Intelligence-Driven Precipitation Control for Enhanced Alumina Productivity with Consistent Quality: A Machine Learning Approach

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Abstract

Alumina extraction from boehmite in bauxite, such as in Central India, poses a unique challenge due to its inherently high energy requirements. Global refineries employing such energy-intensive processes must have an acute focus on energy efficiency to ensure competitive production costs. A pivotal efficiency metric is precipitation productivity or yield, indicative of refinery operational efficiency. Traditionally, maintaining optimum yield involves manual analysis of process sample results, where technical analysts meticulously correlate deviations in process conditions with lab values to identify influential factors. This approach is sensitive and heavily relies on human experience and expertise, underscoring the necessity for automated and intelligent solutions.

In response to this challenge, this article presents a pioneering endeavour to develop a mathematical model utilizing machine learning (ML) algorithms, coupled with Bayer process principles and noise factor considerations, to optimize yield in alumina precipitation. Notably, the model partitions the precipitation process into three segments: agglomeration, new growth, and existing growth. This facilitates a granular understanding and targeted intervention. Crucially, our model integrates constraints within each segment, ensuring that the quality of the resultant alumina remains uncompromised while optimizing yield. A transformative shift towards data-driven precipitation control is anticipated by leveraging the power of ML algorithms to optimize productivity while consistently delivering quality alumina. This intrinsic balance between productivity and product quality constitutes a hallmark of our approach, which not only enhances operational excellence but also underscores the disruptive potential of AI-driven solutions in alumina refining.

Keywords: Alumina Production, Precipitation Control, Machine Learning, Artificial Intelligence, Operational Efficiency.

1. Introduction

Precipitation productivity stands as the key performance indicator for an alumina refinery, measuring the amount of trihydrate alumina extracted per litre of Pregnant Liquor (PGL). This metric is influenced by various factors, including temperature profiles, seed charge, residence time, liquor caustic concentration, alumina supersaturation and seed surface area (SSA) [1].

At Renukoot Alumina Refinery, achieving continuous improvement in precipitation productivity from 73 to 78 g/L involved implementing various process strategies combined with enhanced operational practices. This boost in productivity translated into significant reductions in steam and power consumption for the refinery. However, several instances of lower yield coupled with deviations in quality parameters for calcined alumina, such as occluded Na_2O, < 45 µm fractions and attrition index, were observed.

In the absence of predictive-based control, consistently sustaining the precipitation productivity at this level remained a challenge [2]. Consequently, it became imperative to establish a set of process conditions that not only met but surpassed the targeted productivity level of 77 g/L while ensuring consistent alumina quality.

This paper discusses the stepwise development of predictive and intelligence-driven precipitation control for enhanced alumina productivity with consistent quality using a machine learning approach.

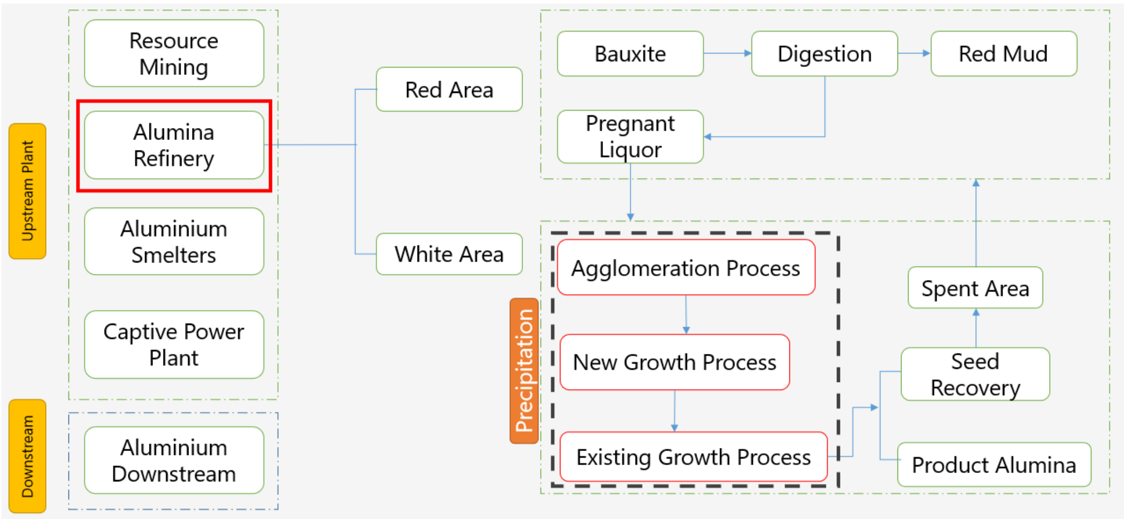

Figure 1. Precipitation process at Renukoot Alumina Refinery.

The precipitation process in alumina refining can be divided into three main process segments namely as shown in Figure 1.

i. Agglomeration
ii. New growth
iii. Existing growth

To ensure a short residence duration, ranging from about 6 to approximately 12 hours, the agglomeration phase of the precipitation process is ideally conducted in a short chain of tanks. These are homogenous tanks, and the slurry is released into a series of larger tanks where the growth occurs. The new growth segment consists of seed addition followed by interstage coolers for optimizing liquor temperature profile. The mid-precipitated slurry is directed from new growth to existing growth segment where sufficient residence time is provided. Lowering soda levels and achieving higher productivity requires optimizing and balancing a number of process variables. Each segment has distinct characteristics and challenges that need to be addressed to optimize the overall precipitation productivity.

2. Technical Details

2.1 Machine Learning and Operations Research Optimization

Machine learning (ML) is a discipline of artificial intelligence (AI) that provides machines with the ability to automatically learn from data and past experiences while identifying patterns to make predictions with minimal human intervention. ML algorithms use computation methods to learn directly from data instead of relying on any predetermined equation that may serve as a model [3].

growth and existing growth tank models were integrated to obtain a single optimization model for precipitation.

3.4 Cloud Computing for Model Lifecycle Management (Architecture)

For model lifecycle management and governance, Oracle cloud computing technology is leveraged to deploy the model and sustain the solutions. Figure 19 breaks down the cloud life cycle into four phases. Every stage paves the way for the one after it, therefore following the order is crucial to the success of the process. The risk involved with cloud projects is decreased by using this stepwise strategy. The services used include:

1. **ODI (Oracle Data Integrator)**: To import data from source to the IT-side database.
2. **ADW (Oracle Autonomous Data Warehouse)**: To store data from DCS and laboratory servers.
3. **Oracle Data Science**: To create machine learning models and host them.
4. **Oracle Virtual Machine**: To create and provide solutions to end-users via a full-stack dashboard.

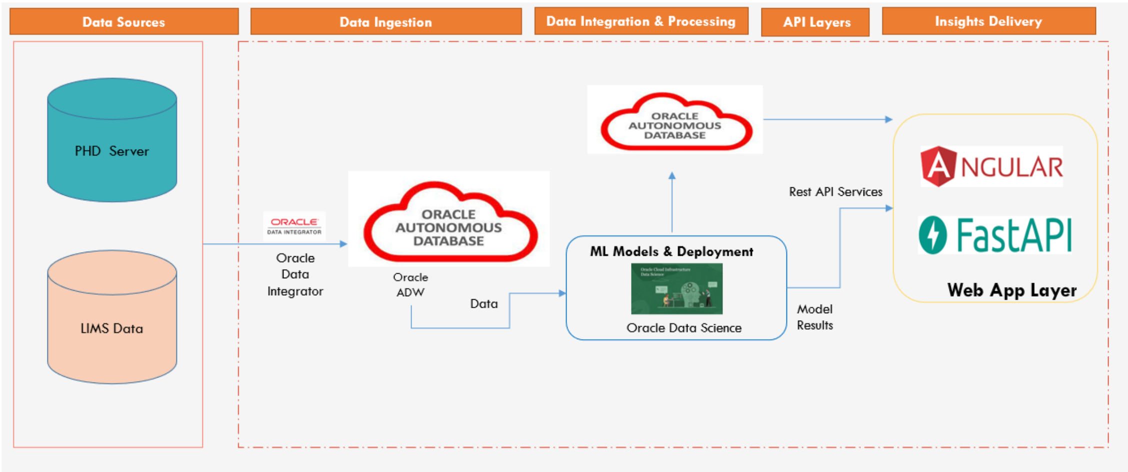

Figure 19. Architecture for cloud computing.

4. Conclusion

The development and deployment of an intelligence-driven precipitation control model using ML has proven to be a significant advancement in optimizing alumina productivity while maintaining consistent quality. By partitioning the precipitation process into agglomeration, new growth, and existing growth segments, and integrating constraints within each segment, our model ensures a balance between productivity and quality. This data-driven approach not only enhances operational excellence but also highlights the potential of AI-driven solutions in alumina refining. The use of cloud computing for model lifecycle management further ensures the robustness and scalability of the solution, paving the way for future innovations in the industry.

5. References

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