Multilevel Robust State Observer for Spatial Alumina Concentration Estimation

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Abstract

In the aluminium smelting process, the information on spatial variations in alumina concentration is crucial for online alumina feeding control. However, the harsh environment of smelting cells renders long-term continuous real-time measurement of alumina concentrations impractical. Model-based state observers can be utilised for real-time estimation of the spatially distributed alumina concentrations, but the challenge lies in addressing model uncertainties, such as those in bath flow velocities and anode-cathode distance. To address these challenges, an H_∞ filter-based multilevel state observer is proposed for estimating spatial alumina concentration. This method can estimate alumina concentrations within a reasonable range and is robust to uncertainties. The effectiveness of this method is validated through experimental studies.

Keywords: Aluminium electrolysis, Process monitoring, State observer.

1. Introduction

In the aluminium smelting process, the control of alumina concentration plays an important role in improving the process efficiency. Inappropriate control can lead to various abnormal conditions, such as anode effects or sludge formation [1-6]. The existing alumina feed control algorithm employs a kind of logic control, which includes different feed windows [7]. To improve the control accuracy of alumina concentrations, reliable information of alumina concentration under different cell conditions is required. Traditional methods for getting alumina concentration information rely on periodic sampling and laboratory analysis, which can be time-consuming [2]. Therefore, online monitoring is necessary to improve the control of alumina concentrations.

The commonly used method for process monitoring is the extended Kalman filter (EKF), and many researchers have applied it in the aluminium smelting process. Shi [7,8] used the EKF to estimate average alumina concentration and utilised the results for control investigations. Yao [10] applied the EKF to investigate average alumina concentration and corresponding dissolution rate. However, since the EKF is designed to minimise the mean-squared error under the assumption of Gaussian noise, it may provide inaccurate estimations when abnormal cell conditions, such as anode effect, occur due to increased noise uncertainty. In contrast, the H_∞ filter can minimise the estimation error in the worst-case scenario [11]. Rao [12] compared the Kalman filter and H_∞ filter, and the results showed that the H_∞ filter can have a better estimation performance under worst-case noise conditions. Poveda [13] also conducted a comparison and concluded that H_∞ filter converges faster than the Kalman filter under additive noise. Therefore, in the aluminium smelting process, H_∞ filter is more robust for the estimation of alumina concentration.

On the other hand, online estimation struggles with variability of alumina distribution due to limitations in spatial information. Based on the aluminium electrolysis mechanism, the localised consumption of alumina is related to the individual anode currents. With spatial information from individual anode current measurements, the distribution of alumina concentrations can be estimated [14]. Additionally, the localised alumina concentrations are also affected by the bath flow patterns, which are difficult to obtain and introduce additional uncertainties into the process system [15]. To address these challenges, an H_∞ filter based multilevel state observer utilising individual anode current measurements is proposed for online estimation of the spatial alumina concentration. By using the data provided by individual anode currents, this method can enhance the spatial resolution and accuracy of spatial alumina concentration estimations.

In this paper, the structure is organised as follows: the process model is first introduced. Then, the design of an H_∞ filter is described. Following that, the structure of multilevel state observer is introduced. Finally, the effectiveness of this method is validated through experimental studies.

2. Process Modelling of Aluminium Smelting Process

The Hall-Héroult process is the commonly applied method for producing alumina in industry. In this process, the dumped alumina dissolves into the molten cryolite and is electrolysed into aluminium. The overall reaction in the aluminium smelting process can be simply represented as follows:

$$2\mathrm{Al_2O_3} + 3\mathrm{C} \rightarrow 4\mathrm{Al(l)} + 3\mathrm{CO_2(g)} \tag{1}$$

$$\mathrm{Al_2O_3} + 3\mathrm{C} \rightarrow 2\mathrm{Al(l)} + 3\mathrm{CO(g)} \tag{2}$$

where the ratio of CO_2:CO in the product is typically in the range between 5 and 10 [12].

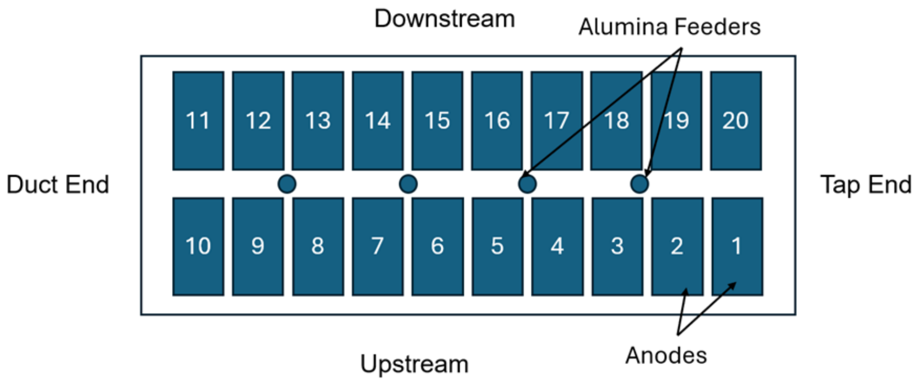

Figure 1. Layout of the anodes.

For an aluminium cell with 20 anodes and 4 alumina feeders, as shown in Figure 1, for a 1-minute time step, the dynamics of alumina concentration can be described by the following process model [15]:

$$C_{Al_2O_3,slow,k+1} = C_{Al_2O_3,slow,k} + t_s\left(-k_{slow}C_{Al_2O_3,slow,k} + \frac{P_{Al_2O_3}m_{feed,k}(1-r)}{m_{bath}}\right) \tag{3}$$

$$C_{Al_2O_3,d,k+1} = C_{Al_2O_3,d,k} + t_s\left(\frac{P_{Al_2O_3}m_{feed,k}}{m_{bath}}r + k_{slow}C_{Al_2O_3,slow,k} - \frac{Fa(I_k)}{m_{bath}}\right) \tag{4}$$

$$ACD_{k+1} = ACD_k + t_s(-\delta_{metal\,accum} + \delta_{anode\,consum}) + b_{m,k} \tag{5}$$

where:

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