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Semi-autogenous mill power model development using gene expression programming

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ABSTRACT

Predicting the performance of the semi-autogenous (SAG) mill is necessary for the best circuit design which is possible by suitable modeling and simulation. Numerous models of the SAG mill are studied in the literature, but the majority of them do not evaluate the predicted model for full-scale mill performance. Mill powers of the semi-autogenous mill have an effective influence on the mill performance. In this regard, a new predictive model based on gene expression programming (GEP) was developed to predict the mill power of the SAG mill. To achieve this purpose, a total number of 186 full-scale SAG mill works were investigated and the most effective parameters on SAG mill power, i.e., feed moisture, mass flowrate, mill load cell weight, SAG mill solid percentage, inlet and outlet water to the SAG mill and work index were measured and utilized to develop the GEP model. In order to determine the relationship between the input and output parameters, the GEP model was developed and the results were compared with non-linear multiple regression (NLMR) method. The results show the capability of the GEP model in predicting the mill power. It shows that the mill power is more sensitive to mass flowrate and work index than other input parameters.

1. Introduction

Semi-autogenous grinding (SAG) has been recently selected as the primary stage of grinding due to the economic considerations in most mining companies. SAG mills have some advantages such as lower physical space requirements, lower investment and maintenance costs and higher processing capacity, compared to the conventional circuits [1]. However, it has greater complexity in operation and control because of its large pieces of equipment. Semi-autogenous mill modeling is difficult because of the interaction between affecting parameters during the process such as mill performance and feed characteristics and inaccessibility of appropriate full-scale circuit data [2]. The Bond approach is based on the size reduction which follows as in Eq. (1):

$$W = W_i\left(\frac{10}{\sqrt{P}} - \frac{10}{\sqrt{F}}\right) \tag{1}$$

where W, W_i, P and F are the specific energy, the work index, the 80% passing size for the product and the 80% passing size for the feed, respectively.

The specific energy of a circuit is higher than what this equation predicts; thus, it is assumed that this equation has less efficiency. Bond's equation with a high applicability is used for the comparison of different circuit designs and specially the use of so-called “operating work index” (OW_i). The operating work index associated with Bond's equation is written as [3]:

$$OW_i = \frac{W}{10}\left(\frac{1}{\sqrt{P}} - \frac{1}{\sqrt{F}}\right) \tag{2}$$

The comparison of different circuits with different feed and product sizes can be carried out using the operating work index in the theory [3]. The refinement of the Bond models and more studies of mill charge detailed characterization enhanced the development of several mill powerdraw models [4,5]. Eq. (3) was developed by the Julius Kruttschnitt Mineral Research Centre as:

$$P_{Gross,JK} = P_{No\ Load} + kP_{Charge} \tag{3}$$

where, $P_{Gross,JK}$, $P_{No\ Load}$, P_{Charge} and k are the mill powerdraw (kW), the empty mill powerdraw (kW), the powerdraw of the entire contents of the mill (kW) and a lumped mill powerdraw parameter, respectively [6].

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The JA Herbst and Associates also developed the powerdraw model (Eq. (4)):

$$P_{Gross,JAH} = C_3 \sin(\alpha) D_m^{0.3} W_C (3.2 - 3V^*) N^* \left(1 - \frac{0.1}{2^{9-10N^*}}\right) \quad (4)$$

where $P_{Gross,JAH}$ is the mill powerdraw (kW), N^* is the fractional critical speed, W_C is the charge mass (t), V^* is the mill fraction occupied by the charge, α is the charge angle of repose (^{0}); and C_3 is a constant [7].

Apelt et al. combined the mill powerdraw, weight models and the related plant measurement to study the indirect measurement of the mill inventories. They showed that the investigation from the weight based models has the least uncertainty [7]. Morrell also predicted the specific energy of the AG and SAG mill using small diameter drill core samples. They developed a new rock breakage characterization test to generate a strength index that can be used for the specific energy of AG and SAG mills [2]. Morrell presented a new method for predicting the specific energy requirement of tumbling mill (grinding) circuits. They showed that the energy utilization efficiency of all studied plant grinding circuits had no significant difference [3]. Salazar et al. presented the dynamic modeling and simulation of semi-autogenous mills for predicting the time-evolution of product flow rate, level charge, powerdraw and load position using the conventional non-stationary population balance approach. This dynamic simulator can be used for milling operations in order to design and evaluate the advanced control schemes [1]. Completed models can be simulated with the lower risk of not piloting than pilot-scale test works based on a range of full-scale circuits [2].

This work investigates the use of feed moisture, mass flowrate, mill load cell weight, SAG mill solid percentage, inlet and outlet water to the SAG mill and work index to obtain the estimated mill power. The SAG mill circuits can be optimized using the modeling and simulation that can predict the throughput, power draw and product size distribution. For this aim, a new predictive model based on GEP is suggested to estimate the SAG mill power. In order to show the capability of the constructed model in predicting SAG mill power, non-linear multiple regression was performed. Finally, the performance predictions of the developed models were compared and discussed.

2. Process description and data analysis

Statistical analysis of the dataset is performed based on the 186 SAG mill operations collected from Aq Darreh gold processing plant 32 km north of Takab city in West Azarbayjan province, Iran. The plant is supplied from the Aq Darreh mine, at a distance of 12 km. The ore contains about 3 ppm gold. Fig. 1 shows the grinding flowsheet of Aq Darreh gold processing. Ore is fed to the jaw crusher for crushing after passing from the grizzly screen. The crusher discharge is fed to the SAG mill for grinding and mill discharge is classified by hydrocyclones. The over flow of hydrocyclones is fed for leaching in order to recover the gold and silver from the ore. The variables of feed moisture [*M*] (%), mass flowrate [*TPH*] (t/h), mill load cell weight [*LC*] (t), SAG mill solid percentage [*S*] (%), inlet [*IW*] (m^3/h) and outlet water [*OW*] (m^3/h) to the SAG mill and work index [*WI*] (kWh/t) are measured for modeling the SAG mill power [*KW*] (kW).

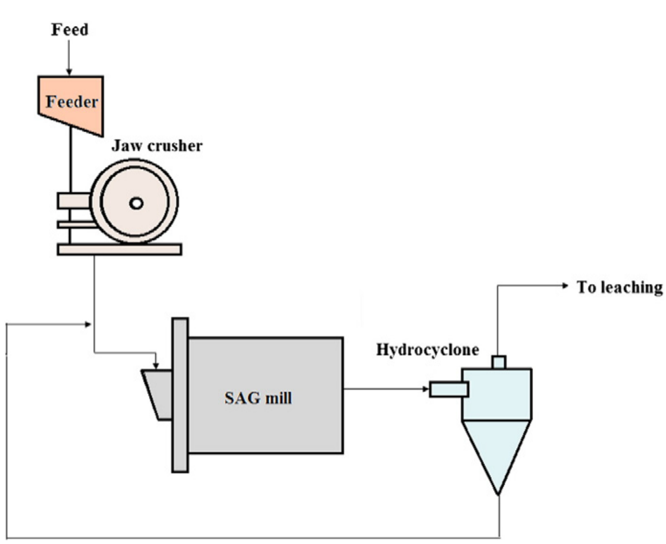

Fig. 1. Primary grinding circuit process flowsheet.

2.1. Data analysis

In datasets, the outlying data points can have an adverse influence on the relationships clear understanding among the variables. In order to make a predictable model of the SAG mill power, the outlying data points are identified from the dataset to be eliminated for building a more homogeneous dataset using multivariate statistical tools of the principal components and factor analyses. The basic descriptive statistical analysis of the original dataset is shown in Table 1. The original dataset box plot is shown in Fig. 2. As Fig. 2 shows, the median of most data groups is not in the box center, which indicates their distribution is not symmetric. The variables of TPH, S and IW do not have any outliers whereas M, OW, LC and WI have at least one outlier.

In order to detect the outliers and natural groups of data, the multivariate statistical tool of the principal components analysis is also used [8,9]. It can be used for the dimension reduction for the problems with high dimensions. Principal components in the PCA are the vectors which explain the most variance of the dataset that is a linear combination of original variables. The dataset correlation matrix is obtained by using the principal components analysis [10].

Table 2 shows the coefficients of the principal components. The percentage of variability explained for each principal component is shown in Fig. 3 using the Pareto chart that shows the relative importance of the differences between groups of data. It is an appropriate way for recognizing the causes of quality problems or loss. It can be also used for deciding the data group with the most attention [9]. The decrease in component variance is shown with the columns in Fig. 3. As Fig. 3 shows, the highest component variance is the first principle component. All variables in the first principal component and LC, WI and KW in the second principal component have the absolute largest coefficients. In the third component, M, LC, S, IW and KW are mainly weighted. The scatter plot of the second principal component (PC2) versus the first principal component (PC1) (Fig. 4) shows that there are no natural groups in the dataset whereas the outlying data points (they were determined with a red circle) can be seen in the dataset. The outlier data (44 data) were removed from the original data to build a more homogeneous dataset that was used for the modeling.

Table 1
Basic descriptive statistics for the original database.

Variable	Unit	Minimum	Maximum	Mean	Std. deviation
Moisture (M)	%	8.800	17.850	11.898	1.694
Mass flowrate (TPH)	t/h	55.218	155.792	110.827	22.182
mill load cell weight (LC)	t	61.040	142.100	98.116	12.486
SAG mill solid percent (S)	%	59.300	68.000	64.815	2.085
Inlet water (IW)	m^3/h	17.830	74.300	51.304	13.768
Output water (OW)	m^3/h	10.400	115.5	85.520	19.816
Work index (WI)	kWh/ton	10.488	24.340	15.001	2.713
Mill power (KW)	kW	1225	1798	1607.488	135.818