor, to incorporate the effect of the fluidity and density of the slurry on the discharge and power consumption of the mill. The mill power is modelled as parabolic in terms of the mill filling and the fraction of solids in the slurry. The cyclone model is based on the well-known Plitt model (Nageswararao et al., 2004). Phenomenological modelling is used to provide functional forms where appropriate, but not if it entails the use of more fitted parameters than necessary.

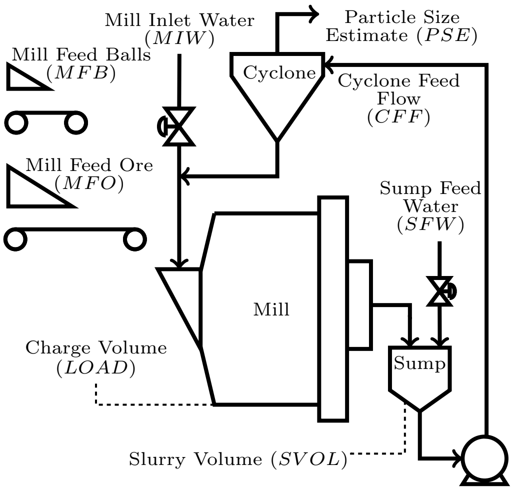


Fig. 1. A semi-autogenous (SAG) mill.

## 4. MODEL IMPLEMENTATION

The SAG mill model was available in Simulink as a result of the efforts of Le Roux et al. (2013) and Wakefield et al. (2018). It was decided to extend the model to expose the variables (listed in Table 1) through the industry standard OPC communication interface. This allowed the model to be used and controlled from an external environment, which was key for MPC development. The model effectively became a virtual plant to be controlled. A commercial OPC server was used to publish the simulated results.

The extension involved the addition of existing OPC blocks at key variables. Three configurations were implemented for controlled variables: PI control, MPC cascaded with PI control, and MPC-only control. This flexibility allowed an external environment to toggle between different configurations in support of prototyping an MPC. A pure simulation mode was also implemented, which allowed the attendees to simulate the model without any OPC interaction.

When OPC communication was in effect, the model simulation speed was controlled to five times that of real-time, allowing attendees to generate results faster while also being able to follow and visualise the process dynamics. This was done with the purpose of streamlining the workshop pace without compromising practical understanding.

The mill model is available for download at:
https://tinyurl.com/mill-simulation.

Running the code requires Matlab and Simulink. The *main.m* file specifies the parameters that are required, as well as various modes of operation that are available for the simulation.

## 5. SOFT SENSOR DEVELOPMENT

Online measurement of the PSE leaving a SAG mill remains challenging. An alternative approach is to use an inferential or soft sensor to estimate this parameter. Accordingly, the first hands on activity of the workshop was to develop a soft sensor for the PSE leaving the virtual mill.

Following an introduction to supervised and unsupervised learning techniques, and the CRISP DM framework (Azevedo and Santos, 2008) shown in Fig. 2, the attendees were taken through a series of steps to develop the soft sensor. Several MATLAB scripts were made available to assist in the process.

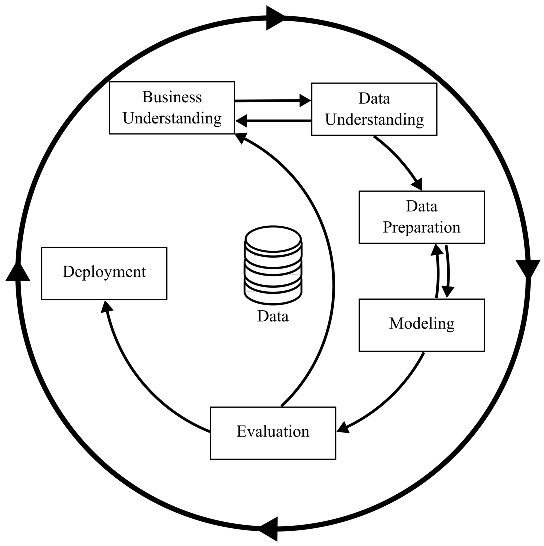


Fig. 2. The CRISP DM Process.

The first step covered was data cleaning and preprocessing, including techniques to handle common problems such as outliers, missing values, and misaligned measurement rates. Following this, a workflow for soft sensor development was proposed. The primary challenge of soft sensor development is that measurements of the target variable are available much less frequently than other process data, due to safety, cost and technical challenges (Kadlec et al., 2009). The proposed workflow addresses this by providing a structured approach to soft sensor development, focusing on the introduction of complexity (in the data and the model) only when simple approaches are not successful.

In particular, the workflow emphasised the importance of a clear problem definition (such as required accuracy and frequency of predictions for the intended use) and establishing training, validation and test data sets before any attempt at model development begins. Then, a range of models (ranging from linear regression to decision trees and artificial neural networks) were fitted to process data which was aligned with the records of the target variable.

If this relatively naïve approach was unsuccessful, unsupervised techniques such as principal component analysis and auto-encoders were used to generate data features from all available process data. These features were then used in the same range of models, again only for records which align with the target variable. Finally, the temporal nature of process data was explicitly included by the use of embeddings, which can be combined with feature extraction techniques as inputs to predictive models.

Although the workflow was relatively simple, few participants were able to progress beyond the first, simple modelling steps. This was due to a combination of factors, including hardware and software challenges, a lack of familiarity with the programming language of the workshop, and an underestimate of the time required for hands-on coding and data analysis, particularly in large groups.

Due to the use of data from a simulated process, which operated around a controlled point, simple linear models were found to provide sufficient predictive accuracy for the intended use, model predictive control. However, the workflow is expected to be of use to participants in more challenging cases.

## 6. MODEL PREDICTIVE CONTROL

During the workshop two flavours of model predictive control (MPC) were discussed: linear and non-linear MPC. The aim was to give delegates a sense of current best practice, as well as to allow for robust discussion of advantages and disadvantages of each approach.

### *6.1 Linear Time Invariant Model Development*

The use of MPC is proven in the oil refining and petrochemical fields (Qin and Badgwell, 2003), and is becoming more prevalent in the area of minerals processing and mining (Brooks et al., 2019). The vast majority of MPC applications deployed in industry use linear time invariant (LTI) models; these models are generally empirically identified using a set of planned experiments such as step tests.

The aim of the workshop was not to discuss the choice of variables for the MPC. A design was assumed to have been done, with manipulated variables (MVs), or inputs, and controlled variables (CVs), or outputs, having been chosen based on experience. However, design considerations were presented, and delegates had developed some insight into grinding circuit control and operations, having been introduced to fundamental concepts during introductory lectures.

To demonstrate the procedure of step testing, and to give delegates the opportunity to use modern model identification tools, a set of step tests was performed on the SAG mill model. Examples of the step tests are shown in Fig. 3 (MVs) and 4 (CVs). The MVs correspond to those shown in Table 1, but do not include the ball addition rate. The cyclone feed density was added as a CV to make the problem non-square.

The theory behind identification of finite impulse response (FIR) models, as presented in Dayal and MacGregor (1996), was briefly covered and the attendees were then given the assignment to use the commercial software to derive the step responses. A step-by-step procedure was given so that the exercise can be completed in reasonable time. The result of identifying all outputs against all inputs is shown in Fig. 5 in the form of finite step responses, derived for three different settling times.

The delegates were encouraged to consider why some of the sub-models are poor, and what could be done to improve them. The use of the LTI models for online control was discussed through the derivation of the quadratic optimisation problem (Garcia et al., 1989). The addition of a linear program based steady-state optimisation was also demonstrated.

### *6.2 Non-Linear Model Predictive Control*

This section of the workshop discussed the non-linearities encountered in mill control of which there are many. Two aspects of non-linearity were covered, namely:

(1) Process non-linearity
(2) Non-linear economic objectives

The former was demonstrated using data from Van der Westhuizen and Powell (2006) shown in Fig. 6, which describes the power and feed as a function of mill filling percentage.

The aim of the non-linear MPC is to maximise the economic performance of the milling circuit as defined by the economic objective function. The achievable economic benefit is affected by disturbances and constraints on the system.

The economic objective function for a mill may be non-linear due mainly to the presence of a maximum in the flotation bank recovery as a function of flotation feed particle size (Wei and Craig, 2009). The mineral value is then a product of the mill feed ore, flotation recovery, head grade and mineral price. The result is that the economic surface is curved as shown in Fig. 7 (Le Roux and Craig, 2019).

The economic objective assumes that the flotation recovery is only a function of the flotation feed size distribution and not of the flotation feed density and flowrate. The MPC therefore trades-off feed size distribution and feedrate to achieve the economic maximum under different disturbances and constraints.

The delegates were shown how these non-linear effects are incorporated into a commercially available robust non-linear model predictive control platform. A hands-on simulation allowed the delegates to explore the effects of disturbances, such as feed hardness changes and spillage into the sump, as well as the effect of changing constraints, for example to increase the flotation residence time by lowering the maximum allowed flotation feedrate, on the economic steady-state optimum, but also get an understanding of how modern multivariable controllers steer the process to the new operating point while dealing with the interaction and constraints of the system.

## 7. WORKSHOP ORGANISATION

The workshop was held over two days. Day 1 focused on the development of a soft sensor for online particle size estimation, while day 2 focused on model predictive control. A detailed agenda is presented in Table 2.

The software required was installed on a virtual machine (VM), which was copied onto delegates' laptops at the beginning of the workshop. Some challenges were experienced, most notably issues related to the hardware capabilities of delegates' laptops, and the configuration of multiple varied machines to run a sizeable VM.

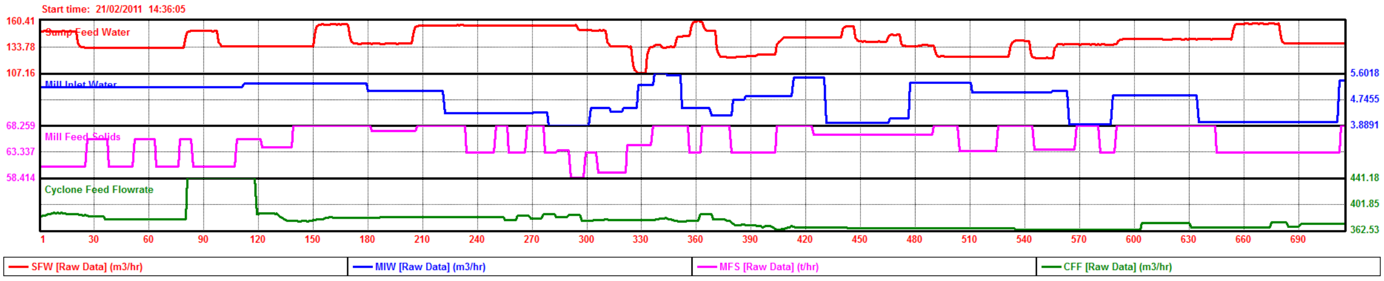


Fig. 3. Step test - manipulated variables.

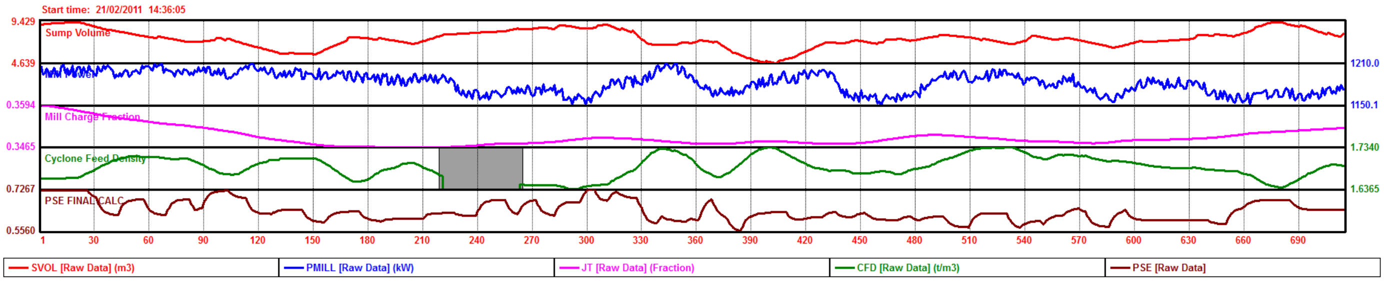


Fig. 4. Step test - controlled variables.

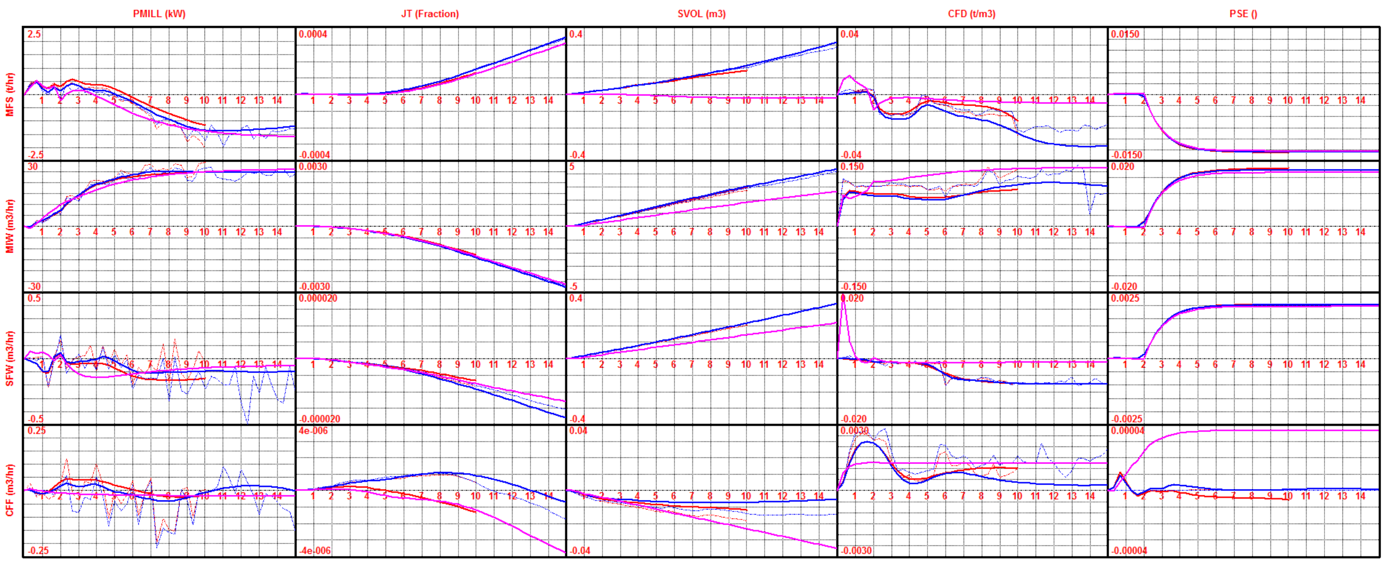


Fig. 5. "Mind switched off" model matrix.

Table 2. Workshop agenda

| Day 1 Topics | Day 2 Topics |
|---|---|
| An introduction to data analytics for soft sensing. | An introduction to grinding circuit control. |
| Principles of grinding circuit operation. | Dynamic modelling and simulation. |
| Data preparation best practices. | Linear model predictive control. |
| Model selection and training. | Non-linear model predictive control. |
| Model maintenance best practices. | |

An alternative approach, is to roll out the VM on virtual private servers (VPSs) in the cloud. This will ensure that all the VPSs have the correct specification and the delegates will only need to log into their dedicated VPS on the day. The delegates' laptops would only need to be powerful enough to connect to the internet and to run a remote desktop session to connect to their VPS. This will, however, place a requirement on the workshop venue to have a fast enough internet connection to facilitate the simultaneous remote desktop connections for all delegates.

## 8. CONCLUSIONS

In this paper, the adaptation of a grinding mill circuit model were presented that were used to explain the complex concepts of APC in a workshop to control academics and practitioners. The use of a real world example in control engineering education is highlighted by the presence of the process complexity. Teaching points from the workshop

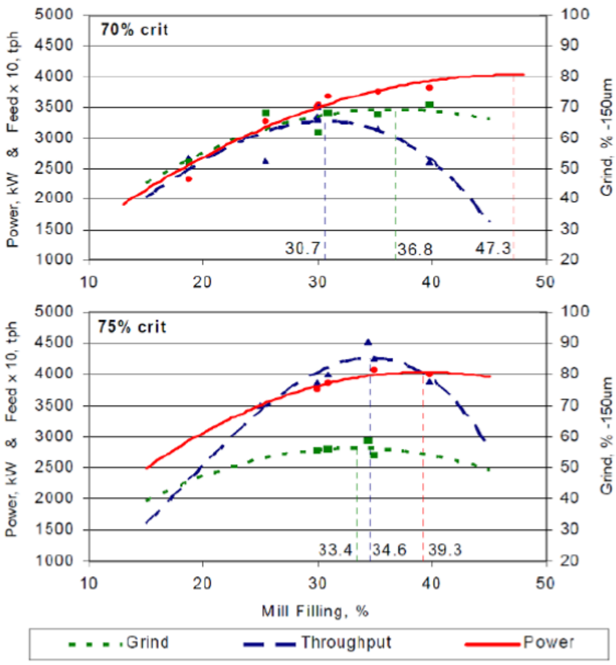


Fig. 6. SAG mill performance curve of mill running at 70% and 75% of critical speed

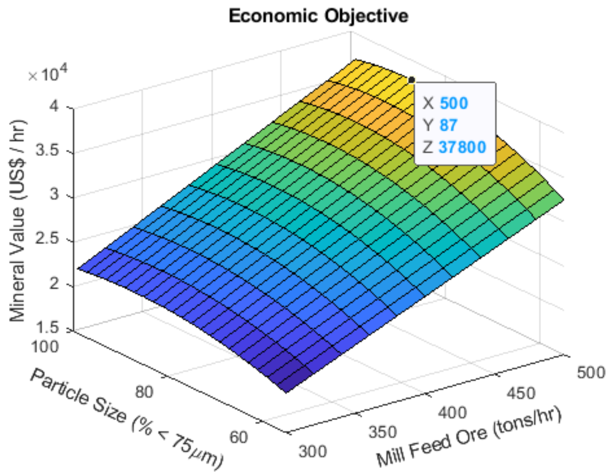


Fig. 7. Economic objective function surface.

were reported here as well as points of improvement such as making the material available as a remote laboratory.

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