Investigation on selected methods for condition and process monitoring in mineral processing of lithium ore

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Abstract. The European Union's goal of achieving climate neutrality by 2050 has accelerated the search for domestic lithium sources. As demand for lithium continues to rise, particularly in the fields of electromobility and energy storage, innovative mineral processing technologies are essential for the efficient exploitation of Li-ores from European deposits. This study presents a comprehensive investigation in the field of condition and process monitoring special in the comminution of Li-ores from European deposits. Optimization goals for machines in the mining sector include increasing throughput and improving product quality, taking into account the varying properties of the raw materials. Fast feedback on the product quality like the size range and ore content would allow for control optimizations to achieve both energy efficiency and an optimized product size range. Methods for determining the product quality and key figures of comminution machines are being investigated in this research.

1. Introduction

Condition and process monitoring is becoming an increasingly important factor in raw material beneficiation, driven in particular by the steadily growing demands for efficiency, product quality, and sustainability. While industrial manufacturing processes typically handle homogeneous feed materials, raw materials within a single deposit often exhibit significant spatial and temporal variability in their properties. Producing a consistently high-quality final product therefore requires besides a flexible and adaptable design of the individual process steps a constant monitoring of relevant specifications.

Most processing machinery consists of stationary installations designed for operating lifetimes of several decades. As a result, it is often not economically viable for operators to replace them entirely with costly new equipment. In industries with narrow profit margins, it is therefore all the more worthwhile to enhance the efficiency of existing machines by retrofitting them with intelligent sensor systems. The ability to transform the acquired data into actionable information and decisions through advanced software solutions further enables upgraded machines to be integrated seamlessly into a modern, highly automated, and technologically sophisticated production process.

Changes in the particle size distribution (PSD) within the feed stream can be detected in one part of the study using a system setup based on a passive-intrusive acoustic sensor system. The focus is placed on monitoring the material flow on a conveyor belt, using the particle size distribution as an illustrative example. A large number of studies exist on the online detection of particle size distributions using various systems [3,4], including approaches based on passive-intrusive acoustics [5-7]. The system presented here is deliberately simplified and is designed only to detect deviations in product quality, such as changes in the particle size distribution. Its commissioning and calibration are therefore significantly easier.

To separate valuable from barren material sensor-based sorting can implemented and got already investigated in different papers [8-10]. Sensor data in crushers getting analysed to get an idea about the content of valuable material in a sample, particle size and wear.

2. Materials and Methods

2.1. Material

The investigations focused on low-grade or mineralogically complex ores from underutilized deposits in europe. Each ore sample contained one of the lithium-bearing micas: zinnwaldite, lepidolite, or petalite. The selected ore samples from various European deposits were systematically characterized in [11] with respect to their mineralogical and physical properties to identify the most suitable mineral processing strategy.

2.2. Systems for condition and process monitoring

A prototype was developed that is capable of detecting changes in the particle size distribution (PSD) of a conveyed material. The system is operated through a simple user interface designed specifically for the present application. In addition, a wireless data transmission link

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was established between a microcontroller and the Raspberry Pi via a WLAN network. Figure 1 illustrates the basic structure of the monitoring system.

The system enables the transmission of the MPU-6050 accelerometer data to the Raspberry Pi. One advantage of this transmission method is that the data can be accessed simultaneously by any device connected to the network, such as a laptop or desktop PC. For wireless data transfer, the ESP-32 microcontroller is used. It is connected to the accelerometer and reads its raw data. In addition, it provides an HTTP server that supplies the acceleration measurement data. The accelerometer is attached to an impactor that is in contact with the material stream, conveyed on a belt conveyor. When the particles in the mass flow collide with the waveguide at mass and velocity, they create an impulse. The height of this impulse depends on the volume of the particles, assuming the same impact velocity and particle density. The vibrations resulting from the collision are measured by an acceleration sensor on the oscillator. Through data processing and analysis, conclusions can be drawn about the particle size distribution.

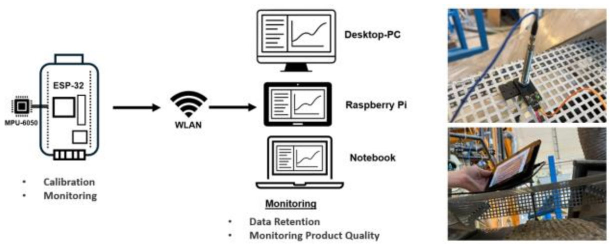

Figure 1. Monitoring system for quality control of the material.

Figure 2 shows the used labarotry jaw crusher. The crusher has jaw dimensions of 110 mm x 160 mm, a crushing chamber height of 300 mm, and a stroke of 10 mm. To measure the occurring crushing forces, four load cells with a measuring range of up to 20 kN are installed in the fixed jaw. As shown in Figure 2, two load cells are positioned in the upper section and two in the lower section of the jaw, allowing the forces in each region to be measured separately.

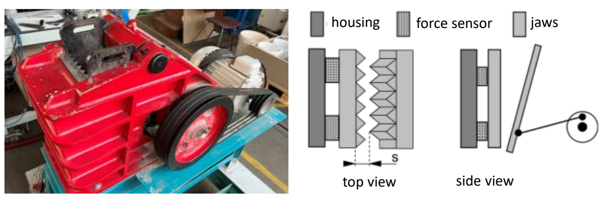

Figure 2. Labaratory jaw crusher (left) & sketch of crusher and force sensors (right)

The following investigations focus on determining the crusher fill level and the lithium content based on sensor data obtained from force measurements.

3. Results and discussion

Different fractions of petalite lithium ore were conveyed under identical operating parameters, including conveying speed. For each fraction, three measurements of 10 seconds each were recorded. The measured values are shown in Figure 4. Smaller particle size distributions result in lower signal values. Measurement accuracy decreases as the material becomes finer. Studies using other sensor types indicate that each particle-size range has a suitable sensor and that the appropriate sensor should be selected according to the specific application.

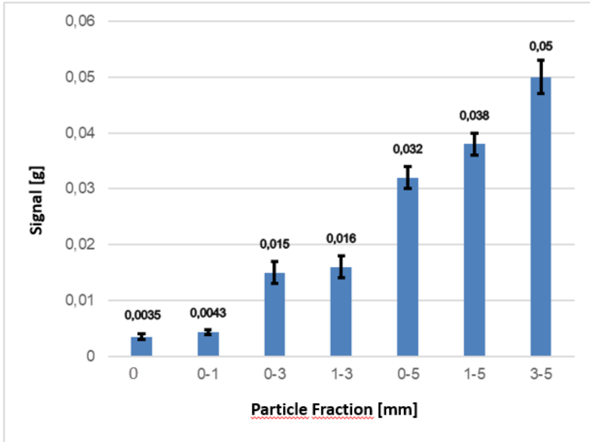

Figure 4. Average values for the measured signals depending on the size fractions

The test material was conveyed and the system was calibrated accordingly. For this purpose, the average signal over a measuring period of 10 seconds was used as the reference value. Samples were taken downstream of the sensor to analyse the PSD by conventional screening. During continuous measurement, using the same 10-second interval, the system computes the average values and compares them with the calibrated reference. If a deviation exceeding the defined limit is detected, the system alerts the operator. In this study, a threshold of 20% of the signal was set. When the measured value dropped by 22%, a sample was taken for further analysis. The results are shown in Figure 5.

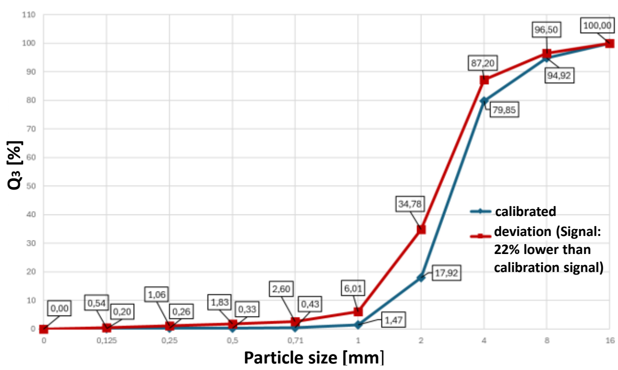

Figure 5. PSD’s for calibration and testing after it failed the quality control of the system

To prevent the jaw crusher from becoming overloaded, it is helpful to know the filling level of the crushing chamber.

In tests with Zinnwaldit and Petalite, the influence of the crusher fill factor on the crushing forces at the top and bottom was investigated. The mean values of the respective measured forces are shown in Figure 6. On average, all crushing forces during the comminution of Petalit were about three times as large as those for Zinnwaldite. For all forces, clear trends as a function of the filling ratio f_B are discernible. The forces in the lower region increased only slightly with the filling degree; the regression lines shown serve only to illustrate the trend and would not intersect the origin if extended. This is because, as the single-grain tests show, even a very low filling degree can lead to high forces at the bottom. Since, as the fill level increases, the forces acting on the upper load cells increase, and since the forces increase more slowly because less crushing occurs in the upper region, the increase in the lower force is nonlinear when considering the entire fill level range. For the average forces at the top $Fm{,}o$, linear increases were observed for both ores, and their regression lines could be extended to the origin with very good accuracy. They are described by the following equations:

$$f_{B\ Zinwaldite} = 0{,}5022 \cdot f_B \qquad (1)$$

$$f_{B\ Zinwaldite} = 1{,}6311 \cdot f_B \qquad (2)$$

The R^2 of equation 1 is by 0,998 and from equation 2 by 0,995. The compressive forces in the upper section can be considered a suitable indicator of the crusher's fill level, provided that a sufficiently large data basis is available to make the variation of these forces predictable as a function of the material properties, such as strength and particle size.

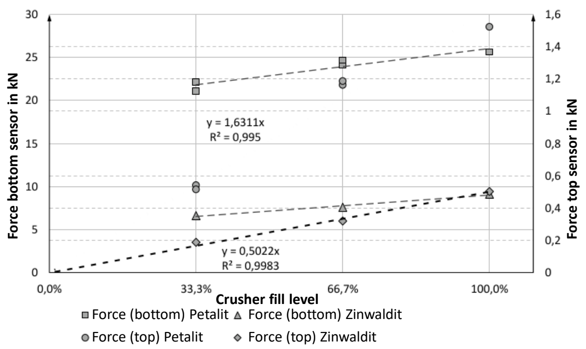

Figure 6. Change in crushing forces in the upper and lower regions of the crushing chamber as a function of the filling ratio for Petalite and Zinnwaldite, feed particle size: 15–30 mm

Figure 7 shows the mean peak forces during the comminution of the 30/50 mm fraction of Zinnwaldite High Grade and Zinnwaldite Low Grade at a gap width of 11 mm. Consistent with the strength values obtained from the Point Load Tests, the measured forces for the High-Grade material are significantly lower than those for the Low-Grade material. An evaluation of sensor data from force measurements or power measurements can therefore provide information about the lithium content of the zinnwaldite.

Results of the sensor-based sorting of Zinnwaldite are published in [10]. The lithium content in the High-Grade class is approximately 2.4 times higher than in the barren class.

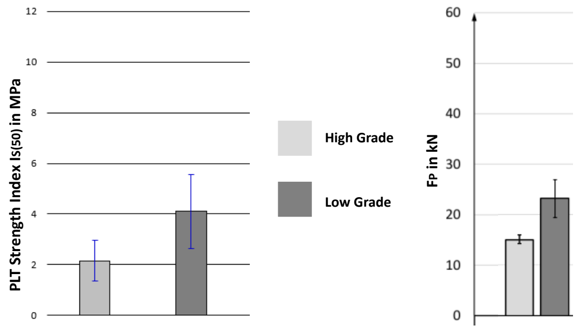

Figure 7. PLT Strength Index (left) and measured force in the jaw crusher (right)

4. Conclusion

The study focused first on detecting changes in product quality, such as the particle size distribution, using a system based on intrusive passive acoustics. A change in PSD can indeed be detected with this approach.

A second focus was the determination of the crusher filling degree using sensor data from the crushing force. The compressive forces in the upper section of the jaw crusher proved to be a suitable indicator of the fill level. The force-measurement data also provided insights into the lithium content of the crushed zinnwaldite, since the compressive strength of the high-grade material is lower than that of the barren fraction.

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