Agglomeration Process Optimization

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https://doi.org/10.71659/icsoba2024-aa017

Abstract

This paper presents a pioneering approach to optimizing the agglomeration process at Hydro's Alunorte alumina refinery through the implementation of a digital twin. This advanced system leverages first principles and data science techniques to provide real-time forecasts and recommendations for critical quality variables, enabling a shift from reactive to proactive process management. The core advancements of this project include the development of precise predictive models, a what-if analysis tool for scenario simulation, and a recommendation tool for operational adjustments. The anticipated benefits of this technology include enhanced product quality, reduced variability, and increased operational efficiency, setting new benchmarks in the alumina refining industry.

Keywords: Agglomeration, Throughput increase, Digital Twin, Predictive models.

1. Introduction

The alumina agglomeration process in the context of hydrate precipitation in the alumina industry is a fundamental step aimed at optimizing the quality and efficiency of the final product. During alumina production, hydrate precipitation involves the formation of alumina hydrate crystals from a sodium aluminate solution. At this stage, agglomeration plays a crucial role by transforming fine alumina hydrate particles into larger, more manageable aggregates. Agglomeration occurs through a series of strategic steps, beginning with the preparation of fine hydrate particles. This preparation includes the classification of the seed, ensuring that the particles are within the appropriate size range for agglomeration. This is followed by a mixing and homogenization phase, where the particles are evenly dispersed, facilitating the formation of consistent aggregates. In the agglomerators, the agglomeration of hydrate particles occurs under carefully controlled conditions. Temperature is a critical factor, as it influences the solubility of the hydrate and the rate of crystal growth. Maintaining the temperature within an optimal range ensures efficient agglomeration, promoting the formation of robust aggregates.

The seed charge, or the amount of fine particles introduced into the agglomerator, is also fundamental to the process. An adequate seed charge ensures that there are enough nucleation points for the formation of aggregates of the desired size. The balance between the amount of seed and the sodium aluminate solution must be maintained to optimize the efficiency of agglomeration.

Residence time, or the duration that the particles remain in the agglomerator, is another essential factor. This time must be long enough to allow the fine particles to fully agglomerate, but not so long as to cause excessive growth of the aggregates. Precise control of the residence time ensures the uniformity of particle size in the final product.

Agglomeration plays a pivotal role in improving the physical handling characteristics of alumina, thus facilitating subsequent processing stages and minimizing dust-related issues. However, the complexity of this process arises from several critical and interdependent factors that require meticulous control to ensure uniform and consistent results. These factors include the control of nucleation – the formation of initial particle clusters; the seeding strategy, which involves introducing "seeds" to promote uniform particle growth; and the control of crystal growth to achieve the desired aggregate size and structure. Additionally, the direct manipulation of the agglomeration process – coalescing smaller particles into larger ones – and ensuring reproducibility and consistency across batches present significant operational challenges. To address these complexities, the refinery has integrated advanced data science techniques and predictive tools. These technologies leverage first principles and empirical data to enhance yield, improve quality, and reduce process variability. The adoption of such innovative approaches not only optimizes the agglomeration process but also sets new benchmarks in operational efficiency and product quality in the alumina refining industry.

The importance of agglomeration in the quality control of alumina cannot be overstated. This process is essential for improving the physical properties of the product, such as density and mechanical strength, as well as increasing reactivity and ease of handling. Producing alumina with particles of adequate size and shape is vital for subsequent processing stages, including calcination and electrolytic reduction, where the efficiency and uniformity of the material directly influence the productivity and quality of the aluminium produced. Therefore, precise control of the agglomeration process during hydrate precipitation is crucial to ensure that the final alumina meets the stringent quality standards required by the industry. This control encompasses everything from the proper classification of the seeds to the optimization of temperature conditions, seed charge, and residence time in the agglomerators, ensuring a high-quality and high-performance final product. Below is being represented the simplified Bayer process and the specific precipitation area with the agglomeration process (Figures 1 and 2).

Table 4. Hyperparameter set and its results for each predicted KPI.

KPI Predicted	Hyperparameters	MAPE
Solids concentration	{'n_estimators': 282, 'max_features': 1.0, 'max_leaves': 12656}	12.26
Supersaturation	{'n_estimators': 130, 'max_features': 0.7766377519728662, 'max_leaves': 6750}	1.11e-05
Agglomeration Index	{'n_estimators': 356, 'max_features': 1.0, 'max_leaves': 6738}	1.86

These models are trained as per lines (specific combination of tanks, sizes, and other parameters. Hence the mechanism can be applied to any line by letting the model being trained for that specific configuration of the line.

6. Conclusion

The integration of digital twin technology into the agglomeration process at Alunorte's refinery represents a significant leap forward in the alumina industry. By employing advanced simulation and predictive analytics, the refinery is ready to shift from a reactive approach to a proactive and predictive management strategy, profoundly transforming process control and optimization.

Thus, the introduction of digital twin technology is poised to bring about significant improvements in the refinery's operations. Enhanced operational efficiency is a primary expected benefit, with the technology's real-time monitoring capabilities anticipated to allow for more effective adjustments in the agglomeration process. This should lead to improved throughput while maintaining quality standards. The predictive aspect of this technology is also projected to make operational processes more time and resource efficient.

In terms of product quality, there is an expectation of marked improvement in the consistency and quality of the alumina produced, thanks to the precise control over process variables that the digital twin technology offers. Additionally, the integration of predictive maintenance is likely to reduce operational downtime, thereby potentially enhancing productivity and the reliability of processes.

The environmental impact of the refinery's operations is also expected to be positively influenced by the digital twin technology. It is anticipated that the technology will facilitate more efficient resource use and waste reduction. The prospect of improved process control leading to decreased raw material consumption and emissions points towards a more sustainable operational model.
Overall, the digital twin technology is expected to be a catalyst for progress in achieving operational efficiency, product quality, and environmental sustainability. These anticipated developments signify a commitment to ongoing improvement and responsible industrial practices.

As per possible future developments, an addition of new KPIs like Mesh -365 and Occluded Soda to the digital twin setup is expected to give a clearer view of the process. These KPIs could provide more details that might help improve the agglomeration process, aiming for better quality and efficiency.

7. References

1. Masoud Bahrami Babaheidari et al., The agglomeration kinetics of aluminum hydroxide in Bayer process. *Powder Technology*, Iran, 12 March 2012, 224, 351-355.
2. D. Ilievski et al. Agglomeration during precipitation II - Mechanism deduction from tracer data. *Aiche*, March 1995, 525 -535.

3. D. Ilievski et al., Agglomeration during precipitation I - tracer crystals for $Al(OH)_3$ precipitation. Aiche, March 1995, 518 -524.
4. Foster Provost et al., Data Science for Business: What You Need to Know about Data Mining and Data-Analytic Thinking, *O'Reilly Media*, July 2013.
5. Trevor Hastie et al., *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. *Springer*. 2001.
6. Gareth James et al., *An introduction to statistical learning with applications in R*. Springer New York, 2013.
7. Ian Goodfellow et al., Deep Learning. *MIT Press*. November 2016.
8. Hal Varian, Big data: New tricks for econometrics. *Journal of Economic Perspectives*, 2014, 3-28.
9. David Lazer et al., The parable of Google Flu: Traps in big data analysis. *Science, 2014,* 1203-1205.
10. Isabelle Seyssiecq et al., Modeling gibbsite agglomeration in a constant supersaturation crystallizer. *Chemical Engineering Science,2014, 55*, 5565-5578.