PREDICTION OF ON-LINE FROTH DEPTH MEASUREMENT ERRORS IN INDUSTRIAL FLOTATION COLUMNS: A PROMISING TOOL FOR AUTOMATIC CONTROL

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Abstract: The pulp-froth interface position is important from a metallurgical point of view because it determines the relative importance of the cleaning and the collection zones. The pulp-froth interface position is measured based on variations of specific gravity, temperature or conductivity between the two zones to locate the pulp froth interface position. In this study, the pressure measurements are used to calculate the values of the froth layer height. These two meters are installed in the upper part of the column at 1.4 m and 2.4 m respectively, from the top of the column. Methods using pressure gauges are commonly used in industrial operations Even though their accuracy is limited (due to assumptions of uniformity of the pulp and froth density), and they always have some error. In the Sarcheshmeh copper industrial plant (Iran), a float was installed near the column with 2.5 m height that was calibrated to 5 cm intervals in order to determine the more exact forth height and compare it with the recorded froth height in control room. In this paper, an algorithm based on Kalman Filter is presented to predict on-line froth height errors using two pressure gauges. This research is based on the industrial real data collection for evaluating the performance of the presented algorithm. The quality of the obtained results was very satisfied. The RMS errors of prediction froth height errors was less than 0.025 m.

Keywords: prediction; accuracy; froth height; Kalman filter; error

Introduction

Nowadays column flotation is an important mineral processing unit. Figure 1 presents a simplified scheme of a flotation column that consists of two principal zones: the collection zone (less than 20% of air) and the froth zone (more than 70% of air). The pulp feed (15–40% solids) enters near the top of the collection zone. Hence, particles

are contacted counter-currently with air bubbles generated near the bottom of the column. Hydrophobic particles collide and adhere to the bubbles and they move upwards to the pulp/froth interface. The froth zone is a mobile bubble bed, approximately 1 m in froth depth, which is contacted counter-currently with wash water (added near the overflow level).

Level control in flotation columns is an important factor that influences the recovery and grade of concentrate from the column. A flotation column is a nonlinear, multi-variable problem with changeable parameters that traditional methods have difficulty controlling.

When the pulp level is too high the concentrate overflows too much and the grade of the concentrate is reduced. When the pulp level is too low the concentrate yield may be reduced, which also results in a reduction in the recovery.
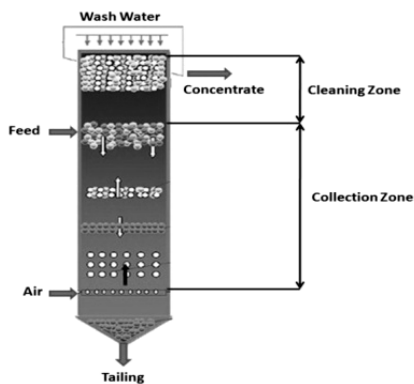

Fig. 1. Flotation column

Many techniques have been proposed in the past for the froth depth measurement. The most common were summarized by Finch and Dobby (1990) and some further developments were presented by Bergh and Yianatos (1995) and Del Villar et al. (1999). All these methods use the difference in physical characteristic, such as specific gravity, temperature or conductivity, between the pulp and the froth to locate the pulp froth interface position. Even though the principles behind these methods are fairly simple, some of them have encountered important operating problems that limit their accuracy. Nevertheless, methods based on the use of a float or pressure gages (one to three) are commonly used and seem to be precise enough for day-to-day process supervision.

Some experimental works, for example Hyma and Salama (1993) as well as Pal and Masliyah (1991), discussed and tested the control of the froth layer height by manipulating the non-floated flow rate in a pilot plant using PI controllers. Del Villar et al. (1999) designed and implemented a distributed PI controller in which the bias and the froth layer height were controlled by manipulating the wash water flow rate and the non-floated flow rates, respectively.

More recently, artificial neural network (ANN) based system identification and model predictive control of a flotation column has been reported by Mohanty (2009). The ANN is an empirical modeling tool, which is analogous to the behaviour of biological neural structures. ANNs are very powerful to effectively represent complex non-linear systems. It is also considered as a non-linear statistical identification technique. He describes the design of a ANN based model predictive controller for controlling the interface level in a flotation column.

The pulp level in a floatation column changes frequently during operation because of changes to the nature of the pulp and the varying discharge rate. Methods using pressure gauges are commonly used in industrial operations even though their accuracy is limited (due to assumptions of uniformity of the pulp and froth density), and they always have some error.

Until now, most studies have focused in importance of froth height system accuracy in floatation operation, and there are not any report in the field of prediction and correction of errors in this system.

This paper aims at presenting a new method to get prediction of froth depth measurement errors using Kalman Filter (KF) on the pressure profile along the column upper section. A KF is an algorithm for obtaining a minimum mean square error point estimate of a random process. In this study, the Kalman Filter method was done using data from case study on CISA flotation column at the Sarcheshmeh copper plant in Iran.

Industrial plant

The Sarcheshmeh copper ore body which may rank as third or fourth largest in the world contains 1 billion tones (1 petagram) averaging 0.90% copper and 0.03% molybdenum. The process consists of grinding circuit with their associated flotation circuits. Figure 2 shows the flotation circuit of the Sarcheshmeh concentrator plant.

The flotation circuit consists of rougher, cleaning and column flotation stages. The rougher flotation bank consists of 8 cells (130 m^3) and the regrind mill is a 3.962 m by 5.791 m ball mill. The cleaner, scavenger banks each have 3 (50 m^3), 5 (50 m^3) cells, respectively. The single stage column flotation operation is composed of a Metso Minerals CISA column with 4 m internal diameter, 12 m height and associated instruments (Fig. 3). A final product with an average grade of 28–30% Cu (chalcopyrite and chalcocite) and 0.7–0.8% Mo are obtained after flotation stages.

The primary objectives are column recovery and concentrate grade, which represent the indices of process productivity and product quality. Common practices to control secondary objectives, such as pH at the feed, froth depth, air flow rate and wash water flow rate. These are usually implemented as local controllers or under Distributed Control Systems (DCS). Ideally, when primary objectives are measured, the control strategy is to change the set points of the controllers under DCS, in order to achieve a good process performance.
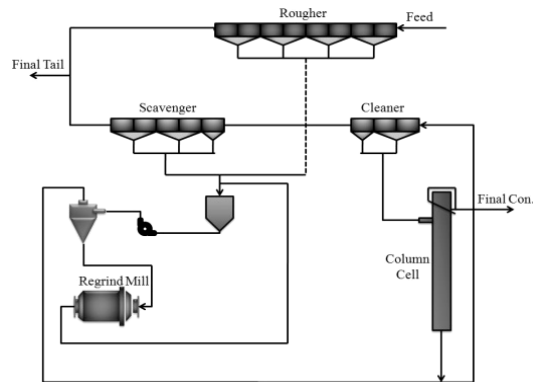
Fig. 2. The flow sheet of flotation circuit of the Sarcheshmeh industrial plant

Fig. 3. Sarcheshmeh industrial plant flotation column

Figure 4 illustrates simplified flotation column instrumentation with all of the variables included. The wash water flow rate is measured by means of an electromagnetic flow meter and controlled by a pneumatic valve. The air flow rate is measured by a mass flow meter and controlled by a pneumatic valve. The pulp feeding is controlled by means of a peristaltic pump with variable speed. Since the non-floated fraction flow rate is not directly measured, it must be inferred from the signal sent to the corresponding frequency inverter. The use of a peristaltic pump to control this flow rate requires special attention, due to the pressure variation at the pump inlet during the operation.

The instruments and the actuators (pumps and valves) are all connected to a data acquisition system which takes care of the analog-to-digital conversion of the output variables and of the digital-to-analog conversion of the manipulated variables.

The pressure measurements (P_1 and P_2 taken, respectively, by LT) are used to calculate the values of the air hold up in the recovery zone and of the froth layer height. These two meters are installed in the upper part of the column at H_1 and H_2, respectively, at 1.4 m and 2.4 m from the top of the column. Each sensor required to 12–53 DC volt energy source and transfer 4–20 mA flow to control system. A real

time data acquisition system was used to store the operating variables on a PC computer hard disk. The ultimate objective of automatic control is to continuously adjust process operation to maintain the best profitability despite disturbances and uncertainties while respecting constraints such as safety and environmental issues. To achieve this goal, a hierarchical indirect optimization structure is often selected.
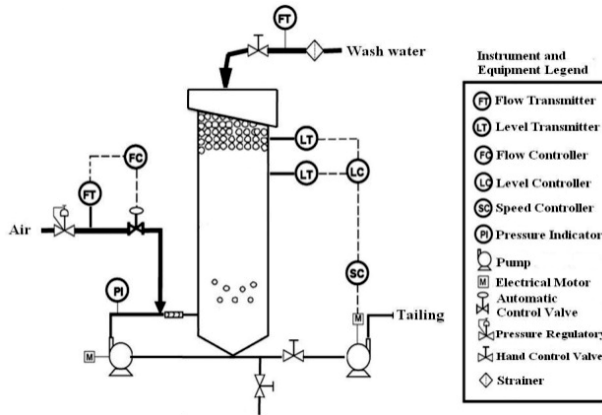

Fig. 4. Schematic diagram of the flotation column and associated instrumentation

Froth height

Interface position is important from a metallurgical point of view, because it determines the relative importance of the cleaning and collection zones. Many techniques have been proposed in the past for froth depth measurement. All these methods use the difference in a physical characteristic, such as specific gravity, temperature or conductivity, between the pulp and the froth to locate the pulp-froth interface position. Nevertheless, methods based on the use of a float or pressure gauges (one to three) are commonly used. The approach privileged in this work is based on the use of two pressure gauges and a float (Fig. 5). The relationships between the pressure values and the process variables can be expressed by:

$$P_1 = (H_1 - H_f)\rho_c g + H_f \rho_f g \tag{1}$$

$$P_2 = (H_2 - H_f)\rho_c g + H_f \rho_f g \tag{2}$$

$$\rho_c = \frac{P_2 - H_f \rho_f g}{(H_2 - H_f)g} \tag{3}$$

The froth layer height is inferred from the measured pressures and is given by equation (4):

$$H_f = \frac{\dfrac{(P_2 - P_1)H_1}{H_2 - H_1} - P_1}{\dfrac{P_2 - P_1}{H_2 - H_1} - g\rho_f} \tag{4}$$

where P_1 and P_2 are the pressure measured values (Pa), $H_1 = 1.4$ m and $H_2 = 2.4$ m (pressure meters distance from the top of the column) and ρ_f and ρ_c are the average value of the froth layer density and pulp in collection zone (kg/m^3), respectively.
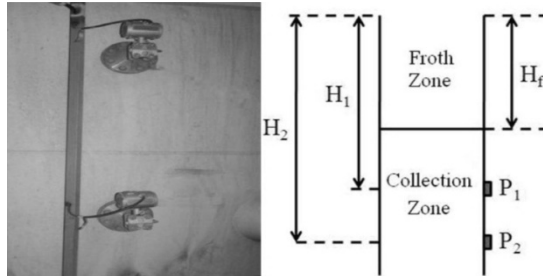

Fig. 5. Two pressure gauges are installed in the upper part of the column

The plant sensors provide raw measurement of secondary variables. Since measurements may be corrupted by bias, noise and even sensor failures, an observer is essential. Observation and data reconciliation, supervised by process and sensor fault detection and diagnosis techniques, extract consistent and reliable information from raw measurements, can infer unmeasured process states or temporarily replace defective sensors, etc. In the Sarcheshmeh copper plant, a float was installed near the column with 2.5 m height which is calibrated to 5 cm intervals, in order to, determine the accurate forth height and compare it with the recorded forth height in control room (measured froth height by two pressure gages) that is observable continuously by camera (Fig. 6).

Fig. 6. Installed float near the column

Research method

Kalman Filter formulation

The KF is an optimal estimation technique that minimizes the estimation error in a well-defined statistical sense. As a linear filter using a recursive algorithm which processes measurement information sequentially in time, the KF involves two main steps: filtering and prediction. Filtering is the estimation of the state vector at the current epoch based on all previous measurement information.

Prediction involves the estimation of the state vector X at a future time (Simon, 2006). The KF system state vector (dynamic model) which evolves with time can be written as:

$$X_{k+1} = \phi_k X_k + W_k . \tag{5}$$

corresponding to the measurement vector (measurement model):

$$Z_k = H_k X_k + V_k \tag{6}$$

where $W_k \sim N_k(0, Q_k)$ and $V_k \sim N_k(0, R_k)$ are the system and measurement noises which are mutually uncorrelated vectors. Subscript k refers to the epoch of time. The processes W and V are independent, zero mean Gaussian proportional to σ_ω^2 and σ_v^2 variances. σ_ω^2 coefficient and also β_1, β_2 are estimated using autocorrelation equations as described below (Mosavi et al., 2010):

$$\sigma_\omega^2 = R_{SS}(0) - \beta_1 R_{SS}(1) - \beta_2 R_{SS}(2) \tag{7}$$

$$\beta_1 = \frac{R_{SS}(0)\, R_{SS}(1) - R_{SS}(1)\, R_{SS}(2)}{R_{SS}^2(0) - R_{SS}^2(1)} \tag{8}$$

$$\beta_2 = \frac{-R_{SS}^2(1) + R_{SS}(0)\, R_{SS}(2)}{R_{SS}^2(0) - R_{SS}^2(1)} \tag{9}$$

$$\hat{R}_{SS}(k) = E\{X(n)X(n+k)\}, \quad k = 0,\ 1,\ 2 \tag{10}$$

where ϕ is the transition matrix. A KF requires that the system model to be in state-space form. In this modeling, the transition matrix can be obtained by using the time-varying Auto-Regressive (AR) model. AR is a famous model, which is used in a discrete-time stochastic process. A time varying AR model of second-order is mathematically described by:

$$y(k) = -a_1(k)y(k-1) - a_2(k)y(k-2) + e(k) \tag{11}$$

where $y(k-i)$ demonstrates the output of the model and $e(k)$ describes the noise value of the system at time k for $k = 1, 2....$ $a_i(k)$ for $i = 1, 2$ is the sets of parameters which describes the model structure. To identify the system, the parameters α_i should be calculated in a way that summation of square errors gets the minimum value. The parameter matrix θ_k may be estimated using the least-squares (LS) method as shown by Mosavi et al., 2002:

$$\theta_k = (F_k^T F_k)^{-1} F_k^T Y_k \tag{12}$$

where matrices F_k and Y_k are calculated as follows:

$$F_k = \begin{bmatrix} y(k-1) & y(k-2) \\ y(k) & y(k-1) \end{bmatrix} \tag{13}$$

$$Y_k = \begin{bmatrix} y(k) \\ y(k-1) \end{bmatrix}. \tag{14}$$

Once the model parameters $a_i(k)$ are known, the value of function $y(k)$ for an arbitrary k can be computed as follows:

$$y(k) = -a_2 y(k-1) - a_1 y(k-2). \tag{15}$$

In order to generate state-space some AR differential equations should be used as the sequence of equations below show:

$$\begin{aligned} x_1(k) &= y(k-2) \\ x_2(k) &= x_1(k+1) = y(k-1) \end{aligned} \tag{16}$$

or

$$\begin{aligned} x_1(k+1) &= x_2(k) \\ x_2(k+1) &= -a_2(k)x_2(k) - a_1(k)x_1(k). \end{aligned} \tag{17}$$

Finally, we are led to the following canonical controllable state-space representation:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{k+1} = \begin{bmatrix} 0 & 1 \\ -a_1 & -a_2 \end{bmatrix}_k \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_k \tag{18}$$

in which, the transition matrix ϕ_k is resulted from:

$$\phi_k = \begin{bmatrix} 0 & 1 \\ -a_1 & -a_2 \end{bmatrix}_k . \tag{19}$$

In the KF formulation, H is the measurement connection matrix. Elements of H are the partial derivatives of the predicted measurements with respect to each stage and must be computed for every epoch.

The respective Kalman filtering algorithm involves Kalman gain (K), covariance update (P_k) and prediction (P_{k+1}^-), in the time update and measurement update steps. The brief description of second-order KF algorithm is as follows (Mosavi et al., 2006):

Step 1: Initialize KF parameters

$$R = [\sigma_\omega^2] \tag{20}$$

$$Q = \begin{bmatrix} 0 & 0 \\ 0 & \sigma_\omega^2 \end{bmatrix} \tag{21}$$

$$P_0^- = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{22}$$

$$\hat{X}_0^- = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \tag{23}$$

$$H = [0 \ \ 1] \tag{24}$$

Step 2: Calculate Kalman gain

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \tag{25}$$

Step 3: Update the estimation process

$$\hat{X}_k = \hat{X}_k^- + K_k (Z_k - H\hat{X}_k^-) \tag{26}$$

Step 4: Update the error covariance

$$P_k = (I - K_k H_k) P_k^- \tag{27}$$

Step 5: Project the state ahead

$$X_{k+1}^- = \phi_k \hat{X}_k \tag{28}$$

Step 6: Project the error covariance ahead

$$P_{k+1}^- = \phi_k P_k \phi_k^T + Q_k .$$ (29)

Data collection

The data for this study were collected during the normal operation of the Sarcheshmeh concentration plant. Flotation column is operated under distributed control of froth depth, and chemical reactive dosages, to collect operation data at steady state. In order to collect real data to assess efficiency of suggested method, 300 observations of froth height were provided in 60-hours simultaneously with float and tow pressure gauges, i.e. that during the measurement period (12 minutes), the froth height was measured at the same time twice, one by pressure gauges and the other by float. Field instrumentation was installed and calibrated, and data signals communicated to a PC computer.

Results and Discussion

The previous section provided the algorithm for the KF and the means for estimating the quantities needed to start the filter. In this section the implementation of the KF for use in predicting the error of the two pressure gages will be described. Figure 7 shows the comparison plots of the measured froth height by pressure gages and the actual froth height for 60-hours data set. The prediction of froth height error by using KF was estimated by the MATLAB software. The results are shown in Fig. 8 and Tables 1.

The performances of the models developed in this study have been assessed using various standard statistical performance evaluation criteria. The statistical measures considered have been correlation maximum, minimum average and root mean square (RMS) error. The RMS criteria is calculated according to the following equation:

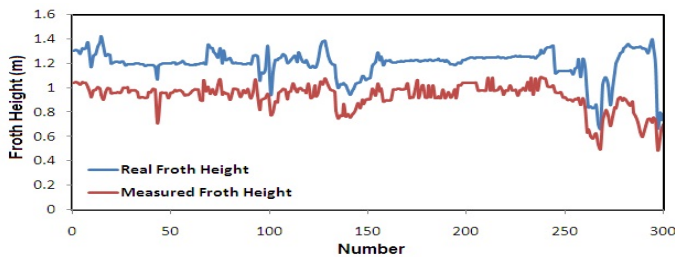$$RMS = \left[\frac{1}{n} \sum (X-Y)^2 \right]^{\frac{1}{2}}$$ (30)

Fig. 7. Comparison of real froth height values
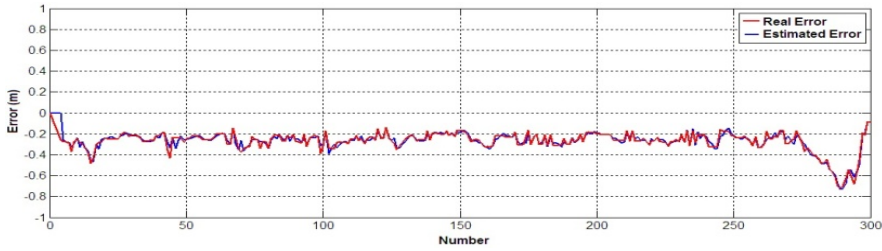in column flotation floatation with measured values

Fig. 8. Comparisonof predicted results using the KF model
with actual errors values for froth height in the flotation column

Table 1. Maximum, minimum, average and RMS errors in the prediction
froth height errors in the column flotation using KF

Parameters	Measured froth height error prediction error (m)
Maximum	0.099
Minimum	–0.1131
Average	0.0002
RMS	0.025

Table 1 presents the error values in the prediction of froth height errors in the column flotation by using KF when RMS is lower than 0.025 m. From these results, a KF model which can be used to predict the error of a sensor with an acceptable error. Also, the result from a test of real data shows that the KF method will guarantee access to more accurate froth height by prediction and correction of sensor measurement errors.

Conclusion

In this paper, we have provided a summary and improvements of the most common techniques used in the flotation column for measurement of froth height. We have shown that the standard implementation of the Kalman filter provides proper forecast of random error. It is able to provide an efficient analysis when measurements are available. The method described in this paper is based on KF using real data from industrial scale in order to predicate measured froth height errors of the Sarcheshmeh copper complex. The quality of the obtained results was very satisfied. The RMS errors of prediction froth height errors were less than 0.025 m. Moreover, with correction of predicted errors, it can be possible to reduce RMS errors in on-line analyzers. Therefore, the implementation of estimators such as Kalman Filter could significantly improve the measuring of the froth depth and as well as the column metallurgical performance. This could lead to great possibilities for plant optimization of the flotation column process.

Acknowledgments

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