AA10 - Predictive Analysis of Industrial Precipitation Cycles Using Population Balance and Deep Learning Methods

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Abstract

Existing advanced control systems are not very accurate in the prediction of the aluminum hydroxide particle size distribution (PSD) and liquor productivity in the precipitation circuits of alumina refineries. The main reasons for this are low rates and high noise contamination of the controlled processes, and big differences in time constants for various parameters. This paper discusses some alternatives for prediction of the precipitation process, i.e. population balance method (PBM) and deep learning method. Though different in their characteristics and possibilities, these methods complement each other. This study also shows that updated PBM equations can be used to predict the main trend and inflection points of PSD oscillation curves, and calculate A/C ratio of the spent liquor over the extended periods. Besides, the set of LSTM blocks enables the creation of artificial neural networks for short-term periods. The predictive capability of such networks is sufficient to perform optimum control of industrial precipitation processes. To operate both methods a specialized software PrecipExpert was developed. The software is designed to develop, configure and fine-tune a consolidated data system of the precipitation area. The developed automated system is currently being tested at the RUSAL Kamensk-Uralsky Alumina Refinery (Russia).

Keywords: Advanced process control, precipitation, population balance, deep learning, self-oscillations.

1. Problems of Precipitation Control at the Refinery

Advanced Process Control (APC) is a method for the optimal control of multivariable objects based on a specified criterion. Such systems comprise a model of the controlled object used to predict the response of the object to the controlled variable(s), and an optimization algorithm that solves the problem with a global extremum (or maximum) for a given criterion under given constraints.

This type of control system has been used in alumina refineries for a long time, to control for example, the parameters of digestion trains, washing lines, and calciners. In the precipitation area they are used to solve secondary problems, such as stream distribution between parallel lines of precipitators, stabilization of the slurry solids content and controlling the temperature in precipitator tanks. Stabilizing the PSD of aluminum hydroxide and increasing liquor productivity are far more challenging tasks for automated control, and such tasks are still managed by process engineers. The theory of automation control attributes the limited use of APC for PSD and liquor productivity control to the specifics of the process (see Table 1).

These process specifics cause control instability; the optimum is not found, self-oscillations appear, and an inverse response of the object to the applied action is observed.

Table 1. Process specifics causing difficulty with PSD and liquor productivity control in the precipitation area.

Process specifics	Examples
Many noisy signals with low Signal-to-Noise ratio	Noise can be caused by changing concentration of solids, injection of fine particles after chemical cleaning of precipitators, varying liquor impurities, daily temperature fluctuations and equipment breakdowns
Low Time-to-Steady-State values	The rate of nucleation and the rate of particle removal from the system are low with respect to the total number of crystals
Inability to directly measure key parameters	The quality of the crystal surface, the number of true nuclei, interface area cannot be measured directly
Big difference in time constants for parameters	Flow is measured at intervals of minutes; A/C and temperature are measured in intervals of hours; PSD is measured in intervals of days or weeks
Presence of the parameters with a strong functional relation	Liquor yield and PSD are functionally related; crystal coarsening causes a decrease in yield and vice versa, making their simultaneous control challenging

Presently the main method for simulating seeded crystallization is the population balance method (PBM). The method is based on sufficiently strict physical and chemical laws to provide for the complete understanding of the ongoing processes. Unfortunately, the literature does not report any examples of the successful use of PBM in actual production control, although this method is widely used in laboratory tests. Population balance models are difficult to set up, and their use for process control would require significant computational resources.

Recently, interest has been focused on predictions by machine learning methods (ML), more specifically, artificial neural networks (ANN). This type of model has become widely used due to its high general performance, the ability to use available historical data to train ANN, and high predictive performance. Among its disadvantages are: the inability to explain why ANN generates this or that forecast, and the loss of the prediction quality of over time due to the shift in the characteristics of the controlled object.

This study aimed to develop mathematical models of both types (population balance equation and machine learning method), for an existing industrial facility – the precipitation area at the RUSAL Kamensk Uralsky alumina refinery (UAZ). Based on the simulation results, the forecasts of each of the models can be compared, allowing the assessment of their applicability.

2. Particle Population Balance Method

An analytical method for the simulation of mass crystallization is well developed. It is based on the compilation and solution of a system of population balance equations.

The generalized population balance equation relates the number of particles in PSD grades to the rate of linear crystal growth, agglomeration, nucleation and breakage of particles [1]:

$$\frac{\partial n_i}{\partial t} + G\frac{\partial n_i}{\partial u} = B_i - D_i \tag{1}$$

where:

n_i number of particles in the ith grade

t time, s

develop and customize the optimization block, the second necessary element of the advanced control system. These results will be presented and discussed in future.

6. Conclusions

The population balance model of Bayer (gibbsite) seeded precipitation circuit has been improved for pregnant liquors with a low A/C ratio. Updated equations for secondary nucleation and particle breakage were proposed which take into account the surface quality and particle strength through the fraction of agglomerates in the population. The model accurately predicts the oscillations of particle PSD and liquor productivity in the studied industrial precipitation circuits.

Recurrent neural networks are effective for mid-term prediction of A/C ratio of the spent liquor and PSD of produced aluminum hydroxide. A set of LSTM models was trained with the use of the historical data of UAZ refinery. The obtained average correlation coefficient was > 0.93 for - 45 µm fraction in 60-days predictions.

PrecipExpert software has been developed, enabling the development of models and performance of calculations using both models.

7. References

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