Powder Technology 291 (2016) 140–146

Contents lists available at ScienceDirect

Powder Technology

journal homepage: www.elsevier.com/locate/powtec

Nonlinear optimization of gravity solids classification based on the feed and deck angles: a law of mass action approach

Nicolus Rotich [a,*], Ritva Tuunila [a], Ali Elkamel [b], Marjatta Louhi-Kultanen [a]

[a] Lappeenranta University of Technology (LUT), School of Engineering Sciences, P.O Box 20, FI-53851 Lappeenranta, South Karelia, FI
[b] University of Waterloo, Chemical Engineering, 200 University avenue west, Waterloo, ON N2L 3G1, CA

ARTICLE INFO

Article history:
Received 27 March 2015
Received in revised form 19 October 2015
Accepted 3 November 2015
Available online 22 December 2015

Keywords:
Gravity-classification
Mineral particles
Modeling

ABSTRACT

Deck screen design parameters e.g. material of construction, deck angle of inclination, the feed throughputs, and physicochemical properties of the particles, are critical factors to consider in solids classification. Two significant and easily manipulated parameters that greatly affect screen performance are the feed rate and design geometry configuration. In this work we apply statistical analysis of variance (ANOVA) and nonlinear least squares optimization with parameter estimation concepts, first, to assess the significance of the two factors and, second to formulate flow prediction models that optimize the feed rate and classification efficiency. Experiments were conducted on a prototype screen of 556.28 cm^2 effective area, (1380 cm^2 total area). For glass beads of sizes 0.75, 1, 2, and 3 mm, with 16 feed batches of 10 g to 160 g, and six inclination angles 5, 10, 12.5, 15, 17.5, and 20°, a maximum efficiency of 66.7% was achieved with a screen loading of 86.5 g, and an inclination angle of 17.5°. These results were then subjected to nonlinear least squares optimization, which showed that a maximum efficiency of 93.2% can be achieved at batch loading as low as 36 g. There was a favorable performance at the range of angles $12.5 \leq \theta \leq 17.5°$, but poor performance outside this range. The screening efficiency did not respond significantly to changes in screen loading, although loading had a significant effect on the screening capacity. Confirmation tests conducted at selected optimum parameters achieved a maximum efficiency of 72% (at 12.5° with 49.6 g batch load), and a maximum rate of 27 g/s at 17.5° with 104 g.

1. Introduction

Solids–solids separation is the process of segregating particles in terms of desired criteria or properties tied to the solids, using an applied force. The properties of the separated particles are dictated by downstream unit operations or end use. In general, the fundamental aim of classification is to separate the behavior of the solids into definite regimes of class patterns [1–2].

To underscore the significance of bulk solids classification in mineral processing for instance, research over the last decade has pointed out that the most energy intensive stage is comminution [3–4]. However, the exact root cause emanates from insufficient classification. Poor classification results in the transfer of excessive barren load to the grinding circuits, which end up consuming prohibitive energies (of 30–70% of the overall consumption), during comminution among other processes [4]. This thus makes classification a significant stage at which a large part of the profiting is determined. It is during classification, that the quality and quantity of the mineral, as well as downstream expenses are compromised [5].

In general, particles classification by screening has a long and exceptional history, with some research citing that it is probably the oldest [6]. It constitutes a large part of particles' classification in most mining, food industries, pharmaceuticals, coal and biomass industries, as well as many other chemical and processing plants.

When dealing with particles classification, a number of factors determine the extent of both capacity and efficiency that can be achieved. Although it is commonly presumed that if a process has been in use for many years, its controlling factors and optimum operating parameters will have been found, this unfortunately is not the case with gravity separation. The reasons being: (i) There are countless materials on earth, each with its own unique properties; (ii) the materials are not treated individually, but as bulk matter with diverse properties; and (iii) the material handling equipment also introduces complexities because of the varied materials and configurations used. The complex of interrelated factors thus makes a supposedly simple process highly complicated. Here is an example where this complexity can be found: in powder material science, flowability can be easily defined as “the ability of granular solids and powders to flow” [7], and the definition is comprehensible and valid. However, when the powder has (inevitably) come into contact with some material handling equipment e.g. hoppers, mesh screens, conveyors etc., the definition becomes inadequate, and instead a more accurate definition has to been coined

* Corresponding author.
E-mail address: nicolus.rotich@student.lut.fi (N. Rotich).

http://dx.doi.org/10.1016/j.powtec.2015.11.007
0032-5910/

"the ability of the powder to flow in a desired manner in a specific piece of equipment" [8]. The former definition while accurate, is somewhat incomplete; the later attempts to expand the definition by including the idea that flowability is never an inherent property on its own, but a compounded concept used to describe the motion of particles over others or an equipment surface.

Solid separators, e.g. deck screens, spiral concentrators, and Reichert cones, are some of the many types of materials handling equipment in use, and such equipment requires immense compromise as regards design and day to day operations. Bearing in mind the numerous materials constituting the bulk properties of solids, the critical factors to consider when using gravity force for solids separation can be classified into intrinsic, extrinsic, and other factors.

1. Intrinsic factors: These factors are easily manipulated by adjusting the mechanical design, e.g., overall configuration of the screen, feed rate, deck angle of inclination, aperture sizes, screen material, feed throughputs, and mesh size.

2. Extrinsic factors: These factors are seldom varied by the user, either because it is not possible, or because manipulating them negatively affects the overall product quality. Such extrinsic factors are: particle sizes, moisture content, shape, densities, purity, relative motion of particles to that of the screen surface, the physicochemical properties of the solids etc.

3. Others: This group of factors accounts for those unknown or known factors that demand great effort in their determination or manipulation, either qualitatively or quantitatively. Examples include the many factors linked to hydro, thermo, electro or even aerodynamic variables.

The number and diversity of the different factors involved underscore the difficulty of identifying an optimal combination of design and operating parameter values. However, it is possible to fit a mathematical function to most of the processes and thus try to understand the whole as a combination of its parts. The chief limitation of most models today is they are based on capacity, rather than the efficiency. For instance the screen is designed based on the amount of material presented to the screen rather than the yield. Realistic models base the design of screens on the actual amount of particles transmitted to the underflow. An example of such a model was formulated by V. Karra back in 1979. The Karra model while it is still useful in designing current processes, it can further be improved by extending it to quantify both undersized and oversize, together with the material loses involved [9]. The current study is primarily based on the law of mass action, which provides a systematic attempt to quantify the three quantities of materials by simultaneously solving a set of state equations (ODEs) that describes the process.

Material throughput and screen deck inclination are particularly significant and easily manipulated operational parameters that affect both the screening capacity (rate) and efficiency. Operating with a large feed throughput makes the screen susceptible to blinding, gives poor flowability and causes an overall reduction in the underflow. Low feed rates, while they increase the efficiency as observed in [10], extends the processing times, resulting in long residence times, affecting the economics of production. On the other hand, low deck angles are good for optimizing the efficiency in terms of separation effectiveness but adversely affect flowability on the screen, and thereby significantly reducing the rate of separation. High deck inclinations deprive the particles of the ability to report to the underflow, the projected screen area becomes narrower; and the flow velocities increase, making the particles ride over the apertures, instead of passing through [2,10].

The objective of this research paper is to conduct a mass balance around a lab scale screen for different sizes and batch masses of glass bead samples, M_o, and measure their undersizes, M_u, overflows, M_ε, overflow fractions, ε and efficiencies η, at six different deck angles of inclination. The measured results are then formulated into an analysis of variance optimization (ANOVA) strategy, taking the angles as treatments, and the 16 glass beads samples as blocks, each with their values as factors. The results are then used to construct ANOVA tables and boxplots with MATLAB [11]. Decisions are then be made regarding the significance of each factor (based on the null hypothesis) and to what extent the factors can be enhanced. The second process involves formulation of nonlinear models based on the Guldberg–Waage law of mass action. The so developed models are then tested for flow prediction before subjecting them to nonlinear least squares optimization. Finally, we take confirmation tests at selected optimal parameters and draw conclusions.

2. Methodology

The numeric data used for this research paper were adapted from [12]. Ideal spherical glass beads of mass (M_o) and mixed known sizes (0.75, 1, 2, 3 mm) were released from an elevation to an inclined multi-sized prototype linear screen, with increasing (1, 2, 3, 4 mm) circular-aperture sizes downwards. Channels were used below each sieve to collect the undersized particles used for this study. The prototype screen measured 30 cm × 46 cm, i.e. approximately 1380 cm^2 in total area. The circular apertures were arranged in a 60° equilateral triangular pattern and spaced at a half-diameter apart. This by default scales the effective perforation to a maximum of 40.31% of the total screen plate area as observed in 2013 [13]. In this case it reduced the effective area to 556.28 cm^2 (Fig. 1). The batch screening process was repeated for six angles θ), (20°, 17.5°, 15°, 12.5°, 10°, and 5°, for each batch (M_o) of glass beads. For all the experiments, the screening time lasted for 2–3 s from batch mass release. The aim was to assess the effect of varied inclination and increases in feed throughputs on the degree of separation rates and efficiencies. The following measurements were taken and recorded: Sample mass; F, mass of the undersized collected on the 1, 2, 3 and 4 mm sieves (m_1, m_2, m_3, m_4); oversize, M_ε; and runtime, t. The following values were calculated directly from the collected data: total undersized mass (M_u); separation efficiency, η computed as the ratio of total mass of undersized M_u to the batch mass F; overflow fraction, ε computed as the ratio of mass of oversize collected to the total sample F; and the mass of material loss, L un-separated or (unaccounted), calculated by subtracting the sum of undersized and oversize from the total sample mass, F. The rates of separation, R were obtained by calculating the mass of the undersized per unit time of separation. Loading coefficient, Ψ is a normalized parameter corresponding to the ratio of the load in grams to the overall largest feed mass used 160 g. [2]. The results of the variations in feed rates and efficiencies with inclinations were then tabulated in Tables 1 and 2.

Using the results as design matrices, analysis of variance (ANOVA) was carried out to assess the significance of the changes in inclinations and the feed quantities on the classification rates and efficiencies. Based on the analysis, the null hypothesis may then be accepted or rejected.

2.1. Analysis of variance (ANOVA)

Analyses of Variance constitute a very important tool in statistical quality control and optimization in engineering. Its main application is to provide guided decision making by comparing the variations caused by certain changes in the factors affecting the process, without making assumptions of pre-existing conditions. It is based on the null hypothesis that a certain group of factors do not have significant effect on the resulting observation.

In this case, for both increase in feed batch masses and inclinations, the null hypothesis is that the two have no effect on the rates and efficiencies observed in Tables 1 and 2. The probability, P of the occurrence of the hypothesis is then calculated and used to make necessary decisions regarding the factors assessed. We will construct two-way ANOVA tables for the feed rates and efficiencies for Tables 3 and 4.

2.2. Formulation of nonlinear unconstrained optimization strategy

The final stage is to formulate an optimization strategy to determine which deck angles and feed rates are sufficient to operate the screening process at optimum performance. The optimization is done keeping in