ISSN (e): 2250 – 3005 || Volume, 06 || Issue, 02 ||February – 2016 ||
International Journal of Computational Engineering Research (IJCER)

Energy-Mass-Size balance model for dynamic control of a wet open circuit grinding mill: Part II – Simulation tests

Augustine B. Makokha
Moi University, School of Engineering,

Abstract

A simple dynamic model combining energy balance and population balance has been utilized to assess the dynamic response of the mill to changes in mill operational parameters for purpose of establishing a predictive control tool. The manipulated parameters are feed rate, feed % solids and ore hardness index while the response variables are mill power draw, mill temperature and mill product size distribution (d_{80}). The results demonstrate a good dynamic response of the model to variations in mill operational parameters. Thus, the model could be integrated in the overall mill control scheme to assist mill operators and process engineers in timely decisions with regard to mill control.

Keywords: *Energy balance, Dynamic control, Grinding mill, Mixing, Simulation, Mill power, Mill temperature*

I. Introduction

Secondary grinding mills are popularly utilized in ore dressing circuits for finer size reduction in order to efficiently liberate the minerals and optimize the recovery during flotation stage. In order to achieve optimal performance whilst maintaining energy efficiency, closer and more effective mill control strategy is needed. Satisfaction of this need would result in stability of the entire mineral processing circuit, thereby reducing the overall cost in mineral extraction. By monitoring mill dynamic behaviour, the individual effect of mill operational parameters on mill performance can be studied and clarified, leading to effective control and optimisation of the milling circuit.

While the advances in instrument technology and computer capabilities have enabled the development of special instruments and measuring techniques to monitor the mill dynamics, it hitherto remains a challenge that, the target data captured by the measuring instruments is more often presented to the mill operators in an ambiguous format which requires further interpretation before necessary mill control actions can be implemented. This creates a possible scenario for inadequate interpretation of data as well as data misinterpretation. Dynamic simulation models provide a means to address this shortfall by intelligently relating the measured parameters that define the mill performance to key mill operating variables. This approach, due to reduced interpretational uncertainties, would assist in easily identifying the sources of concerns, and allow confident implementation of mill control actions.

In this paper, dynamic simulation tests are performed using an energy-mass-size balance model to assess the model response. The model is presented in Part I of this paper. The model is based on the energy and mass flows in the mill. This research builds on the earlier work by Moys *et al* [1] who estimated the density of the mill discharge through an energy balance model around the mill discharge sump. In another study, Kapakyulu [2] modelled mill temperature based on an energy balance approach around the mill. The success of their works hints to the fact that monitoring of the mill temperature could be the closest technique available for controlling the in-mill properties. Indeed any change in ore characteristics, slurry properties and feed size distribution would be reflected in changes in-mill temperature and power draw.

II. Methodology for simulation

The dynamic energy-mass-balance model developed in Part I of our work is implimented here in MATLAB/SIMULINK programming environment. The mill is depicted as system of N perfectly mixed cells of equal volume, V with a net volumetric flow rate, F_f and recirculation rate, F_b. The Figure 1 is the conceptual framework of the model. The total flow rate through stages 1 and N is $F_f + F_b$ while the flow rate through stages 2 to N-1 is $F_f + 2F_b$. The temperature of the mill discharge is assumed to be equal to the temperature in the last mixer and so is the solids concentration in the slurry. The model differential equations describing the energy balance, particle breakage and mass - size balance are presented in Part I of our work and shall only be referred to without repeating the equations here.

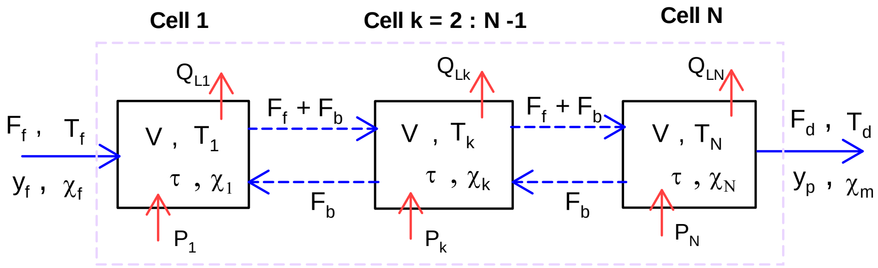

Figure 1: Depiction of mass and energy streams in a mill represented by N= 4 equally sized and fully mixed segments with back-mixing.

The numerical solution of the model differential equations is obtained using MATLAB inbuilt ODE45 solvers [3]. The model differential equations are presented in the form S-Functions in the MATLAB simulation structure. The model contains various input parameters as depicted in the model simulation structure presented in Figure 2. The input parameters are the breakage and selection function parameters, mill feed rate, mill dilution water, feed % solids, feed size distribution and ore characteristics. Other input parameters that are kept constant in the simulation are mill rotational speed and mill fill level. The mill output variables are the mill discharge temperature, mill power and the product size distribution (psd). The input parameters are entered by the user through a simple graphical user interface.

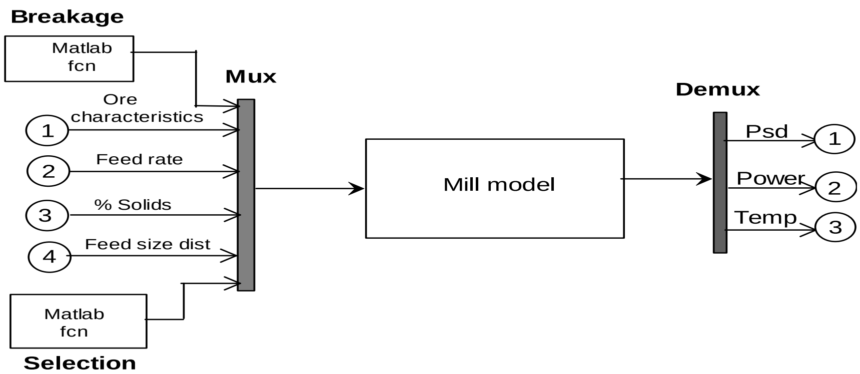

Figure 2: Representation of mass and energy streams in the MATLAB simulation structure

Particle breakage is simulated using the selection and breakage functions [4] but modified to account for ore hardness and solids flow. All mixers have the same breakage function and residence time. The ore hardness is simulated by defining the time varying hardness index (λ_p) in the breakage function. The values of hardness index are derived from Mohs' scale of mineral hardness [5].

III. Simulation test results

Presented here are test results showing the dynamic response of the mill model to changes in mill feed solids, ore hardness index, feed dilution water and feed rate. The mill parameters are entered into the simulator interactively using a simple user interface. The analysis of the predictions from the dynamic model is based on the simulations representing the operation of the mill under varying conditions of, feed flow rate, slurry % solids, mill dilution water and ore hardness index.

Figures 3(a, b) show the particle size distribution of the mill product after 30 minutes of grinding for both experimental and simulated cases (mill residence time, τ = 30 min). Also included is the particle size distribution of the mill feed. The parameters used in the size-mass balance model are shown in Table 1 while the mill parameters are presented in Table 2. Clearly, the results indicate the model predicts the grinding characteristics quite well.

Table 1: Parameters used in the breakage and selection functions

Breakage parameters		Selection function parameters	
β	4	A_T (min)	0.9
Φ	0.4	α	1.18
γ	1.6	μ	12
		Λ	3.1

Table 2: Mill operational parameters and ore characteristics

Specific heat capacity (kJ/kg.K)	Ore Characteristics	Mill parameters
$C_{p\ (Solids)}$: 0.31	Hardness (λ_p): 1 to 2.4	Filling fraction (J): 0.3
$C_{p(Water)}$: 4.18	Density (ρ_{solids}): 3000 kg/m^3	Speed (N): 75% Critical
	Poisson ratio (υ): 0.3	

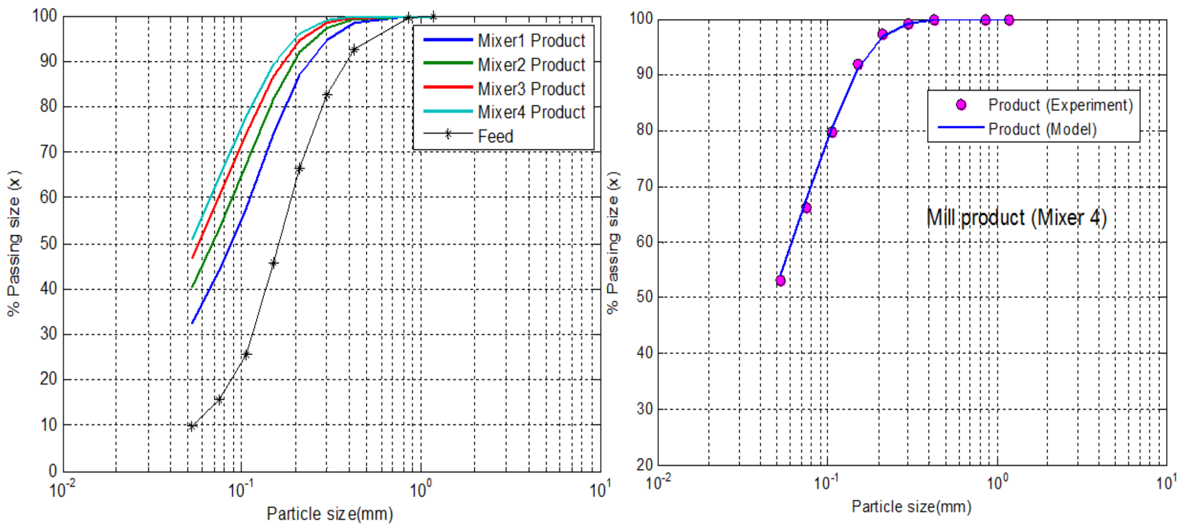

Figure 3: Particle size distribution after 30 min of grinding (a) for each mixer (b) for mixer number 4 - Experimental versus simulated results

Figures (4-6), show the variations in mill operational variables considered in this study (mill feed rate, ore hardness index, feed dilution water and feed solids fraction) over a duration of 90 min. The mill has the residence time of 30 min.

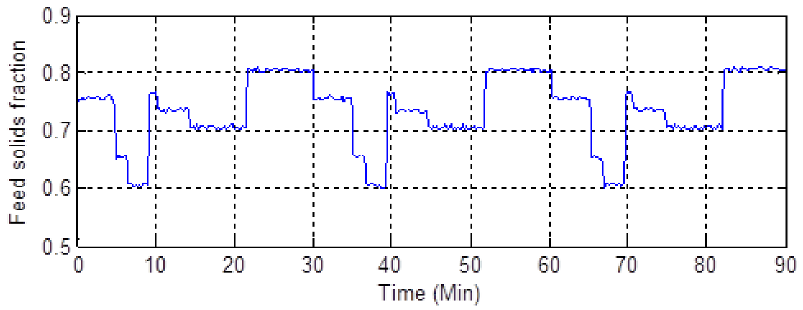

Figure 4: Variation of mill feed solids fraction over 90 min of mill operation

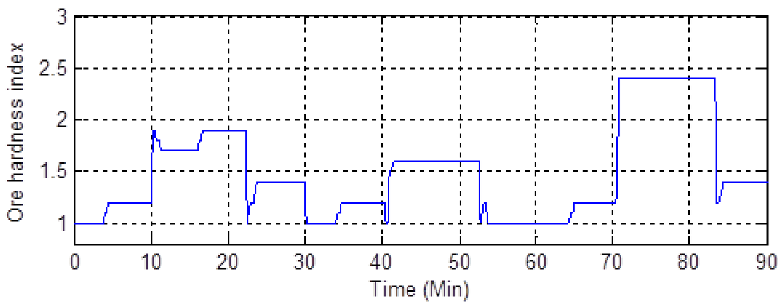

Figure 5: Variation of ore hardness index over 90 min of mill operation

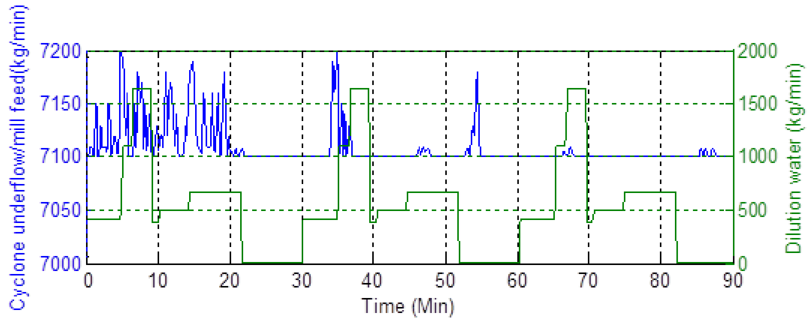

Figure 6: Variation of mill feed rate and feed dilution water of 90 min of mill operation

The dynamic response of the simulator to changes in mill process variables is demonstrated in Figures (7-10). The effect of variation of ore hardness, feed solids fraction and feed rate on the mill temperature, mill power draw, in-mill solids fraction and 80% passing size of the mill product (d_{80}), is evident.

The in-mill solids fraction only shows a marginal variation in response to changes in mill operational parameters, which is not unexpected for an open circuit milling configuration (Figure 7). On the other hand, the 80% passing size of the mill product and mill temperature both display strong sensitivity to changes in mill operational parameters as depicted in the results in Figures 8 and 9. It is interesting to note in Figure 10 that the increase in dilution water increases the mass feed rate. But since the mill is overflow, the volume holdup is almost constant hence the increase in dilution water lowers the feed density and subsequently the mass holdup and hence power drops.

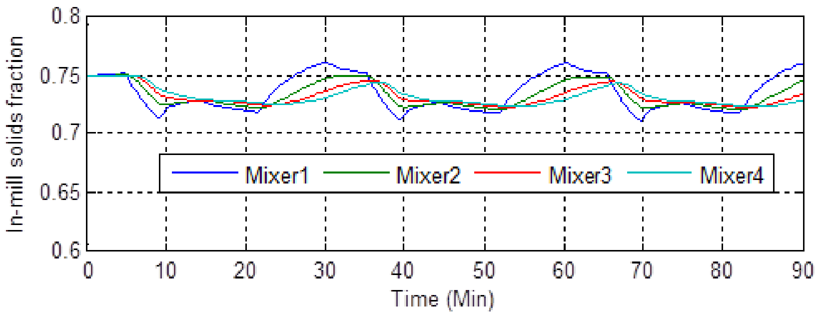

Figure 7: The response of in-mill solids fraction to variations in ore hardness index, mill feed rate and feed solids fraction.

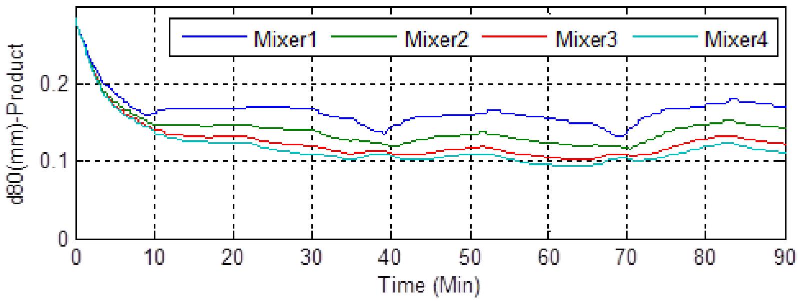

Figure 8: The response of 80% passing size of mill product to manipulations of ore hardness index, feed rate and feed % solids

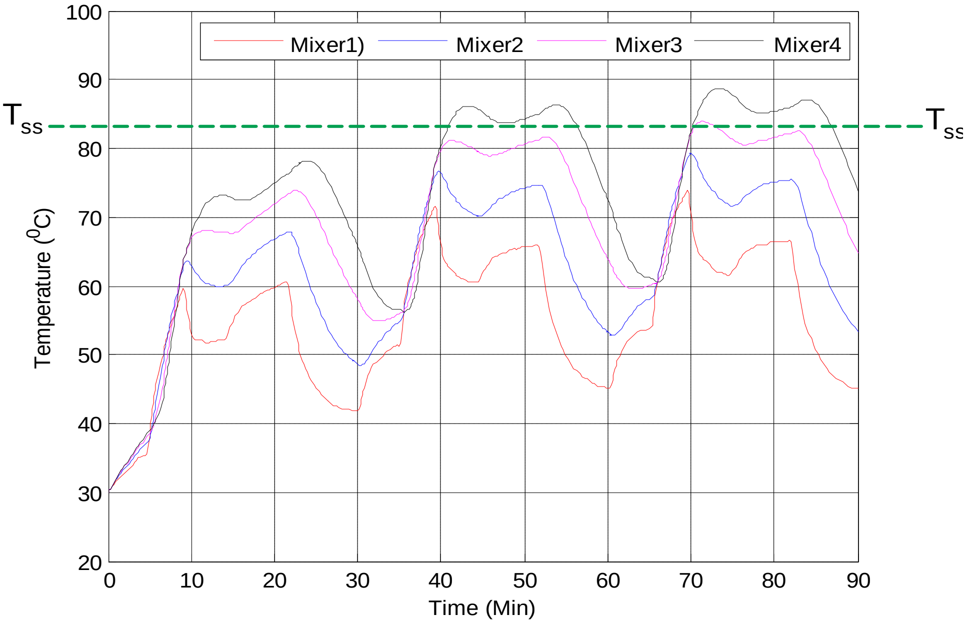

Figure 9: Temperature response to manipulations of process variables

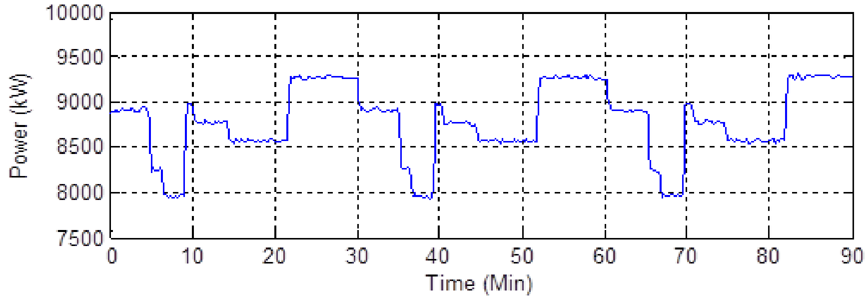

Figure 10: Response of mill power draw to manipulations of process variables

IV. Conclusions

An energy-mass-size balance model has been successfully applied to simulate the dynamic response of an open circuit grinding mill. Simulation results have been obtained showing the dynamic response of the mill to changes in mill operating parameters. Simulations were implemented in a MATLAB programming environment. The mill parameters were entered into the simulator interactively using a simple user interface.

Although the validation of the model is still work in progress, which requires rigorous experimental tests, the model has demonstrated adequate response to changes in ore hardness, feed solids concentration, feed rate and feed particles size distribution. This indicates that, the model represents well the physics of the milling system considered.

References

[1] Moys, H. M., Bwalya, M., Van Drunick, W., 2005. Mathematical modelling for optimization of mineral processing operations, *J.S.Afr. Inst. Min. Metall*. **105**: 663-674.

[2] Kapakyulu, E., 2008. Development of a model for temperature in a grinding mill, MSc Thesis, University of the Witwatersrand, Johanneburg.

[3] Mathworks Inc, Technical Literature Web Page: Http://www.mathworks.com/ products/ technicalliterature.jsp

[4] Austin, L., Klimpel, R., and Luckie, P., 1984, Process engineering of size reduction: Ball milling. Society of mining engineers, pp 341-384.

[5] Mohs' scale of mineral hardness: http://www.geology.com/minerals, accessed January, 2016.