Real time Prediction of Gas Suspension Calciner Performance Using ML Based Soft

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Abstract

In alumina refineries, the major energy intensive unit operation is the calcination process, consuming almost 1/3rd of total energy required for the production of Alumina from Bauxite. Technological advancements with new generation gas suspension calciners have offered gradual reduction in energy consumption. The calcination process involves both removal of moisture from hydrate, and phase transformations to produce desirable smelter grade alumina. However, fraction of particles having spent lower residence time leads to a high Loss on Ignition LOI whereas particles exposed to higher temperatures with higher residence time leads to conversion from γ-alumina to α-alumina. For better control on product quality, operator needs to take decision of the set point based on the product quality (Alpha content and LOI) obtained through laboratory analysis. This analysis takes considerable amount of time and the lagged information is used for decision making by operators retrospectively. Therefore, extensive work was carried out to generate real time prediction of these quality parameters which will assist the operator to take proactive process control decisions without waiting for the lab data to achieve operational excellence along with consistent product quality.

Through this work, a Machine Learning (ML) based predictive models were developed and validated based on plant data historian of calcination process. Entire data was split into 70 % for training the model while remainder has been used for testing the model accuracy. Advanced algorithms viz., random forest, Extreme Gradient Boosting algorithm XG -boost was used over the pre-processed data with optimized hyper parameters to achieve higher accuracy for a predictor variable. The model accuracy for the prediction of alpha alumina content was found to be in the acceptable range of 85 % to 90 %.

The predictions were validated using real-time Distributed Control System (DCS) plant data on a minute-wise basis. Through a web-based Graphical User Interface, GUI platform, real time predictions from the model and actual plant measurements were pulled, displayed and compared to showcase the critical parameters for the prediction accuracy.

Keywords: Alpha alumina, Gas suspension calciner, Machine learning model, Soft sensor.

1. Introduction

Thrive of Alumina refineries hinges on energy as well as alumina quality. The most critical process operation contributing these factors is the calcination process. The calcination process is the most energy intensive process consuming ~30 % of total energy of refineries [1]. The calcination of aluminium tri-hydrate to alumina is represented by Equation (1). Although its theoretical energy requirement is in the order of 2393 kJ per kg of alumina, calciners are operated with 12-22 % higher energy in practical [1, 3]. Minimizing these variations not only saves energy but also produces consistent product as calcination process is sensible to operation variations.

$$2Al(OH)_3 \xrightarrow{800-1000\,^{\circ}C} Al_2O_3 + 3H_2O \quad (1)$$

Calcination (Equation (1)) seems to be a simple one step reaction happening at 800 – 1000 °C to produce desirable alumina phases with an LOI less than 1 %. Alumina calcination process involves various stages viz., unbound moisture removal, phase and structural transformations in which hydroxides are converted to oxides. Residual hydroxide content starts to decrease with temperature and time in a calcination process. Most of the reduction in free moisture present in the feed hydrate is observed in temperatures lower than 250 °C after which at a reducing rate of LOI, phase and structural transformations takes place.

Phase transformations play a crucial role in an alumina calcination process for the production of desired alumina phases. During the calcination process, alumina has a significance of existing in various metastable forms including γ, χ, κ, δ, η, θ and in the final stable α-alumina phase [1]. The reaction pathway to several alumina phases are majorly characterized by particle sizes and heating rates. On-set of phase transformation to alumina mono hydroxide (Boehmite) from gibbsite starts at temperatures lower than 250 °C after which several phase transformations based on heating rates and particle sizes to χ, and desirable γ-alumina takes place at temperatures between 300 to 800 °C. Stable alpha alumina formation occurs at temperatures greater than 1000 °C.

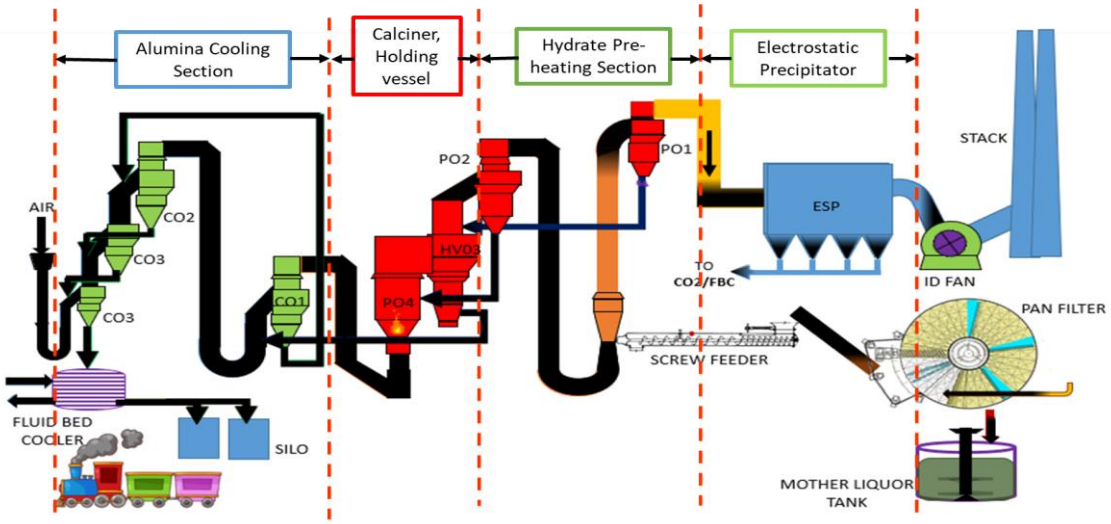

Figure 1. Process flow diagram for alumina calcination.

In modern day Gas Suspension Calciners (GSC) as in Figure 1, gibbsite particles are fed into a series of preheaters maintained at around 300-500 °C for removing moisture and initiating the conversion of aluminium tri-hydroxide to mono-hydrated alumina (boehmite) and transition to alumina. In the calciner furnace and holding vessel sections, production to a desirable smelter grade alumina is carried out. Post calcination, heat associated with alumina is recovered using a

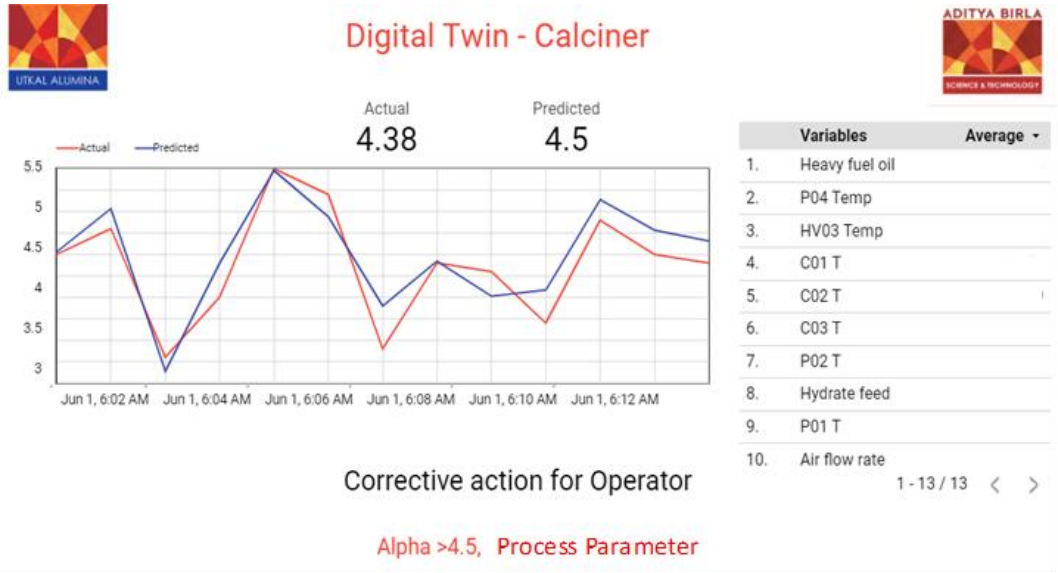

Figure 7. Sample dashboard for the real time predictions of alpha alumina.

The sample dashboard designed for GUI development; graphic user interface/dashboard was developed to display the results of the predicted alpha alumina content minute wise/hourly along with actual alpha content (Figure 7). In addition, it also involves the display of important variables /features which played a key role in the model prediction in the order of their respective ranking. On top of that, past trends of each variable, predictions and the reports can be generated for the benefit of the DCS operating personnel to understand the past trends and the respective decisions made during the period.

4. Conclusions

On the conclusive note, the current work focused on carrying the following technical methodologies viz., A) Data Analysis: Identification of critical variable affecting the process. B) Predictive model development based on data analytics techniques for product quality. A strong seasonal effect on the operating variables and the corresponding variations in heavy fuel oil consumption and product quality in terms of alpha content are observed. After testing various models XG- boost algorithm gave a better result in terms of predicting the Alpha alumina content. The developed Machine learning model is capable to predict the Alpha alumina with accuracy of 85-90 %. This model is further utilized in developing the web-based platform where predicted and actual alpha alumina will be displayed along with other critical parameters of process. This platform will be useful for operators to control process in a better way and take corrective action against the current practice of taking corrective action post laboratory analysis of the alumina. Further study focuses on developing the web-based platform which will accommodate the predicted values of alpha alumina from ML models as well as actual lab measurements of alumina.

5. References

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