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Technical note

Implementation of a model for Falcon separation units using continuous size-density distributions

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ABSTRACT

Falcon concentrators are commonly used in the mining industry to separate ores. Recent research yielded a predictive model for their separation performance in the form an analytical expression, based on a mechanistic understanding of the separation physics in these devices. While giving good results for lab-scale concentrators, in the form it is given, this model is not ready for industrial applications because of two limitations: its strong dependance on high quality measurements of size-density distributions, and its sensitivity to the discretization of data. These two shortcomings are solved by representing the distributions using continuous polynomials functions, in order to produce a robust model that makes it possible to validate the predictions for industrial scale Falcon bowls.

1. Introduction

Falcon concentrators are commonly used by the mining industry to achieve physical separation of fine particles in high tonnage slurries. They have proven to be efficient density-based separators that operate well over a wide range of conditions, so there is great interest in their application to challenging separation processes such as light fine material recovery as needed in Waste Electrical and Electronic Equipment (WEEE) treatment (Duan et al., 2009), tailings dewatering in the oil sands industry, handling of dredged sediments (Kroll-Rabotin et al., 2011a) and coal processing (Oruç et al., 2010). The only missing piece to build the bridge between these challenging industries and the use of Falcon concentrators is a robust predictive model of their separation performance that would make it possible to identify cases when Falcon concentrators could be used without relying on field-testing.

These concentrators are made of a fast spinning bowl in which the slurry flows in a thin film at the wall (McAlister and Armstrong, 1998). The centrifugal force due to the spin acts as an enhanced gravity field that makes it possible to separate particles based on their differential settling velocities, even in the ultrafine size range (Deveau and Young, 2005; Deveau, 2006). A predictive separation model has been derived from a physical analysis of the separation within those bowls (Kroll-Rabotin et al., 2010, 2013) and validated in lab conditions (Kroll-Rabotin et al., 2011b):

$$C_p = \max\left(0, \min\left(1, \frac{\pi}{9}\lambda_0(1-\lambda_\phi\phi)Q^{-1}\omega^2(\rho_p-\rho_s)d_p^2\mu^{-1}R_{\min}R_{\max}H_{\text{bowl}}\right)\right) \quad (1)$$

in which C_p is the recovery to concentrate, Q and ω are the operating parameters (volume flow rate and rotation rate), $R_{\min}, R_{\max}$ and H_{bowl} are the dimensions of the spinning bowl (bottom and top radii, and height) and d_p and ρ_p are the size and density of each particle class p.

The model makes use of two calibration constants, λ_0 and λ_ϕ, that account for the slight difference between actual Falcon bowls and the conical shape assumed in the model, and for solid interactions in concentrated conditions. The constants have been estimated using experimental and numerical investigations which yielded values of $\lambda_0 \approx 0.68$ and $\lambda_\phi \approx 1.6$. The density ρ_s has been identified as the mixture density in the overflow (Kroll-Rabotin et al., 2013):

$$\rho_s = \rho_f + \phi \iint (\rho_p - \rho_f)(1-C_p)f_{\text{feed}}\,\mathrm{d}d_p\,\mathrm{d}\rho_p \quad (2)$$

where f_{feed} is the washability of the processed slurry, that is the particle distribution per sizes and densities. Its presence in the calculation of ρ_s is the way the model accounts for the effect of the feed slurry on the separation function for concentrated suspensions.

For concentrated feed slurries, the dependence of the separation on the particle size–density prevents the original model from being a useful engineering tool since operating data sets are usually not sufficiently detailed, and information that is missing from the field data, as well as discretization issues can change the model's predictive capabilities significantly. For the model to be able to process industrial data, such data must be expressed in a form that allows the model to properly 'guess' the missing values, without

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any knowledge from the operator about the model's formulation. In the present study, polynomials are used to represent particle distributions in order to overcome this limitation.

2. Polynomial implementation of the model

The separation function (C_p) is a product of the different physical quantities, each with its own scaling exponent, so that when applied to a polynomial function, the result is still a polynomial function. However, there is complication that arises due to the bounded function in Eq. (1) that cannot be captured by polynomials.

2.1. Evaluation of the integrals

Multiplicative terms that do not depend on particle properties are grouped in a single coefficient (K), and the separation function is split into three domains with specified conditions for particle sizes and densities:

$$C_p = \begin{cases} 0 & , \text{ if } \rho_p < \rho_s \\ 1 & , \text{ if } \rho_p > K^{-1} d_p^{-2} + \rho_s \\ \overbrace{\frac{\pi}{9}\lambda_0(1-\lambda_\phi\phi)Q^{-1}\omega^2\mu^{-1}R_{\min}R_{\max}H_{\text{bowl}}}^{K}(\rho_p-\rho_s)d_p^2 & , \text{ otherwise} \end{cases} \tag{3}$$

Using this expression, the minimum and maximum functions in Eq. (2) can be accounted by redefining the integration domain:

$$\rho_s = \rho_f + \phi \int_0^\infty \left[\int_0^{\rho_s} (\rho_p - \rho_f) f_{\text{feed}} \, \mathrm{d}\rho_p + \int_{\rho_s}^{K^{-1}d_p^{-2}+\rho_s} (\rho_p - \rho_f)(1 - K(\rho_p - \rho_s)d_p^2) f_{\text{feed}} \, \mathrm{d}\rho_p \right] \mathrm{d}d_p \tag{4}$$

The integration and composition of polynomials yield polynomial functions. However, here, the upper integration bound for the density is not a real polynomial as it contains negative exponents. In the particular case of this model, this issue can be circumvented as the final value that is expected is a scalar (ρ_s) that can be evaluated directly with scalar integration bounds.

2.2. Definition of polynomials over finite intervals

As polynomials cannot asymptotically tend to zero, the polynomial representation of finite distributions must be defined on bounded intervals. This is particularly well suited for processing tabulated data, since such data comes with its own definition domain for each cell. Eq. (2) becomes:

$$\rho_s = \rho_f + \phi \sum_k \int_{d_{\min}^{(k)}}^{d_{\max}^{(k)}} \int_{\rho_{\min}^{(k)}}^{\rho_{\max}^{(k)}} (\rho_p - \rho_f)(1 - C_p) f_{\text{feed}}^{(k)} \, \mathrm{d}\rho_p \, \mathrm{d}d_p \tag{5}$$

where $f_{\text{feed}} = \sum_k f_{\text{feed}}^{(k)}$, and $f_{\text{feed}}^{(k)}$ are defined on intervals $[d_{\min}^{(k)}, d_{\max}^{(k)}] \times [\rho_{\min}^{(k)}, \rho_{\max}^{(k)}]$.

From Eq. (3), it comes that the integration domain can be reduced to $[d_{\min}^{(k)}, d_{\max}^{(k)\prime}] \times [\rho_{\min}^{(k)}, \rho_{\max}^{(k)\prime}]$, with $\rho_{\max}^{(k)\prime} = \min\left(\rho_{\max}^{(k)}, \rho_c(d_{\min}^{(k)})\right)$ and $d_{\max}^{(k)\prime} = \min\left(d_{\max}^{(k)}, d_c(\rho_{\min}^{(k)})\right)$, where:

$$\rho_c(d_p) = K^{-1} d_p^{-2} + \rho_s \tag{6a}$$

$$d_c(\rho_p) = \frac{1}{\sqrt{K(\rho_p - \rho_s)}} \tag{6b}$$

Also when $d_c(\rho_{\max}^{(k)\prime})$ is between $d_{\min}^{(k)}$ and $d_{\max}^{(k)\prime}$, the integration according to particle size must be split into two integrals to account for the change of integration bound:

$$\begin{aligned} \iint^{(k)} & 1 - K(\rho_p - \rho_s)d_p^2 \, \mathrm{d}\rho_p \, \mathrm{d}d_p \\ &= \int_{d_{\min}^{(k)}}^{d_c(\rho_{\max}^{(k)\prime})} \int_{\rho_{\min}^{(k)\prime}}^{\rho_{\max}^{(k)\prime}} 1 - K(\rho_p - \rho_s)d_p^2 \, \mathrm{d}\rho_p \, \mathrm{d}d_p \\ &\quad + \int_{d_c(\rho_{\max}^{(k)\prime})}^{d_{\max}^{(k)\prime}} \int_{\rho_{\min}^{(k)\prime}}^{\rho_c(d_p)} 1 - K(\rho_p - \rho_s)d_p^2 \, \mathrm{d}\rho_p \, \mathrm{d}d_p \end{aligned} \tag{7}$$

where $\rho_{\min}^{(k)\prime} = \max(\rho_{\min}^{(k)}, \rho_s)$. As long as the distribution in the feed stream (f_{feed}) is expressed in a piecewise polynomial form, all the integration steps but the last one yield polynomials. The only one that may not produce a polynomial result is $\int_{\rho_{\min}^{(k)\prime}}^{\rho_c(d_p)} p \, \mathrm{d}\rho_p$, where the upper integration bound is not a polynomial function. Nevertheless, since size intervals are known from the particle size distributions, this integration bound can be evaluated as a scalar, so that the result is a scalar and there is no need to carry logarithmic terms. Finally, Eq. (2) can be calculated directly for any piecewise polynomial representation of f_{feed}.

3. Evaluation of the new implementation using tabulated data

3.1. Comparison with the discrete approach: example of coal recovery from fine tailings

The discrete implementation of the model has already been used to predict separation efficiencies of the Falcon concentrator for fine coal recovery (Kroll-Rabotin et al., 2013). The results were calculated using the tabulated data presented in Table 1, under the assumption that the volume distribution was constant in each cell. This washability was discretized using 500 sizes × 500 densities to run the simulations.

Fig. 1(a) shows that the results may depend significantly on the input discretization since 20 particle classes ($\sqrt{20} \approx 4.5$ on the horizontal axis) would already be an uncommonly fine discretization among mineral processing studies. Consequently, it may be a severe limitation of the model to require the operator to discretize his data before using the model, as the process may introduce significant error. The same tabulated data set turned into flat volume-based distributions has been simulated with the new polynomial implementation, and Fig. 1(a) shows that it perfectly matches the finely discretized results of the former model.

Fig. 1(b) shows the predicted overflow densities for varying operating conditions. The three curves respectively show the piecewise continuous distributions used earlier, the discrete distribution from Table 1, and an hybrid distribution (discrete densities, continuous in size). Comparing the three curves shows again that too coarse discretization impacts the predicted result, and confirms that the continuous model is necessary, as using the raw tabulated data yields spurious predictions.

3.2. Benefits of polynomial interpolation for data reconstruction

The coal washability used previously was well described, so linear interpolation of the cumulative distributions (which yields piecewise constant probability density functions) gave good results. Because it is very difficult to measure coupled size-density distributions experimentally, data of such quality are very rare for industrial applications.

A sample distribution for a dredge sediment is presented in Table 1. A significant amount of ultrafine particles is found between 0 and 10 μm, and it is hardly satisfactory to assume a flat distribution by volume in this size range. The cumulative distributions have thus been fitted using cubic Hermite splines, as shown