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EVALUATION OF BULK MATERIAL BEHAVIOR CONTROL METHOD IN TECHNOLOGICAL UNITS USING DEM. Part 1

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ABSTRACT

Nowadays pelletizing drums are widely used in the steel industry. These units are characterized by high endurance and low cost of maintenance. However, use and control of these units in the process of coarsening have a number of issues. For most of the cases pelletizing drums are "black box" and control accuracy can not be estimated exactly. It is explained by low existing theoretical basis of this production process. Particularly it is tied up with the variability of the bulk materials (charges) parameters supplied to the unit.

Overcome of this issues can be reached with development of intelligent control systems for drum pelletizing machines. Main requirement for such systems is possibility to level or consider the effect of charges properties variability in control. However, it is necessary to study the behavior of bulk materials inside the units. Visual assessment of pelletization does not allow to evaluate the ongoing physical processes. Development of mathematical and numerical models can help studying the process and take a lot of parameters into account including charges properties and even interaction with water. But the adequacy of the resulting models also has to be clarified using physical devices to record or capture bulk materials behavior inside the units.

This research proposes a DEM simulation test of the concept for bulk material behavior control through the recognition of the mixture movement fragments using special capsules. This part is dedicated to the simulation model set up and extracting the particles trajectories for further processing.

Introduction

The production of pellets is one of the currently widely used methods for sintering thin iron ore concentrates [1–3]. For a good understanding and control over the processes occurring in the pelletizing drums, it would be useful to observe the behavior (movements) of the furnace charge inside the pelletizing drums.

Based on various sources [4–5] three to five characteristic motion modes of granular material in a drum pelletizer are distinguished: overrolling, waterfall, cyclic, shuttle and rolling. The first three modes are the most common and most fully characterize the process of pelletizing (**Fig. 1**). The second two modes: shuttle and rolling are inherently transitional between overrolling and waterfall modes.

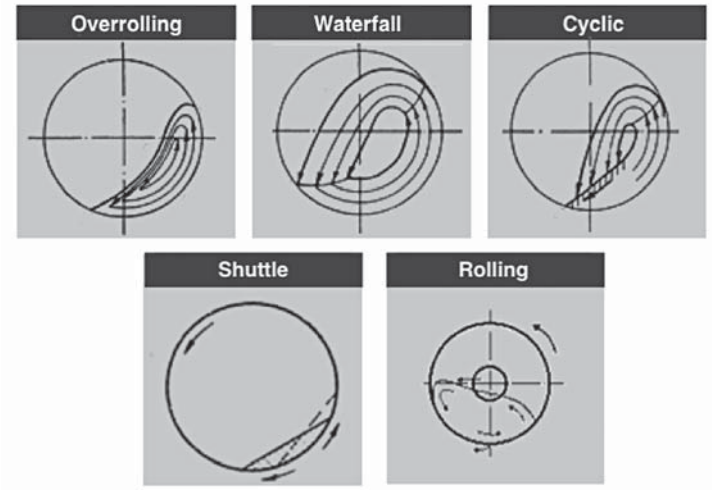

Fig. 1. Modes of bulk materials movement in pelletizing drum

1.1. Effect of furnace charge movement on pelletizing parameters

The movement of the furnace charge inside the pelletizing drum comprehensively characterizes the parameters of the process [6–7]. For example, the wear of drum pelletizing machines (one of the main problems affecting the service life of this type of aggregates) is associated with the behavior of bulk materials in the process [8]. Wear rate during particle enlargement is depending on the motion mode of the charge.

The emergence and maintenance of certain modes is inextricably related to the process characteristics. Those include the angle of inclination of the unit, humidity of the charge, the rotation speed of the drum and the flow rate of the feed [4]. The formation of pellets in the overrolling mode occurs as a result of mixing layers of material between themselves. The free fall of material portions from the upper sections of the inner surface of the drum is observed mostly in a waterfall mode. It happens due to friction forces carrying along the material on the lining of the unit. The cyclic mode is characterized by an increase in the angle of incidence of particles that leads particles to fall on the lining of the unit. In this case material fall occurs along more elongated parabolic curves than in the waterfall mode.

The main differences between the modes are their intensities (particle velocities and the height of their fall). The abrasive properties of the charge moving in the unit

(it directly determines the lining wear) largely depend on these parameters. Thus, in areas with a cyclic movement of the charge there is a significant abrasion of the lining and decrease in the height of the lifters. It happens due to the high values of particle speeds and fall heights.

1.2. Existing methods for determining the movement of the charge

At the moment, the assessment of the charge motion modes in real time at technological facilities is not performed. There are several reasons for this. First of all, mode recognition requires charge behavior observation by any technical measuring instruments. One of such solutions could be technical vision systems to monitor the behavior of the material [9]. But there is a significant dusting of the working area of the unit.

An alternative approach is to classify the modes by indirect factors, such as the particle size distribution of the raw pellet at the outlet of the unit [10] or by walls vibration of its housing [11]. Another indirect way to monitor the pelletizing conditions can be considered as a direct measurement of the lining wear. For example, using the Lidar laser scanning technology and scanning the pelletizer lining to get 3D lining model from the resulting point cloud [12]. However, it is necessary to implement unit shutdown in this case. Obviously it is economically inefficient.

The most appropriate approach is to determine the mode based on the required characteristics of the pellets using numerical simulation [13–15] or data obtained on laboratory test rigs [16]. Laboratory scale experiments do not allow a sufficient study of the process. It is explained by the influence of the geometric parameters of the units on the motion modes. The results of the analysis carried out using numerical modeling, in turn, largely depend on the set parameters of bulk materials (charge friction coefficients, cohesion parameters). Determination of such parameters is currently difficult due to the lack of universal methods to obtain them [17–18]. Even minor simplifications and assumptions made in the models can affect its adequacy with respect to the real scope.

Determination of motion modes, characteristics of the incoming charge and process characteristics using devices that repeat and record particle movements in the technological unit could be useful to improve the control. Understanding particle motion specifics in pelletizing drums will also make possible to evaluate the adequacy of process numerical model. It can be reached by bulk materials parameters determination (inputs in the software for numerical models) using the developed measurement methods and comparing the resulting models with the results obtained in real process.

2. Methodology

In the article [19], a team of authors proposed a model for assessing the motion modes of bulk materials in a pelletizing drum using special devices — capsules that repeat and record the movement of material in the unit. The proposed approach consists in the recognition of the charge motion modes in the unit. Special capsules must be supplied to the apparatus along with the charge to track the trajectories of material movement. Capsules are equipped with an electronic device consisting of an accelerometer, a microcontroller and a radio module for transmitting sensor readings to a computer. Accelerometer readings represent changes in capsule acceleration over time. If we consider a capsule commensurate in size with an infinitesimal portion of bulk material within the framework of this task, then we obtain accelerations of a specific point of the charge flow in the unit.

The task of determining the pelletization mode (charge movement) by material accelerations (which are indirect parameters) relates to classification problems [20]. It is advisable to use machine learning methods, such as neural network classifiers to solve this class of problems. Neural network classifiers already successfully used for recognition of audio recordings, physical activity of a person, images, etc [21–22]. Neural network training requires a lot of data forming a dataset. As a rule, a dataset is formed on the basis of real observations and measurements accumulated over a rather large period of time. Since in this case we are only talking about the concept of the device, then to test the proposed solution, we will use the dataset obtained on a digital model of the technological process.

Since the pelletizing process takes place mainly in a granular medium the method of discrete elements (DEM) should be used. DEM gives the most detailed reflection of the physical nature of the process and taking into account the nature of the material [23]. The construction of a pelletizing drum model is discussed below.

2.1. DEM modeling

Before setting-up a model of a technological process it is very important to decide the purpose of modeling. Particularly, choose the characteristics of a real process that should reflect this model and what requirements should it meet. For this task, the main purpose of modeling is to reproduce the motion paths of the charge in the pelletizing drum body under various pelletizing modes. The material should sufficiently reproduce various modes of material movement in the cross section of the pelletizing drum (while the quality of the pellets and some other process parameters are not so important). The movement modes of the material obtained as a result of modeling should differ for different parameters of the process.

To test the proposed idea, a series of numerical experiments are carried out in order to obtain the trajectories of the charge. For this, a model of the technological unit was built taking into account the geometric characteristics of the pelletizing drum model widely used in russian enterprises (**Table 1**).

Table 1. **Geometrical parameters of the pelletizing drum CAD-model**

Parameter, units	Value
Volume, m^3	407.15
Length, m	10
Outer diameter of the drum, m	3.6
Angle of inclination, degree	3

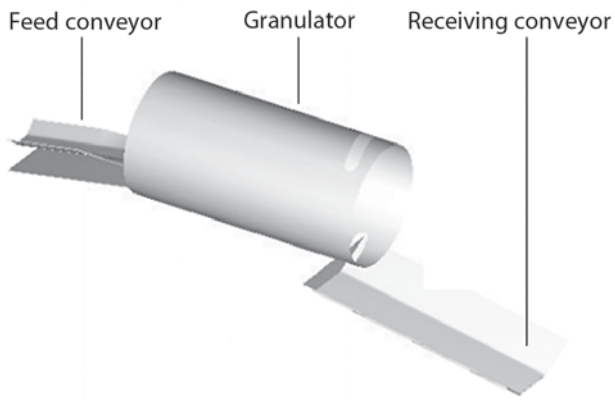

Fig. 2. CAD model of a pelletizing drum

Table 2. **Simulation parameters**

Property, units	DEM model		Geometry
Particle size, mm	Fine	Seed	–
	3	10	
Density, $kg \cdot m^{-3}$	600		7900
Poisson's ratio	0.3		0.3
Young's modulus, GPa	0.15		100
Drum rotational speed, rpm	–		4–7
Drum load factor, %	–		9–15

Table 3. **DEM-parameters**

Interaction	Particle-particle	Particle-geometry
Coefficient of restitution	0.1	0.1
Coefficient of static friction	0.5	0.5
Coefficient of dynamic friction	0.3	0.3
Coefficient of rolling friction	0.5	0.5

To build a three-dimensional model of the device, the AutoCAD software package is used. Next, the constructed CAD model (**Fig. 2**) was loaded into CAE tool for modeling bulk materials using the discrete element method (Rocky DEM).

Reproduction of various pelletizing modes in the DEM model is obtained by varying drum rotational speed, charge consumption and its moisture. In Rocky DEM it is set through cohesion parameters in order to more likely reproduce wet iron ore (**Table 2**).

Moreover, DEM-parameters of bulk material were set (as for mining ore, **Table 3**).

20 numerical experiments are carried out during which the movement of each particle along the pelletizer body was recorded. As a result of simulations the trajectories of the charge are obtained for various modes of pelletizing.

In the Rocky environment the simulation results are presented in the form of a three-dimensional visualization of particle movements in the unit. However, the built-in Python Shell interpreter and open API (application program interface) made possible to extract the coordinates of the particles that was changing as they moved in the device. Extraction of the particles coordinates is realized using macro written in the Python 2.7 programming language.

The data obtained are arrays of trajectories of charge particles and their velocities. The trajectories most fully characterize the mechanism for moving bulk material in the drum pelletizing body and allow determine the flowing mode of pelletizing.

3. Results and discussion

The trajectories of the particles in the pelletizing drum are obtained with different operating modes based on the results of numerical simulations. The **Fig. 3** shows the trajectories of the movement of bulk material in the drum mainly in two forms. Fig. 3, *a* shows the particle path with visualizing the distance traveled by the particle and characterizing the formation of the pellet (highlighting modulo is the velocity vector). Fig. 3, *b* shows the trajectories of particles with illumination along the Z coordinate.

It is important to note that in real pelletizing process the charge moves along a complex path, which depends on the intensity of pelletizing. Most often, the intensity at the feed conveyor is low, then by the middle of the unit it reaches a maximum, and at the output it decreases again. This leads to the fact that several pelletizing modes coexist in the pelletizer at once. It is the ratio of different modes that determine the quality of the pellet. According to the results of experiments, this theoretical position was confirmed. **Fig. 4** shows one of the numerical experiments during which three modes were simultaneously observed in the granulator. At the beginning of the unit, the charge was rolled in overrolling mode (mode 1), then closer to the middle of the unit in cyclic mode (mode 2), and closer to the exit in rolling mode (mode 3). In other experiments, similar situations are observed.

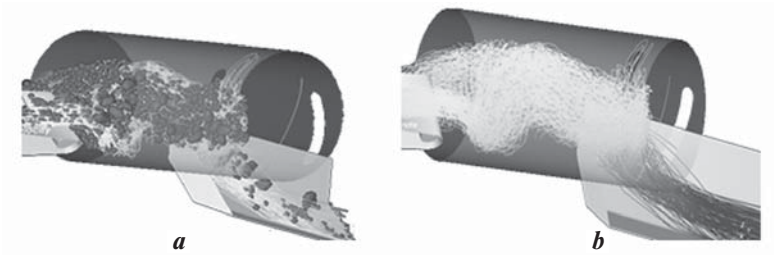

Fig. 3. Rocky DEM Pelletizing Drum Model

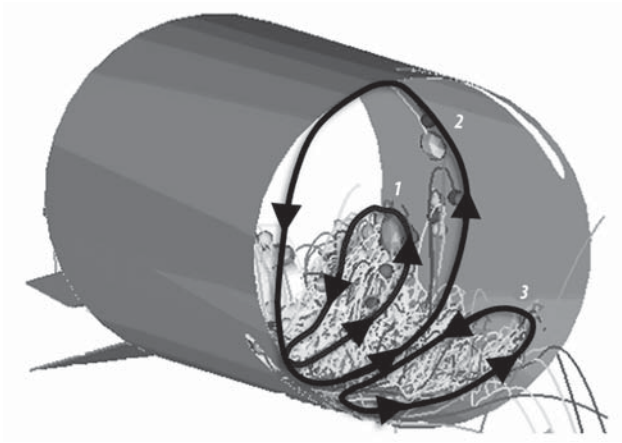

Fig. 4. Coexistence of several modes inside the device

In total, 20 numerical experiments produced 10,981 trajectories of various types. Further, this data is processed through neural algorithm which is used to recognize the modes of bulk material movement in pelletizing drum.

Conclusion

A number of numerical experiments were performed using DEM modeling to test the methodology for determining the modes of bulk materials movement in the housing of drum units using capsules. The possible trajectories of the bulk materials movement in the pelletizing drum are determined, which will be used to recognize the charges movement modes in the case of the technological unit. In order to get different trajectories two parameters was varied: drum rotational speed (from 4 to 7 rpm) and drum load factor (from 9 to 15%). Only 20 numerical experiments produced 10,981 different particles trajectories. Moreover, the models are partially reproduces real bulk material behaviour in technological units. For example, coexistence of several modes inside the device was observed.

Further, we will discuss converting the obtained trajectories into sensor readings and then processing this data using a neural network algorithm. An analytical comparison of several algorithms will be made and the results of recognition of the modes will be presented.

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