

Modeling Gas-Particle Transport in Mills and Classifiers

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Abstract

Mills and classifiers are primarily used for fine grinding and sorting of particles across various industries, including paper, paint, plastic, pharmaceuticals, ceramics, cosmetics, foods, and fine chemicals. They are typically used to achieve a targeted particle size distribution or specific particle shape. Given the substantial volume of particles processed in industrial contexts, even marginal improvements in grinding efficiency can lead to significant economic benefits. This review summarizes advancements in understanding and modeling processes taking place from the microscale (intra-particle scale) to macroscale (device scale). The review concludes with a brief perspective on future research directions, including the use of machine learning (ML) and artificial intelligence (AI) for constitutive modeling and design optimization.

Keywords: Fluidization, Mills, Classifiers, CFD-DEM, Particle Breakage

1. Introduction

- Mills and classifiers
 - Effect of operational parameters on breakage of silica in a jet mill [8]
- Multi-scale aspect
 - Microscale: Approaches that capture intraparticle stress distribution and predicts breakage

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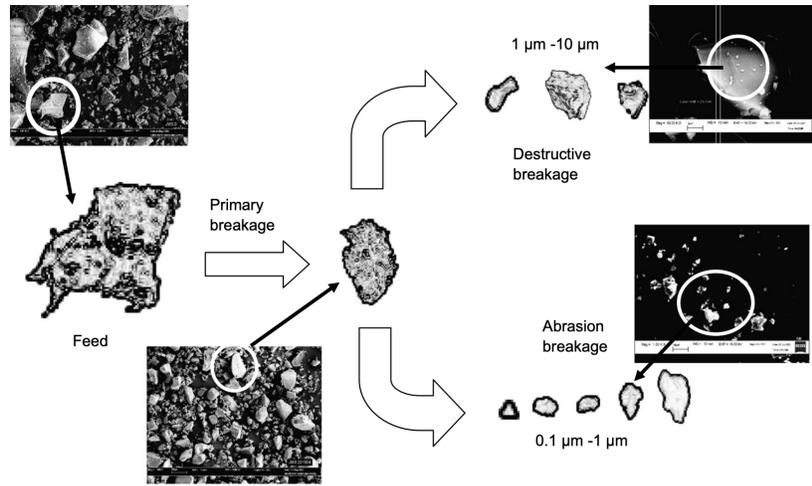


Figure 1: Breakage mechanism of silica ground in jet mill [8].

- Macroscale: System-level description that relies on models to estimate breakage at large volume
- Energy efficiency
- Role of machine learning/AI.
 - A simulation framework capable of predicting particle breakage at system scale will require accurate constitutive models describing the microscale. Due to the high dimensional space that controls breakage, accurate/reliable models maybe intractable. An alternative approach that might prove to be successful is to use machine learning for describing the very fast / small dynamics (i.e., replace constitutive models with ML).
 - ML can also be used to describe outcome of large-scale quantities of interest

2. Microscale Description (Intra-particle Scale)

Discrete element model (DEM) described interactions between particles but simplifies intra-particle deformation into single spring-dashpot model. Capturing breakage at the mesoscale (scales larger than individual particles) requires an approach to efficiently account for stress distribution within the

particle. These can be classified into Eulerian (grid)-based approaches and Lagrangian (meshless) approaches. Note that although these are more affordable than the microscale modeling approaches listed above, simulations using these techniques would likely be limited to a small number of particles using state-of-the-art computing architectures.

- Grid-based (Eulerian) approaches
 - eXtended Finite Element Method (XFEM) [1, 4]. In order to evaluate stress intensity factors for the advanced crack, the finite element mesh needs to be updated, a process which has been shown to be challenging. This has led to the development of alternative computational methods to handle propagating cracks, among them the
 - Boundary element method for crack propagation: Mi and Aliabadi [6]
- Meshfree (Lagrangian) methods:
 - Smooth particle hydrodynamics: Benz and Asphaug [2]
 - Peridynamics provides the means to account for intra-particle deformation and fracture due to contact forces between particles. Peridynamics has a significant advantage in the simulation of particle breakage owing to its treatment of discontinuities and fractures. Recent hybrid Peridynamics-DEM (PeriDEM) approach: Jha et al. [5]. Single-particle breakage: Wan et al. [10]
 - DEM: first application [7], probabilistic models, population balance models using energy-based breakage rates (e.g., Tuzcu and Rajamani [9])

3. Macroscale Description (System Scale)

- Population-balance equation (PBE)
- Two-fluid models

4. Machine learning

- Physics-informed deep learning for particle breakage: Chen et al. [3]
- Impacts of grain morphology on grain crushing strength: Wang et al. [11]
- Combining DEM with artificial neural networks for ball mills of different sizes, where ML is used to predict correlation between impact energy and the grinding rate constant: Chen et al. [3]

5. Conclusions

5.1. Summary Points

- Current state of DEM
- Current state of macroscopic models

5.2. Future Issues

- Improvements/directions for intra-particle modeling
- Use of ML/AI to improve macroscopic modeling and optimization

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