Machine Learning and Time Series Data Used in the Prediction and Regulation Model of Alumina Hydroxide Particle Size Distribution

Long Duan[1], Lijuan Qi[2], Yanfang Zhang[3], Shuai Shao[4], Qiaoyun Liu[5] and Linyu Li[6]
1, 4, 5, 6. Engineers
2, 3. Professor Level Senior Engineers
Zhengzhou Non-ferrous Metals Research Institute of Chalco (ZRI), Zhengzhou, China
Corresponding author: yanfang_zhang@chinalco.com.cn
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Abstract

Particle size control in the precipitation process of alumina production directly affects product quality and energy efficiency. To address challenges such as strong lag and large particle size fluctuations in traditional manual experience-based control, this study proposes a particle size distribution (PSD) prediction model and a dynamic control model based on machine learning and time series data. By integrating multi-source time series data, including equipment parameters, material characteristics, and process conditions, a high-dimensional dynamic dataset is constructed. Leveraging the multi-scale features of production data, a particle size distribution prediction model based on a CNN-LSTM (Convolutional Neural Network – Long Short-Term Memory) time series network is developed. A feature attention mechanism is introduced to enhance sensitivity to key process parameters, effectively capturing the non-linear coupling relationship between particle size variations and process parameters, thereby achieving prediction of PSD. Based on the prediction results, an optimized control model is established, which derives the control ranges of key parameters through reverse deduction, ultimately realizing stable control of particle size during the precipitation process. In this study, the average accuracy of PSD prediction exceeds 95 %, and particle size fluctuations are significantly reduced after control. This study not only verifies the effectiveness of time series data feature mining and machine learning modelling in process industries but also offers a "prediction-diagnosis-control" closed-loop paradigm for the intelligent optimization of high-dimensional coupled production systems, providing valuable guidance for the intelligent upgrading of alumina production.

Keywords: Seed precipitation, Particle size analysis, Machine learning, Prediction model, Production control.

1. Introduction

The Bayer process for alumina production offers the advantages of low energy consumption and high product quality. Seed precipitation is one of its key processes. By adding an appropriate amount of aluminium hydroxide $Al(OH)_3$, also known as alumina trihydrate ($Al_2O_3 \cdot 3H_2O$), or ATH) seeds to the supersaturated sodium aluminate liquor, alumina precipitates from the liquor in the form of ATH crystals through gradual cooling and continuous agitation. The particle size and strength of the alumina product largely depend on the particle size and morphological structure of ATH particles produced during the precipitation process. If the particle size of the ATH seeds in the seeded precipitation process is too fine, it can lead to poorer product quality; conversely, if the seeds are too coarse, the precipitation rate will decrease, which lowers the overall production yield [1, 2]. Therefore, accurately monitoring the seed PSD during the precipitation process and promptly adjusting production parameters are essential measures for stabilizing the seed PSD and improving product quality.

Due to the long process flow, numerous pieces of equipment, and complex material transformation in the precipitation process, key indicators such as the particle size of the produced

ATH are affected by multiple factors, including liquor composition, precipitation temperature setting, quantity and quality of seeds, precipitation time, impurity levels, and agitation intensity [1, 3]. Moreover, the process itself is characterized by large inertia, non-linearity, multiple disturbances, and complex correlations. As a result, relying solely on manual experiences and mechanism-based models fails to deliver timely and effective control strategies, leading to significant PSD fluctuations during the precipitation process.

With the advancement of automation and digitalization in alumina refineries, mature sensing devices can acquire equipment data in real time, while advanced detection technologies can periodically obtain material data from laboratory analyses. Effectively leveraging these vast amounts of production data makes it possible to extract key data features from complex data relationships, enabling the prediction of critical process indicators, and thereby guiding production control [4–8].

In this study, equipment and material data from the precipitation process in an alumina refinery were collected to extract time series information and construct a time series dataset. Based on machine learning methods, a PSD prediction model was developed, and optimization techniques were employed to identify the optimal feature. This approach ultimately guided production control, stabilized the PSD and reduced costs.

2. Data and Methods

2.1 Data Acquisition

The data used in this study were obtained from the Excellence Technology Center of Chalco and included equipment and material data from the precipitation process of three production lines over a period of three months (January to March 2025). The precipitation process consists of 14 precipitators, 7 heat exchangers, cyclone classifiers, and vertical disc filters, with each precipitation cycle of 44 hours. The equipment data cover measurements from the 14 precipitators and 7 heat exchangers, while the material data include PSD information of precipitation green liquor, precipitation spent liquor, and filter cake from the vertical disc filters. Detailed data are shown in Table 1.

In the seeded precipitation process, the precipitation green liquor flows sequentially from precipitator F1 through precipitators F2 to F14, with each precipitator equipped with agitation devices. The plate heat exchangers, labelled H1 to H7, are installed between precipitators F2 and F9 to progressively cool the sodium aluminate solution, thereby facilitating the precipitation of qualified ATH. A cyclone classifier is positioned above precipitator F11. Its underflow is directed to the horizontal disc filter, while the overflow and remaining slurry are returned to tank F12, re-entering the precipitation system. The slurry from precipitators F13 and F14 is collectively conveyed to the vertical disc filter. The resulting filter cake is fed into the seed tank to continue participating in the precipitation cycle, the filtrate proceeds to the evaporation stage, and the overflow is returned to precipitators F13 and F14.

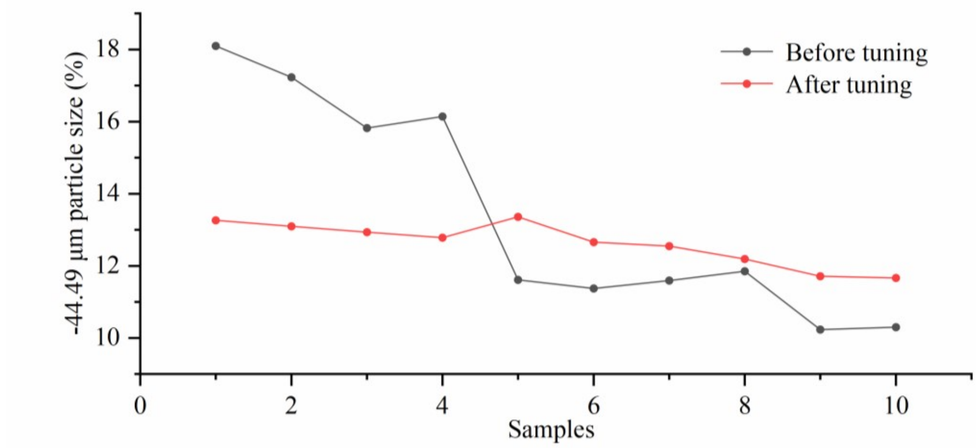

Figure 9. Tuning effect of the -44.49 µm particle size.

5. Conclusions

This study adopts machine learning techniques to establish a PSD prediction model and a control and optimization model based on production time series data, thereby realizing the early prediction of process indicators and the generation of production control strategies. The main contributions are as follows: Data on equipment and materials during the precipitation processes from three production lines over three consecutive months were collected; By integrating multi-source time series data, including equipment parameters, material characteristics, and process conditions, a high-dimensional dynamic dataset was constructed; By incorporating multi-scale features of production data, a PSD prediction model based on a CNN-LSTM time series network was developed. A feature attention mechanism was introduced to enhance sensitivity to key process parameters, effectively mapping the non-linear coupling relationships between particle size variation and process parameters. As a result, the model achieved prediction of the particle size distributions of -44.49 µm, -80.72 µm, and -101.9 µm, with accuracies of 91.74 %, 94.98 %, and 97.05 % respectively. Based on the prediction results, an optimization and control model was established. By reversely deriving the control ranges of key parameters, stable control of PSD in the precipitation process was achieved, reducing the standard deviation of -44.49 µm particle size fluctuations from 3.03 to 0.60. This study not only demonstrates the effectiveness of time series data feature extraction and machine learning modelling in process industries but also provides a "prediction-diagnosis-control" closed-loop paradigm for the intelligent optimization of high-dimensional coupled production systems, offering significant potential for promoting the intelligent upgrading of alumina production.

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