Online Detection Method for Bauxite Composition

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https://doi.org/10.71659/icsoba2025-bx008

Abstract

To address issues such as delayed determination of bauxite composition, poor sample representativeness, and manual errors in alumina production, this study proposes an online detection method for bauxite composition. By using high-energy pulsed laser excitation to generate plasma spectra on the bauxite surface and combining spectral preprocessing with machine learning modelling, quantitative analysis of three major components (Al_2O_3, SiO_2, and Fe_2O_3) was achieved. The average relative errors for detecting these three major components were all below 5 %. A prototype device was designed and developed, integrating the detection model for production condition simulation. The dynamic spectral processing method was optimized to reduce the interference of complex sampling environment variations on spectral data. Ultimately, real-time online detection of bauxite composition was realized, with detection time under 1 minute and average relative errors for the three major components were all below 5 %. This study has developed an online detection technology and equipment for bauxite composition, providing a technological paradigm for online monitoring of other materials in alumina production. It will promote intelligent control and process optimization in alumina production and support the industry's smart transformation.

Keywords: Bauxite, Online detection, Composition analysis, Spectral analysis, Machine learning.

1. Introduction

Metallurgical alumina (Al_2O_3) is an industrial-grade aluminium oxide produced from bauxite via the Bayer or sintering process, accounting for more than 95 % of total alumina output. As a core raw material for aluminium electrolysis, its physicochemical properties directly affect electrolytic efficiency and energy consumption. The first step of the Bayer process is the slurry preparation, which involves mixing bauxite, lime, and recycled spent liquor in specific proportions to form raw slurry. The composition of bauxite determines the material ratio for slurry preparation. An inappropriate composition ratio can negatively impact the entire alumina production process, leading to reduced digestion and precipitation efficiency and declining product quality [1]. Analysing the three major components of bauxite, namely Al_2O_3, SiO_2, and Fe_2O_3, allows for optimal material addition strategies. Currently, the industry primarily uses manual sampling and laboratory testing, which has several technical limitations: the offline, time-based analysis model cannot meet the needs of real-time process control, and manual errors can directly affect blending accuracy, resulting in deviations in the caustic ratio of sodium aluminate solution and abnormal particle size distribution in the slurry. Therefore, developing online detection technology for bauxite composition is essential for achieving intelligent control of the blending process, improving product quality management, reducing operational costs, and enabling the full-process intelligent upgrade of alumina manufacturing.

Technologies currently used for online ore composition detection include X-ray fluorescence (XRF) [2], neutron activation analysis [3], near-infrared spectroscopy [4], and laser-induced breakdown spectroscopy (LIBS) [5]. XRF and neutron activation analysis have high sample state requirements and typically need to be combined with sampling and preparation equipment for online analysis, with the added concern of radiation exposure. Near-infrared spectroscopy detects based on the information of molecular functional groups corresponding to the spectral lines and is generally suitable for major component analysis (above 0.1 %). It features broad peaks and requires chemometric methods for analysis, with relatively low detection limits and accuracy. LIBS is a laser-induced plasma spectroscopy technique mainly used for analysing heavy metal elements. It has sharp spectral peaks, requires minimal sample amounts, causes little damage, and can be applied to solid, liquid, and gas samples with almost no sample preparation, enabling fast, real-time, online analysis. LIBS enables wide spectral range acquisition, allowing for simultaneous detection of multiple elements with ppm-level sensitivity, and is applicable in fields such as industrial metallurgy, geological exploration, environmental monitoring, biomedicine, and mineral beneficiation [5–10].

For bauxite composition detection, XRF and neutron activation analysis are currently applied in China, while near-infrared spectroscopy is used abroad; however, application remains limited. With the continuous advancement of laser and spectrometer technologies, LIBS is gradually being adopted in industrial applications, leveraging its strengths in online, real-time, and in-situ detection.

In this study, spectral data of bauxite samples were collected and processed using spectral preprocessing and machine learning modelling, achieving quantitative detection of bauxite composition. By developing a prototype device and integrating the detection model, real-time online detection of bauxite composition was ultimately achieved, providing technical support for intelligent control in alumina production.

2. Materials and Methods

2.1 Experimental Platform Setup

As shown in Figure 1, an experimental platform was built consisting of a laser, a spectrometer, a timing controller, and a control computer [11]. In addition, an XY-axis displacement platform for spectral data acquisition and a circular rotating stage simulating a production conveyor (with a maximum linear speed of 3 m/s) were established.

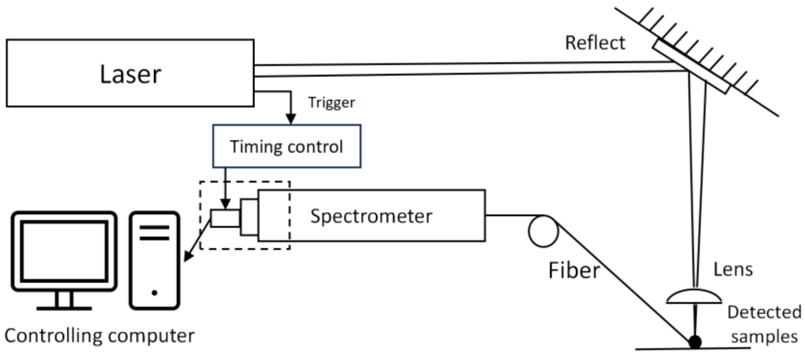

Figure 1. Experimental platform.

2.2 Sample Acquisition

This study focussed on online analysis of three components, Al_2O_3, SiO_2, and Fe_2O_3. From June to October 2024, 100 bauxite samples were collected in six batches to construct a spectral dataset for quantitative modelling development. To expand the detection range and improve the robustness of the detection technique, bauxite samples of varying grades and types were selected, with some sample forms shown in Figure 2. After developing the detection technology and prototype device, 120 online samples were collected during field testing (each sample: ore exposed to laser within 10 minutes, shovel-sampled at regular intervals, total 5 kg) to validate the performance of the detection technique.

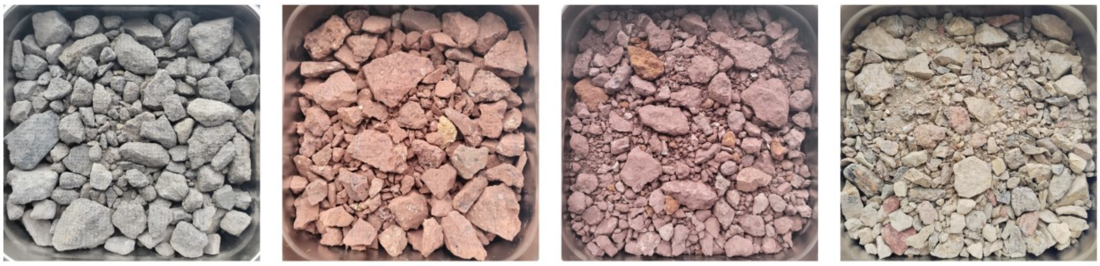

Figure 2. Representative bauxite samples.

2.3 Detection Modelling Development

In online ore detection, fluctuations in ore surface height, compositional variation, particle size, and moisture content can cause physical and chemical matrix effects on spectral data. Therefore, raw spectra must undergo spectral preprocessing prior to model building to correct spectral distortions and reduce interference, improving the accuracy of quantitative detection [12, 13]. A spectral preprocessing pipeline tailored to bauxite was developed, as shown in Figure 3. It includes spectral data reading, spectral stitching, noise removal, spectral screening, baseline correction, normalization, standardization, and spectral averaging.

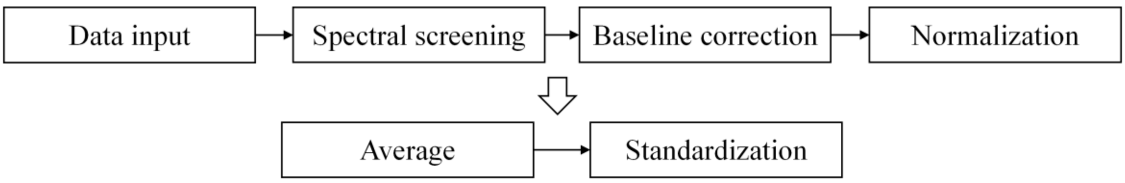

Figure 3. Spectral preprocessing flow.

During detection model development, separate models were built for each of the three major components Al_2O_3, SiO_2, and Fe_2O_3. Ten modelling methods, including partial least squares regression, support vector regression, BP neural network, convolutional neural network, and XGBoost, were evaluated. Basic model structures were optimized to effectively filter noise and capture composition-relevant features from massive spectral data. Mean relative error (MRE) and mean absolute error (MAE) were used to evaluate model performance. MRE was calculated using Equation (1), and MAE using Equation (2).

$$MRE(e,e') = \frac{\sum_{i=1}^{n}\left|\frac{e_i - e'_i}{e_i}\right| \times 100\%}{n} \tag{1}$$

$$MAE(e, e') = \frac{\sum_{i=1}^{n}|e_i - e'_i|}{n} \tag{2}$$

where:

e_i	True value of index i
e_i'	Predicted value of index i
n	Number of data points

2.4 Prototype Device Development

Based on production site requirements, the online detection device must be thermostable, moisture-proof, shock-resistant, and dustproof to ensure stable operation in industrial environments. Considering both laboratory results and actual field conditions, the prototype device was designed as shown in Figure 4, consisting of four core components (laser, spectrometer, timing controller, and industrial computer) and auxiliary subsystems (water cooling and air cooling). The water-cooling system is used to cool high-heat components such as the laser and industrial computer, while the air-cooling system cools lower-heat components like the spectrometer and timing controller.

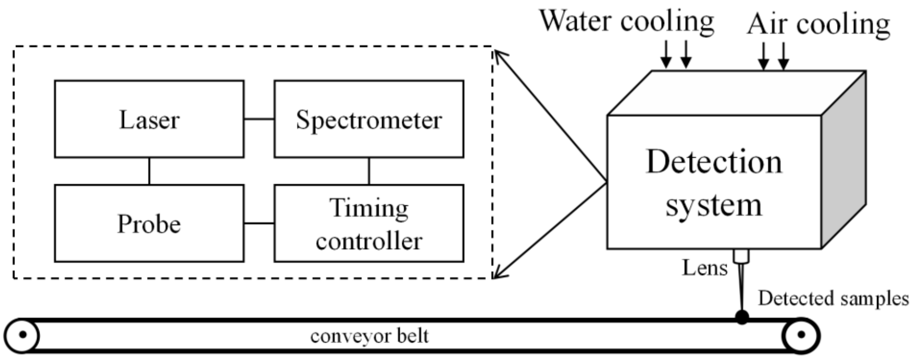

Figure 4. Prototype device design.

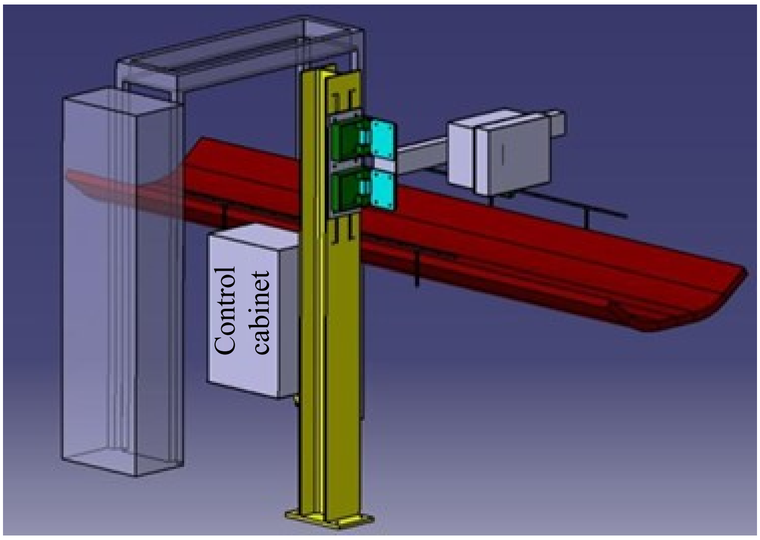

Figure 5. On-site installation diagram.

An installation plan was developed for the production environment, and the device was mounted on a bauxite conveyor belt at the production site for field testing. As shown in Figure 5, the detection system probe was positioned directly above the conveyor belt, while the control cabinet was placed alongside on a steel support column. The detection probe can swing 90° to align with the side of the belt, allowing for convenient maintenance and servicing.

3. Results and Discussion

3.1 Dataset

The component distributions of Al_2O_3, SiO_2, and Fe_2O_3 in the 100 samples collected for modelling are shown in Figure 6. Al_2O_3 ranged from 37% to 72 %, with an average of 51.89 %; SiO_2 ranged from 2 % to 32 %, with an average of 10.90%; Fe_2O_3 ranged from 2 % to 37 %, with an average of 17.41 %. A wider component range improves the robustness of the detection technology and allows it to adapt to more application scenarios. For modelling, the 100 samples were split into a modelling set and a test set at a 4:1 ratio. The modelling set was subjected to 8-fold cross-validation with a 7:1 split. The top three models by accuracy were selected to predict the test set, and the average of their outputs was used as the final result. Two outliers in the SiO_2 data were removed during modelling.

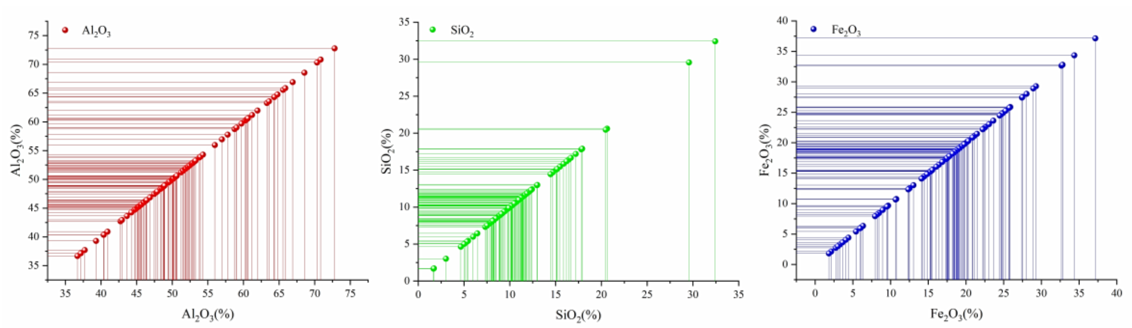

Figure 6. Composition distribution of modelling samples.

After the device was installed on-site, the composition distributions of Al_2O_3, SiO_2, and Fe_2O_3 in the 120 online samples collected are shown in Figure 7. Al_2O_3 ranged from 48 % to 56 %, with an average of 51.88 %; SiO_2 ranged from 8.5 % to 15 %, with an average of 11.28 %; Fe_2O_3 ranged from 12 % to 23 %, with an average of 17.84%. All on-site data fell within the composition ranges of the modelling dataset.

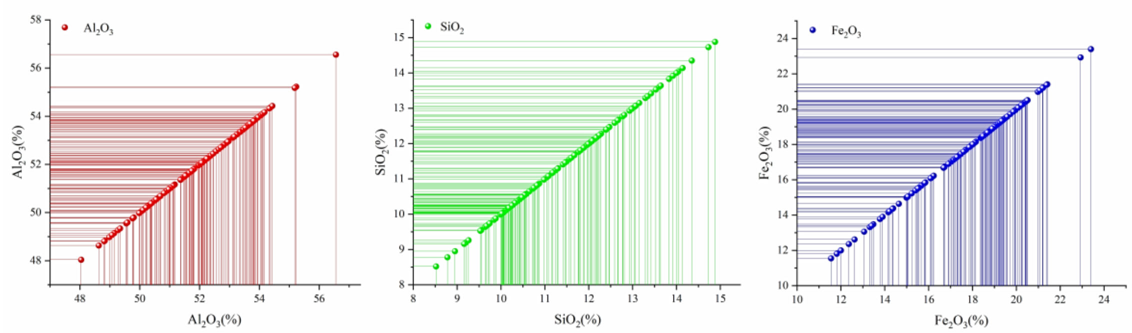

Figure 7. Data distribution.

3.2 Detection Model Results

Modelling results showed that the optimal detection model for bauxite Al_2O_3, SiO_2, and Fe_2O_3 components was a convolutional neural network consisting of five convolutional layers and two parameter-free attention modules. Errors for the modelling and test sets are shown in Table 1. The MRE for all three components was below 5 %; the MAE for Al_2O_3 was below 2 %, and for SiO_2

and Fe_2O_3 below 1 %, demonstrating high detection accuracy and successful quantitative analysis. Al_2O_3 showed a lower MRE but a slightly higher MAE due to its role as the primary component in bauxite, with a broader range of fluctuation compared to SiO_2 and Fe_2O_3. As more ore samples are collected and the component distribution is enriched, expanding the modelling dataset, the MAE for Al_2O_3 and MRE for SiO_2 and Fe_2O_3 are expected to improve.

Table 1. Prediction model errors.

Error	**Al_2O_3**		**SiO_2**		**Fe_2O_3**	
	Modelling	**Test**	**Modelling**	**Test**	**Modelling**	**Test**
MRE（%）	1.05	3.13	2.07	4.68	2.77	4.09
MAE（%）	0.56	1.64	0.17	0.55	0.32	0.59

Figures 6–8 show the performance of the Al_2O_3, SiO_2, and Fe_2O_3 detection models, covering both the modelling and test sets. It can be observed that the predicted and actual values of all three components exhibit strong linear correlations, with the relative error for nearly every sample within 5 %. Some ore samples with relatively high prediction errors had uneven particle size distribution and a higher proportion of large ore chunks, limiting the laser's ability to cover the entire surface and reducing data representativeness. When the sample weight increases and the particle size distribution becomes more uniform, the detection system can capture more representative spectral data from the ore, leading to more accurate detection results.

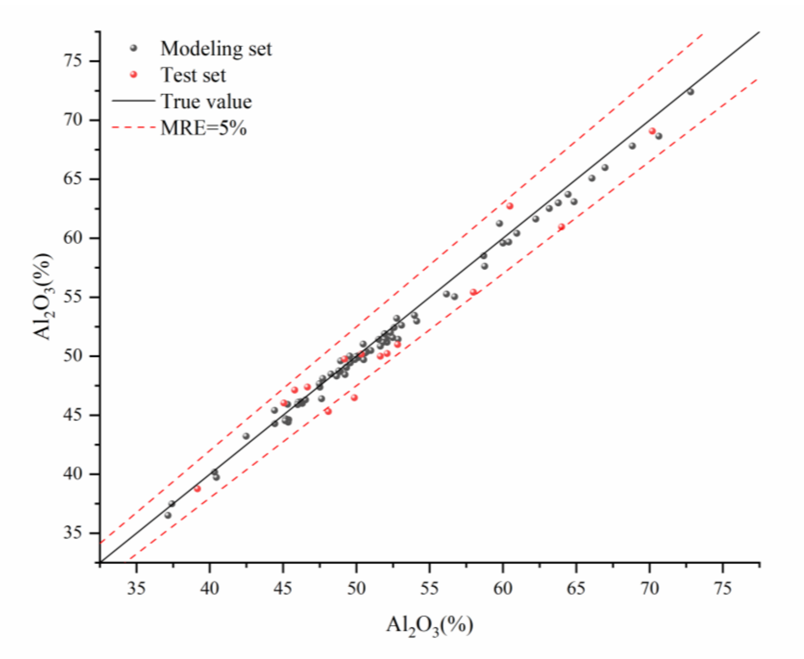

Figure 6. Al_2O_3 detection modelling results.

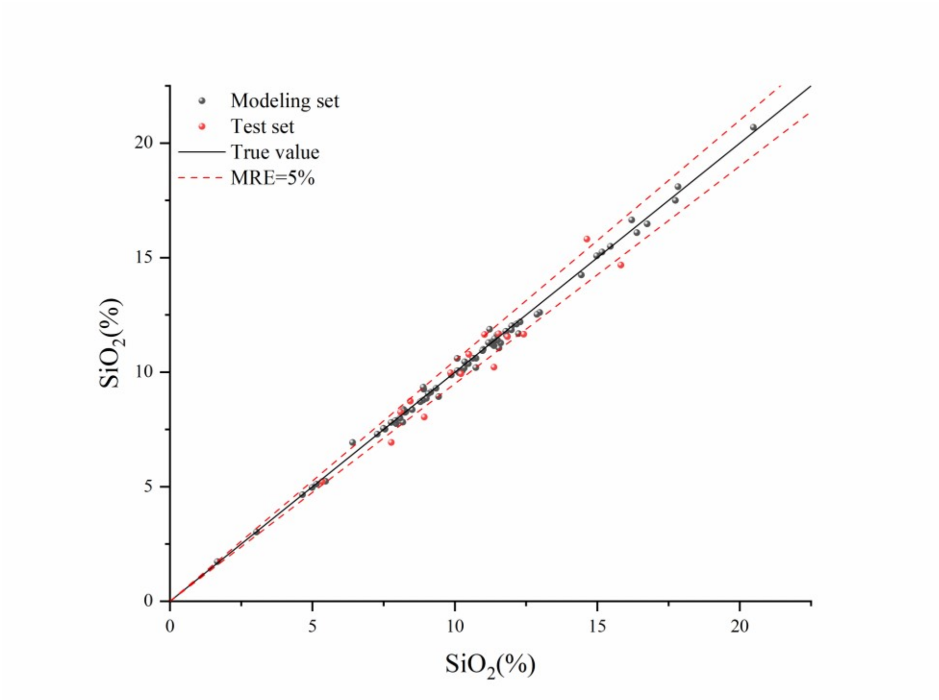

Figure 7. SiO_2 detection modelling results.

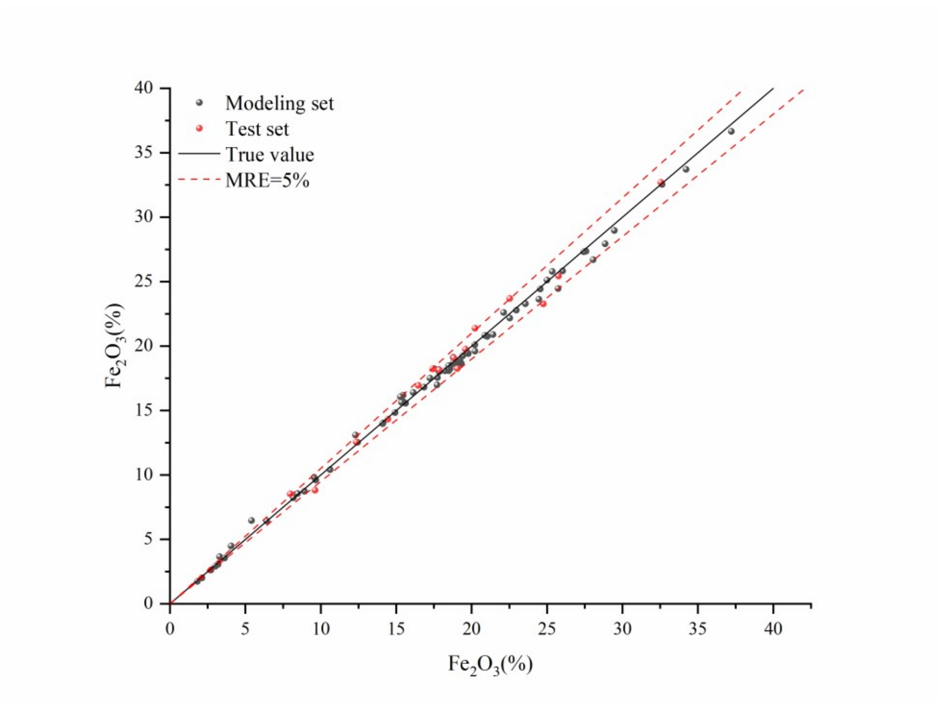

Figure 8. Fe_2O_3 detection modelling results.

3.3 Online Detection Results

After modelling was completed, a laboratory-based belt operation simulation was conducted, with simulated detection performed at six different speeds. The simulation results are shown in Table 2. Variations in speed did not affect the detection results, further validating that the detection system and model developed in this study can effectively detect dynamically moving samples.

Table 2. Simulated detection results.

	Speed	V0	V1	V2	V3	V4	V5	Average
		0.3 m/s	0.6 m/s	0.95 m/s	1.4 m/s	1.57 m/s	2.2 m/s	
MRE (%)	Al_2O_3	2.30	3.28	4.35	5.05	4.20	2.69	3.64
	SiO_2	4.26	3.89	4.81	4.30	4.35	4.00	4.27
	Fe_2O_3	3.74	4.02	5.12	6.33	5.06	2.80	4.51

The online detection technology and prototype equipment developed in this study have been installed and tested at an alumina plant. During testing, the detection performance was continuously monitored over 40 days, with the system outputting multiple detection values per minute. A total of 120 online samples collected in multiple batches were used to verify the effectiveness of the detection technology. The detection errors for Al_2O_3, SiO_2, and Fe_2O_3 are shown in Table 3. All MRE values were below 5 %, and all MAE values were below 0.8. The MRE values for Al_2O_3 and SiO_2 were better than those during modelling, and the MAE for Al_2O_3 was significantly lower than during modelling. This is because the component distribution of ore samples used in modelling was relatively wide, while in real production, after ore blending, the component range is narrower with less fluctuation. This aligns with production requirements, where stable raw material composition is essential. The online detection technology developed in this study can further reduce material variability, as shown by results in Figures 9–11. The values for all three components exhibit good linear trends with the laboratory assay values, confirming that the detection technology and equipment developed in this study can accurately and continuously obtain ore composition in real time.

Table 3. Online detection errors.

Error	Al_2O_3	SiO_2	Fe_2O_3
MRE (%)	1.56	4.62	4.33
MAE (%)	0.80	0.51	0.76

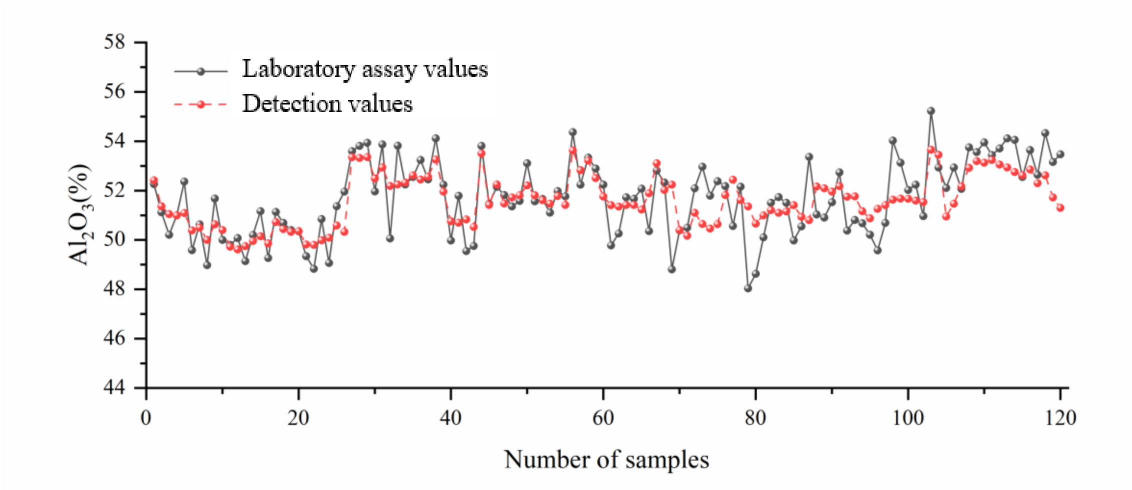

Figure 9. Online detection results of Al_2O_3.

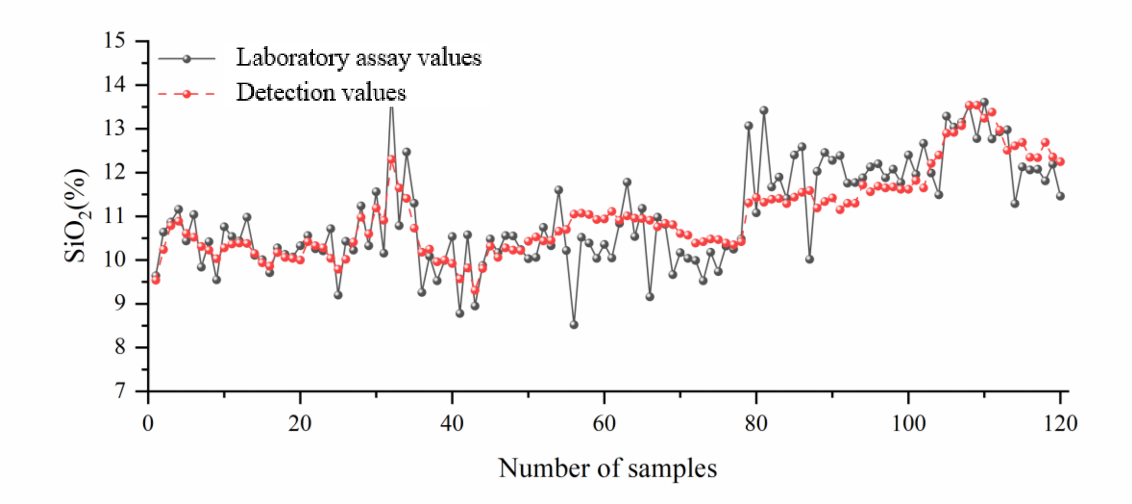

Figure 10. Online detection results of SiO_2.

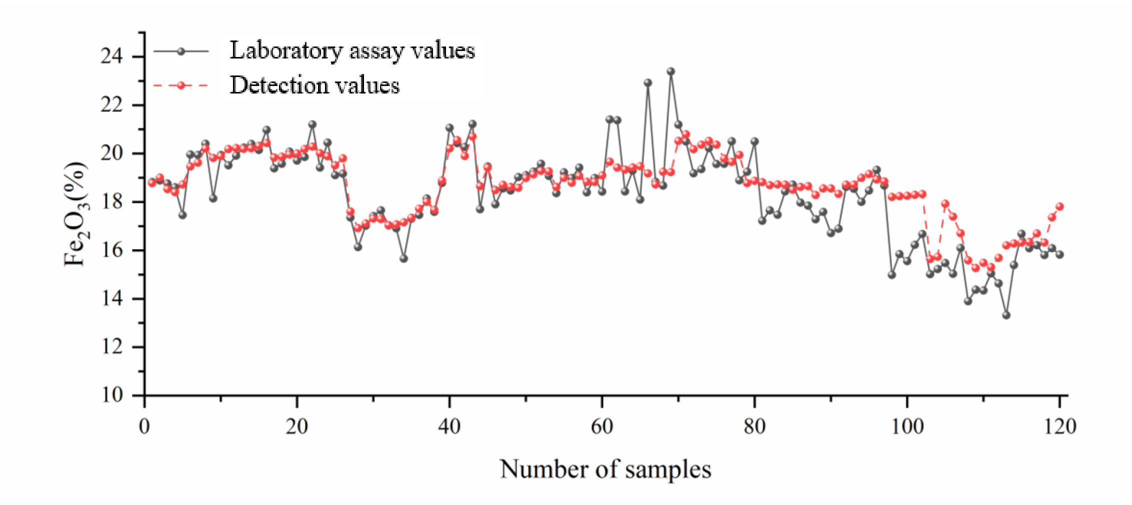

Figure 11. Online detection results of Fe_2O_3.

4. Conclusions

This study proposed a real-time detection technology for bauxite composition and developed a prototype device for on-site testing in production, addressing issues such as delayed determination, poor sample representativeness, and human error in alumina production. The main achievements are as follows:

-a wide-range bauxite sample set was collected to construct a spectral dataset; through spectral preprocessing and machine learning modelling, quantitative analysis of the three major components (Al_2O_3, SiO_2, and Fe_2O_3) was achieved, with detection MREs all below 5 % and MAEs below 2 %;

-a prototype device was designed and developed, integrating the detection model and simulating production conditions, ultimately realizing online detection of bauxite composition;

-the developed technology and equipment can operate stably in real production environments, and 40 days of continuous online sampling showed MREs below 5 % and MAEs below 1% for Al_2O_3, SiO_2, and Fe_2O_3, with a detection time under 1 minute.

The bauxite composition online detection technology and equipment developed in this study provide strong data support for intelligent control and process optimization in alumina production, while also offering a technical paradigm for online detection of other materials, contributing to the industry's intelligent upgrading. Future research will focus on expanding detection items, improving the robustness and generalizability of the detection technology, and effectively using real-time detection data to optimize production.

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