Bauxite Mill Charge Control Based on Vibration Signal and Computer Vision

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Abstract

Grinding is one of the crucial processes in alumina production, and its stability and quality directly influence the extraction of the useful component (alumina) from bauxite ore. In order to ensure stable grinding conditions, it is necessary to maintain the optimum slurry filling rate, solid phase content in the slurry, and the number and size of grinding media in the mill. Stabilisation of the ore grinding conditions enables to improve the fractional composition of the ore in the product from the area, increase the area capacity, reduce specific energy consumption, and optimise the overhaul period of the mill lining. Since the raw materials may vary in particle size distribution, composition and other parameters affecting grinding, it is not possible to control the mill filling level sufficiently accurate with the slurry directly by using ore and liquor feed flow meters only. One of the ways to indirectly assess the degree of mill filling is to analyse the vibrations that occur when grinding media and material fall inside the mill. This method analyses the spectrum of the signal from vibration sensors and builds a mathematical relation between the resulting value and the level of mill filling. RUSAL Engineering and Technology Centre (RUSAL ETC) has developed a system that includes models for classifying mill feed ore by fractional composition, feed ore throughput, and identifying non-ore materials using computer vision methods. The paper presents the results of the application of the bauxite mill charge control system on one bauxite-lime grinding unit of RUSAL Krasnoturyinsk and its impact on the process performance indicators. The mill charge control system based on vibration signal and computer vision can be applied at almost every alumina refinery both in the ore grinding area and in coal mills; moreover, the system can be applied at beneficiation plants where various wet and dry grinding systems are used.

Keywords: Ball mill, Grinding, Vibration analysis, Computer vision, Advanced process control.

1. Introduction

Drum mills are extensively used for fine grinding of materials in various industries. In terms of structure, they consist of a hollow cylindrical or cylindrical-conical drum closed by end covers. Trunnions carried by bearings are attached to said covers. Rotation of the drum ensures grinding of the material due to the colliding, crushing and abrading impact of the grinding media, which allows achieving fine grinding [1].

The grinding is of key importance in alumina production, where it is necessary to obtain finely dispersed raw materials such as bauxite or nepheline for further processing into alumina by the

Bayer or sintering process. The fineness of the grind directly affects the efficiency of chemical reactions, namely the degree of aluminium extraction from the ore in digestion.

The grinding can be dry or wet. Dry grinding is effective for fine grinding of large grains; while wet grinding is used to obtain finely dispersed and ultrafine disperse fractions [2].

At RUSAL Krasnoturyinsk, wet grinding is used for fine grinding of the bauxite-lime mixture mixed with the evaporated spent liquor. The mixture is ground in two stages in single-chamber ball mills with slurry classification in hydrocyclones (HC). High-quality mechanical grinding of the ore and dosing of alkali to the slurry provide for efficient extraction of alumina in digestion. Figure 1 shows the process flow diagram of grinding the bauxite-lime mixture at RUSAL Krasnoturyinsk.

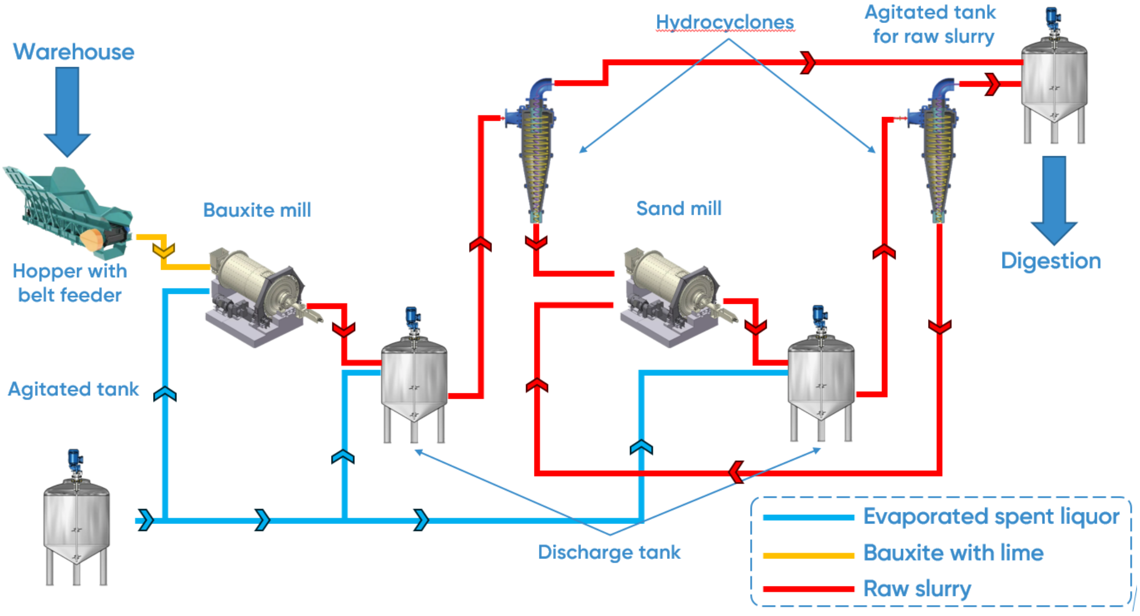

Figure 1. Process flow diagram of grinding the bauxite-lime mixture at RUSAL Krasnoturyinsk.

Presently, at RUSAL Krasnoturyinsk the level of the mills filling in the wet grinding area is determined by listening the sound of the balls hitting the mill lining. There is no weight measuring equipment on the mill feeder; therefore, the bauxite feed mass flow rate is calculated using a formula that depends on the speed of the belt feeder, the bulk density of the bauxite and the cross-sectional area of the bauxite layer on the belt feeder. The bulk density and the cross-sectional area of the bauxite layer on the belt feeder are entered into the calculation formula as constants. There are no systems for in-process quality control of the ore supplied to the area from crushing (size of the supplied ore, presence of non-metallic inclusions); there is no system for detecting ore congestion in bunkers and clogging of the mill chute when bauxite stops flowing into the mill. All these factors do not allow for effective control of the ore grinding process in the wet grinding area [3].

Currently, vibroacoustic sensors area available in the market for measuring the level and amplitude of the spectrum of signals from the mill during its operation, for example, Bruel & Kjaer (Denmark), ViKont (Russia), GlobalTest (Russia), Ronds (China), but they cannot be used without a mathematical model to show the correlations between the vibration energy of mills and the quality of ore grinding.

Therefore, a mathematical model of grinding the bauxite-lime mixture was developed, configured, and served as a core of the mill charge control system. The mill charge control system includes a set of equipment (vibration sensors, machine vision cameras and a computational server) and allows analysing mill charge, specifying the consumption of bauxite feed to the mills, detecting non-compliances in grinding, congestion of bauxite in bunkers and clogging of mill chutes, as well as providing the recommendations on the control and distribution of bauxite on the lines of the grinding facility, thus, improving the quality of grinding process control and increasing alumina extraction by 0.2 % on average.

2. History of Vibration Analysis

Vibration analysis as a method for monitoring mill filling has been known for a long time and has gone through several stages of development associated with improvements of sensors, computing technology and signal processing algorithms. Table 1 presents the main milestones and development of the vibration analysis:

Table 1. Main milestones and development of the vibration analysis.

#	Period	Equipment	Methods
1	1960-1990	Piezoelectric sensors, oscilloscopes	Highlighting key signal values
2	1990-2010	Digital ADCs	Fast Fourier transform, wavelet transform
3	2010-2025	Wireless sensors	Machine learning

The main research in analysing key signal values to study mill charge dynamics was conducted by Liddle and Moyes [4]. They investigated the mill charge dynamics including the distribution of grinding media and material as a function of rotation speed, filling ratio and mill design.

The main research of frequency spectrum evaluation was conducted by Zeng and Forsberg [5]. They generated power spectra of vibration signals and established relationships between the signal characteristics and key grinding parameters such as power input, feed rate, slurry density, and ground product size. Zeng used an accelerometer at nine points on the pivot of an industrial ball mill and analysed the vibration power spectrum data using principal component analysis. He determined that to collect the maximum amount of relevant vibration data, the vibration sensor should be placed on the pinion shaft bearing.

Under present-day conditions, the performance of equipment and mills is analysed using mathematical models based on machine learning and deep learning methods. Huang et al. studied the relationship between the filling level and the angular position of the point of maximum vibration on the mill body by recording vibration with an accelerometer on the mill body [6]. Sulaiman Aburakhia et al. used machine learning to predict the condition of the equipment based on FFT analysis [7].

Thus, the development of vibration analysis reflects the general trend of automation and digitalization of industrial processes, providing more accurate and reliable control of process parameters.

3. Mill Charge Control System

The mill charge control system uses a method for monitoring the process load on a group of mills, based on the correlation between the mill charge parameters, process components (solid raw material, grinding media, spent liquor added to mill, and return product) and the level of its noise field.

The proposed system determines the optimal charge level and minimizes the risks of overgrinding the ore or underloading the mill with ore by a comprehensive analysis of correlations between the main process parameters (raw material properties, grinding media loading, other process parameters of the process area). The vibration analysis allows for the prompt detection of faults (e.g. under loading of the grinding media) by monitoring the vibration signals. The system can be easily integrated into SCADA platforms, providing online monitoring, remote control, and intelligent recommendations on optimizing the mill performance.

The system equipment includes the following:

- Data cabinet.
- Vibration sensors.
- Machine vision unit.

The data cabinet performs the functions of collecting and processing data from the process equipment, as well as the server of the mill charge control system. The vibration sensor is a piezoelectric accelerometer with a matching amplifier and is designed for continuous vibration monitoring of a drum ball mill. The machine vision unit is designed to collect photographs of the ore feeding bauxite mills for subsequent data analysis using machine vision methods. The machine vision unit includes as follows: a machine vision camera in a protective casing, lights and a vibration-insulating platform. Figure 2 shows the system equipment.

Figure 2. Data cabinet (1), vibration sensor (2) and machine vision unit (3).

3.1 Relationship between Charge Level and Noise of the Ball Mill

Mill noise is the vibration of the mill casing caused by the balls colliding with the lining. Ball-to-ball collisions have much smaller impact due to the weak (not rigid) mechanical encounter with the lining.

If we consider a single collision, then when a ball hits the same point of the housing position with the same force vector, but at different moments in time, the vibration is completely reproduced by the level (amplitude) of the vibration signal. The full spectrum of the acoustic noise of the mill is the sum of impacts with the lining of many balls with different normal components of the force vector to the lining surface, at different distances from the vibration sensor and in different stress states of the housing, caused by previous impacts.

In order to compare the vibration response of the mill with the movement of the mixture and other events occurring inside the mill, it is very important to understand the dynamics of the mixture (composition of the ore, change in particle size distribution, lime content, etc.). For these purposes, pilot tests of the mill charge control system were carried out on four mills in the ore wet grinding area at RUSAL Krasnoturyinsk. During the tests, RUSAL's specialists collected and analysed samples of the slurry from mills, overflows and sands from HC of the 1st and 2nd classification stages to assess the quality of automatic mill charge control.

3.2 Mathematical Model of the Mill Charge Level

The mathematical core of the mill charge control system is based on the frequency spectrum analysis of the signal taken from the readings of the piezoelectric transducer, followed by the conversion of the data to the mill charge level in percent using a linear regression model. The core of the system is based on technologies that seem outdated, but their use is justified by some solid reasons. Use of machine learning to assess the mill charge level implies solving two types of tasks with some relative restrictions:

- Classification, i.e. dividing the mill operating status into several grades, for example, normal operation and emergency operation. Solving such tasks is useful for assessing the overall operating condition but is not suitable for integration of the model in the automatic control loop of the mills.
- Regression, i.e. estimating the mill charge level using some values that describe the current mill charge level. A larger set of actual mill charge level data is needed to train the model to the required level of accuracy.

The linear regression model is included in many machine-learning models, although it is a simplified version of it [8, 9]. This fact does not make the linear regression model unsuitable for analysing the level of mill charge; moreover, it allows reducing the number of experiments for training the mathematical model (2 experiments in extreme mill charge conditions). Nevertheless, around the mathematical core of the mill charge control system there are add-ons based on deep learning models, which allow improving the quality of the entire system [10].

3.3 Vibration Signal Analysis

The original signal from the vibration sensor is an analogue signal and a function of time, which is defined within a certain time interval [11]. A multi-channel external audio card is used to convert the signal to a digital form. The use of audio equipment allows for increased flexibility of the system, as it enables to expand the range of applied input analogue equipment (use of an analogue vibration sensor of a different type or connect an industrial microphone) and adjust the system horizontally (the current implementation of the system allows for connecting and processing 18 audio devices in parallel). The accuracy with which the analogue signal is converted to a discrete one is determined by the sampling frequency and the channel bit capacity. Figure 3 shows an example of a signal from a vibration sensor installed on a bauxite mill.

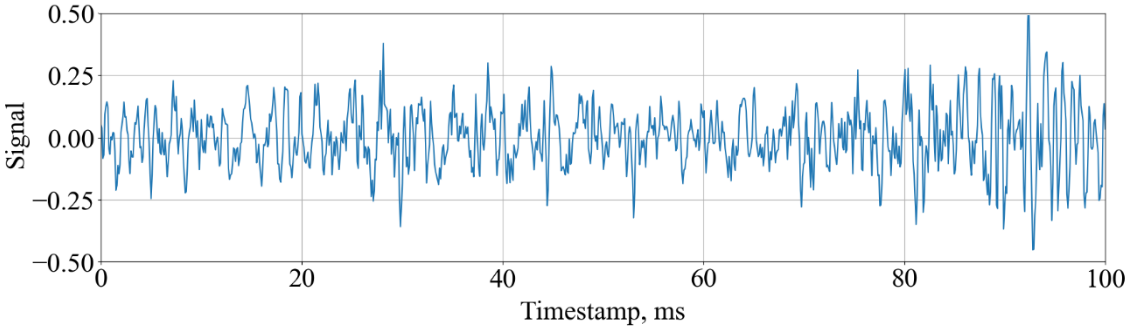

Figure 3. Signal from a vibration sensor installed on a bauxite mill.

The choice of parameters for converting an analogue signal into a discrete one is determined by the conditions of the relevant task. If the signal resolution is insufficient, the vibration sensor does not capture high-frequency signal oscillations and an aliasing effect occurs. If the signal detail level is excessive, the processor load increases and the amount of resources required to store the vibration sensor operation history increases. The proposed method for analysing the vibration signal generated by the mill in the operating mode uses a sampling frequency of 10 kHz, which allows decomposing the signal into a frequency spectrum of up to 5 kHz.

The analysis of the mill charge level uses the amplitude-frequency characteristic (hereinafter referred to as the AFC) of the vibration signal that is obtained by applying the fast Fourier transformation to the generated signal. The linearly normalized integral component of the AFC within a given frequency range (from 10 to 4 000 Hz) determines the mill charge level. Figure 4 depicts an example of the AFC of a vibration signal from a bauxite mill.

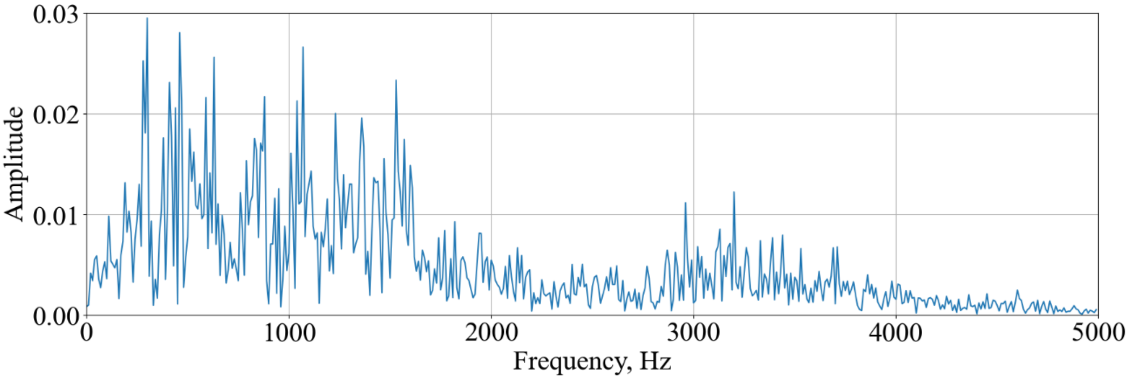

Figure 4. AFC of a vibration signal from a bauxite mill.

After the signal AFC is obtained, the integral of the signal amplitude is calculated in the given frequency range and the calculation results are averaged for an interval of 25 seconds. Figure 5 shows a simplified algorithm of the vibration signal analysis model.

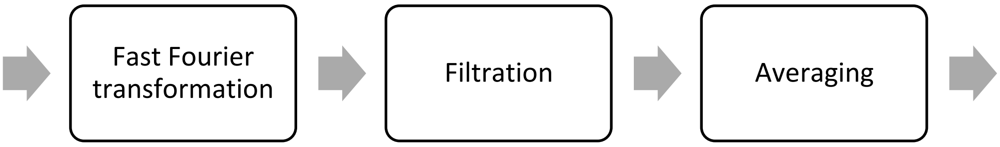

Figure 5. Main stages of vibration signal analysis.

3.4 Machine Vision Algorithms

The developed mill charge control system uses a machine vision unit that solves the following tasks:

- classification of the ore entering the bauxite mill (rocky, sandy).
- calculation of the cross-sectional area of the bauxite layer on the plate feeder of the mill.
- search for non-metallic materials in the mill feed.
- detection of bunker congestion or mill chute clogging.

All the above tasks are solved in the mill charge control system by using machine learning models based on pre-trained neural networks for computer vision with additional training on labelled data obtained from machine vision cameras.

The apron feeder ore classification algorithm is used to distribute the ore entering the mill chute into two grades: stony and sandy ore. The classification is of subjective nature, since the stone content degree is determined by a specialist at the stage of preparing the data for training models by marking frames. Figure 6 shows examples of sandy and stony bauxite, respectively.

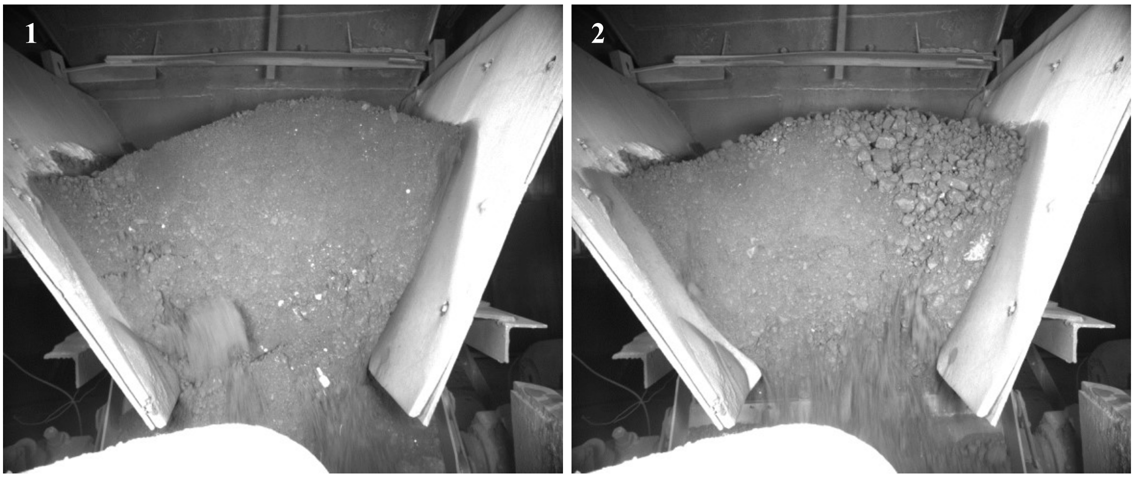

Figure 6. Example of sand (1) and stony (2) bauxite on the apron feeder.

The algorithm for determining the cross-sectional area of the ore layer on the apron feeder is used to refine the formula for calculating the consumption of bauxite entering the mill chute in real-time mode. The algorithm for searching non-metallic materials warns the operator about existing problems in previous stages of production, as well as enables to promptly solve power problems with the feed in order to prevent emergencies. Figure 7 demonstrates these algorithms.

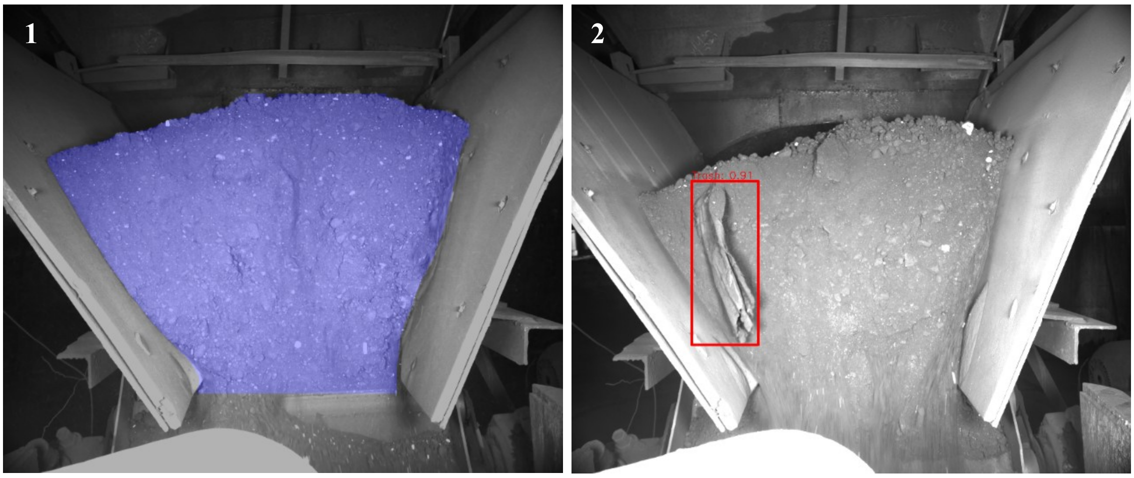

Figure 7. Determining the cross-sectional area of the ore layer on the apron feeder (1) and searching for non-metallic materials in ore entering the mill (2).

The bunker congestion or mill chute clogging detection algorithm warns the operator of existing problems on the mill feeder and enables to respond promptly to the problem. Examples of the bunker congestion or mill chute clogging detection algorithm are shown in Figure 8.

Figure 8. Bunker congestion (1) and mill chute clogging (2) detection.

4. Pilot Test Results

The mill charge control system has undergone pilot tests on the grinding mills for the bauxite-lime mixture at RUSAL Krasnoturyinsk. Based on the obtained statistical data of the system performance, the following analyses were carried out:

- the impact of particle size distribution on the level of mill charge.
- the impact of ball load on the vibration sensor signal.
- the impact of bauxite consumption on the level of mill charge.
- the impact of automatic maintaining the level of mill charge on the quality of ore grinding.
- the influence of automatic maintaining of the level of mill charge on the caustic molar ratio (α_k) of the blow-off slurry.

α_k is calculated using the following formula:

$$\alpha_k = 1.645 \cdot Na_2O_k \, / \, Al_2O_3 \tag{1}$$

where:
Na_2O_k concentration of caustic alkali in the solution, g/L
Al_2O_3 concentration of alumina in the solution, g/L

4.1 Analysis of the Influence of Particle Size Distribution on the Charge Level

The results of the ore classification model were used to analyse the effect of the ore type on the degree of filling of the mill. Figure 9 presents the results of the analysis; thus, it is evident that when feeding the mills with stony ore, the degree of filling of the vessel is higher. This effect is presumably associated with the accumulation of ore inside the working space of the mill as larger pieces of ore require more time to grind to a fraction carried away by the liquor flow, as well as with an increase in the thickness of the ore fine-dispersed layer to the lining.

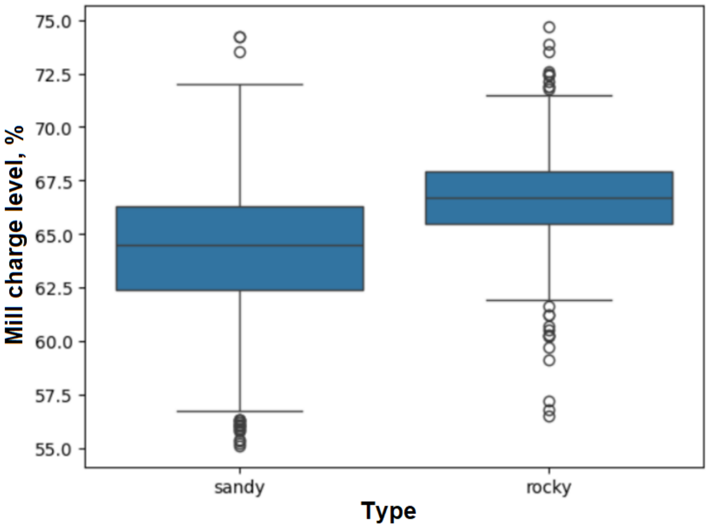

Figure 9. Boxplot of the relationship between ore type and mill charge level.

4.2 Analysis of the Influence of Ball Loading on the Vibration Sensor Signal

The analysis of the influence of ball loading on the vibration sensor signal showed that at the moment of loading an additional quantity of grinding media (balls) to bring their quantity to the technological standard inside the mill, the amplitude of the vibration sensor signal increases over the entire studied frequency range, while the signal structure with local maxima is preserved. The increase in the signal is associated with vibrations created by balls rolling into the chute. After filling the mill with balls and the mill reaches the steady state, the amplitude of the vibration signal becomes higher, which accordingly leads to changes in the results of the model analysis of the degree of filling of the mill. The frequency response of the vibration sensor signals at different moments of loading additional balls into the mill are shown in Figure 10.

It is noted that with a decrease in the mass of grinding media in the working space of the mill, due to the absence of additional loading of balls, the amplitude of the vibration signal is systematically reduced. Within the framework of the algorithm for automatic control of mill charge, it allows maintaining the grinding quality at the process standard by reducing the consumption of the bauxite fed to the mill chute to ensure the target degree of filling of the mill. Figure 11 shows the graph of the change in the consumption of bauxite feed to the mill with automatic maintenance of the mill filling at a constant level during a long period without additional loading of grinding media due to technical limitations in the area.

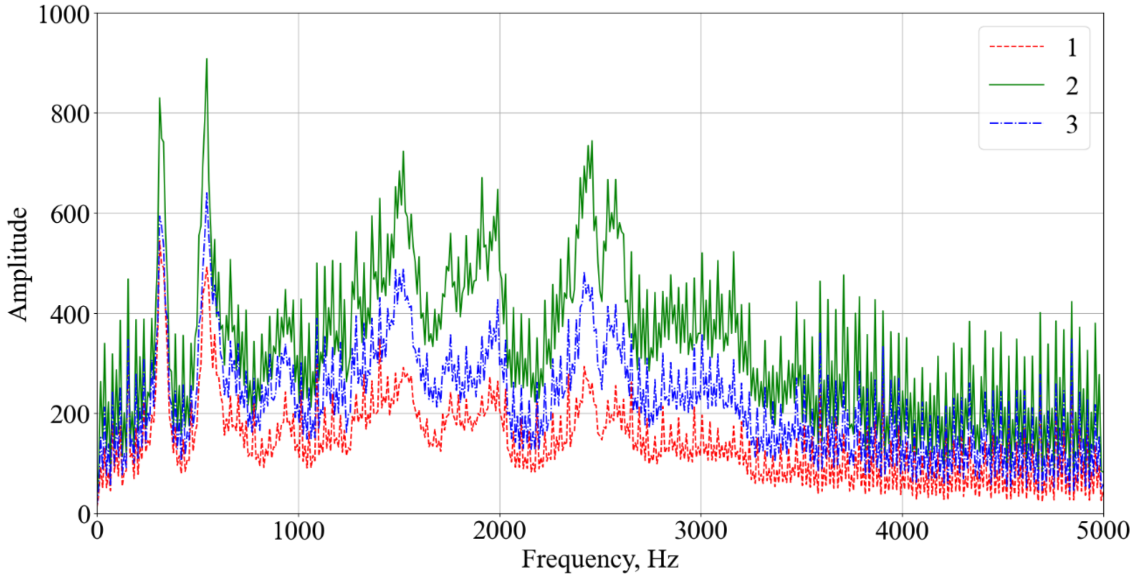

Figure 10. Analysis of the influence of ball loading on the vibration sensor signal (1 – frequency response before loading, 2 – frequency response at the moment of loading, 3 – frequency response after loading an additional number of balls).

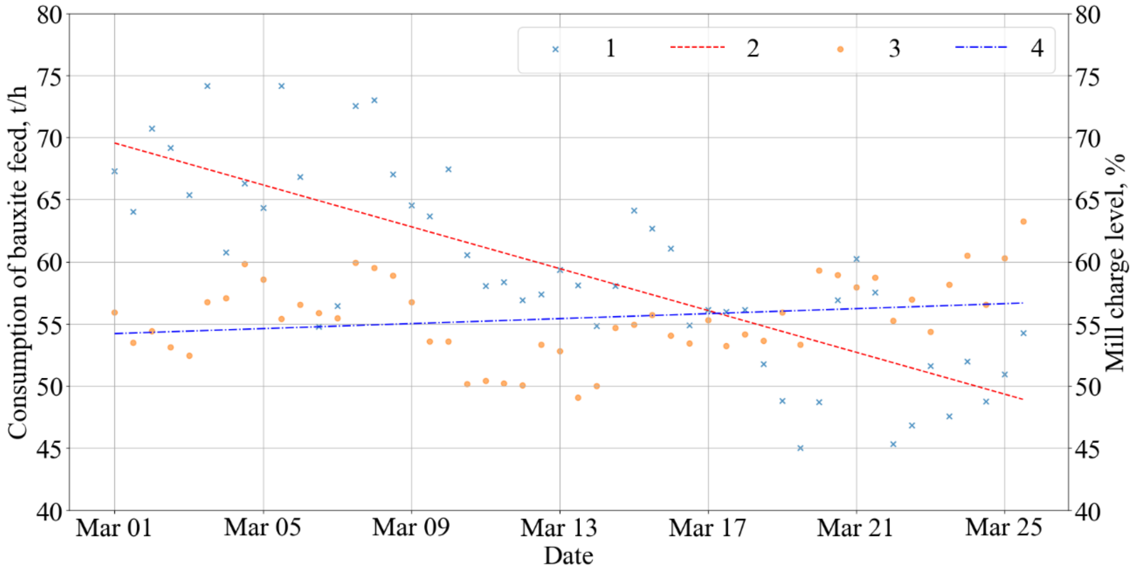

Figure 11. Change in the consumption of bauxite feed to the mill during some period without additional loading of grinding media (1 – bauxite feed, 2 – linear regression of bauxite feed, 3 – mill charge level, 4 – linear regression of mill charge level).

4.3 Automatic Mill Charge Control

The amplitude of the recorded vibration signal depends on the degree of absorption of the energy of the falling balls by the ground material and, therefore, it is an indirect feature of the amount of material in the mill and the grinding coarseness. Stabilization of the vibration signal amplitude enables to reduce deviations in the grinding size of the raw slurry by controlling the amount of material loaded into the mill.

The control system uses a proportional-integral-differential controller (hereinafter referred to as the PID controller), which controls the bauxite flow rate to the mill based on the discrepancy between the setpoint and the current mill charge rate. The signal on the current mill charge rate is generated for the controller in a special way by the mill charge control system. Figure 12 shows an example of the PID controller operation, where the mill charge rate is set at 55 %, the bauxite flow rate varies in the range between 51 and 78 t/h to ensure the target mill charge rate.

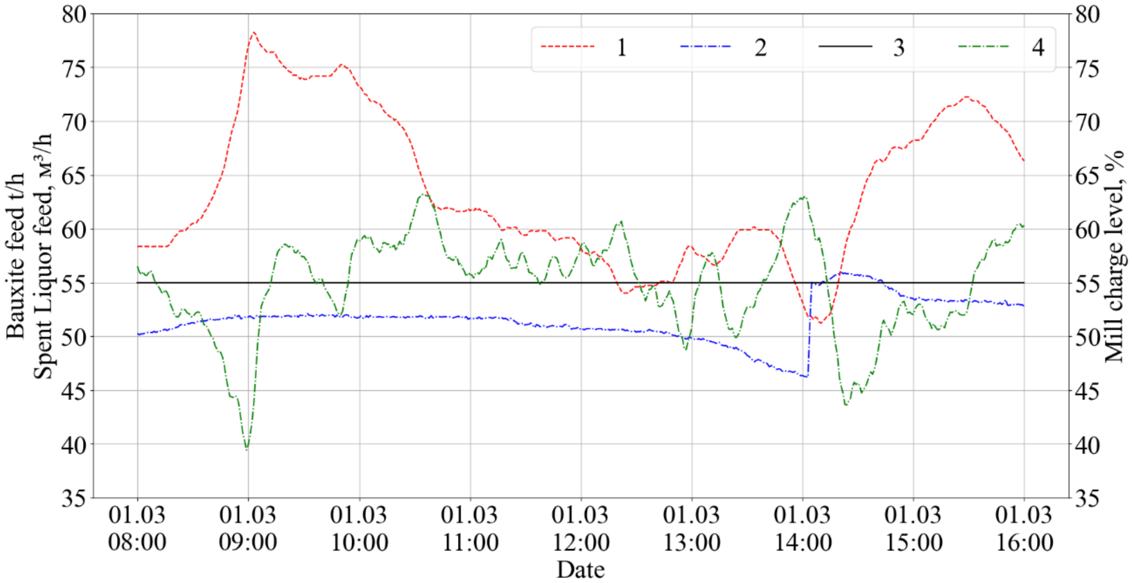

Figure 12. Operation of the PID controller at the mill (1 – bauxite feed, 2 –spent liquor feed, 3 – the mill charge level task, 4 – the mill charge level value).

4.4 Analysis of the Influence of Automatic Mill Charge Control on the Grinding Quality

Automatic control tests showed that the system allowed to ensure grinding compliant with the target values, moreover it enabled to increase the share of the fraction minus 0.056 mm by 1.1 % and 6.6 % in the overflow of the HC of the 1st and 2nd stages and to decrease the share of the fraction + 0.16 mm by 2.4 % in the overflow of the HC of the 2nd stage as compared to the period of operation of the area in the manual mode of mill charge control. Table 2 presents the results of analysis of samples of raw slurry from the overflow of the HC of the 1st and 2nd classification stages in the manual and automatic modes of mill charge control.

Table 2. Results of analysis of samples of raw slurry from the HC overflow.

Average mass fraction, %	Process regulation	Manual mode 11.02–26.02	Automatic mode 26.02–12.03	Abs., %
+ 0.16 mm of 1 stage HC o\f	≤ 2.8	1.8	1.8	0
- 0.056 mm 1 stage HC o\f	≥ 75	89.0	90.1	+ 1.1
+ 0.16 mm of 2 stage HC o\f	≤ 2.8	4.0	2.4	- 2.4
- 0.056 mm of 2 stage HC o\f	≥ 75	73.2	79.8	+ 6.6

4.5 Analysis of the Influence of Automatic Mill Charge Control on the α_k of Blow-Off Slurry

Automatic control tests showed a 1 % convergence of the average value to the target value (1.63 units) and a 14 % decrease in the root-mean-square deviation (hereinafter r.m.s. deviation) of the values. Table 3 and Figure 13 present the results of the analysis of the blow-off slurry before and after using the automatic mill charge control system.

Table 3. Results of the analysis of the blow-off slurry before and after using the automatic mill charge control system.

Parameter	Manual mode	Automatic mode	Rel. difference, %
Average α_k, units	1.654	1.641	-1
RMS deviation of the α_k, units	0.060	0.052	-14

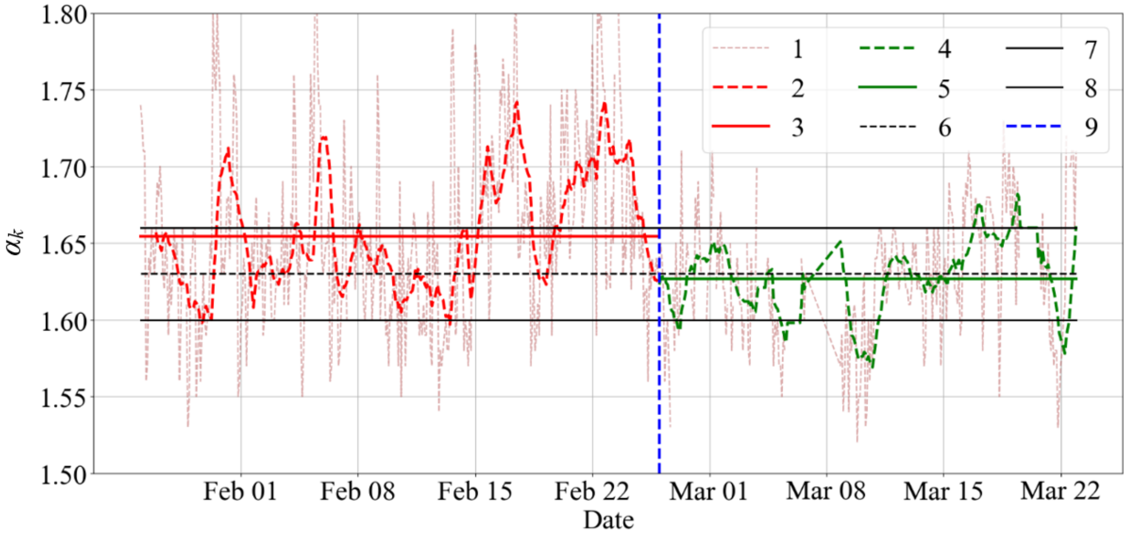

Figure 13. Results of the analysis of the α_k of the blow-off slurry before and after the start of the tests (1 – Plant Data, 2 – Moved Average before Test, 3 – Average before Test, 4 – Moved Average after Test, 5 – Average after Test, 6 – target α_k, 7 and 8 – Allowable Min and Max Deviation from the Target, 9 – Start of Test).

As of the time of data processing, the algorithms for determining bunker congestion or mill chute clogging were not implemented, therefore, the periods of long-term bunker congestion or mill chute clogging and mill shutdowns for repairs, which affect the α_k of the blow-off slurry, these periods were excluded from consideration in the present paper for both manual and automatic mill charge control modes.

5. Conclusion

A mill charge control system is based on the analysis of vibration signals from vibration sensors installed on ball mill supports and supplemented with machine learning model. The system provided the following:

- Continuous measurement of the mill charge level by analysing the vibration sensor signal.
- Adjustment of the mill model in terms of the quantity and size of the feed using computer vision.
- Implementation of an automatic mill charge control circuit.

These properties of the system allowed achieving the following performance indicators of the mills in the wet grinding area at RUSAL Krasnoturyinsk:

- The fineness of the raw slurry grinding was maintained within the regulatory values, increasing the share of the minus 0.056 mm fraction in the overflow of the HC of the 1st and 2nd classification stages by 1.1 % and 6.6 %, respectively, and decreasing the share of the + 0.16 mm fraction at the 2nd stage of the HC by 2.4 % as compared with the period of operation in the manual mill charge control mode.
- The standard deviation of the α_k of blow-off slurry from the target value (1.63 units) was reduced by 14 %.
- The increase in alumina extraction by 0.2 % was confirmed due to the stabilization of modes and the reduction of process disruptions in the grinding of bauxite-lime charge in wet grinding. This leads to a reduction in the specific consumption of bauxite and alkalis in alumina production.

The mill charge control system has been implemented at four mills and is recommended for testing and implementation at other RUSAL's refineries.

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