AI-Driven Anode Effect Prediction in Hindalco Renukoot Smelter

Rupesh Pandey[1] and Faraz Khan[2]
1. Assistant Vice President
2. Data Scientist
Hindalco Industries, Renukoot, India
Corresponding author: rupesh.pandey@adityabirla.com
https://doi.org/10.71659/icsoba2025-al052

Abstract

The Hall-Héroult Process is used to produce aluminium from alumina using the electrolysis process in an aluminium reduction pot. Alumina is usually fed into the pot at regular intervals, using a point-feed mechanism. At very low alumina concentration (< 2 %) cryolite decomposition occurs and perfluorocarbon (PFC) gases evolve in the process. These gases form a highly electrical resistive layer underneath the anode, which suddenly increases the pot voltage, resulting in an anode effect (AE). High anode effect frequency (AEF) and anode effect duration (AED) may lead to reduced anode life, high heat generation, crust collapse, ledge melting, low current efficiency, high fluoride emission, and the possibility of pot leakage. Therefore, high AEF and AED contribute significantly to PFC emission and global warming. Apart from the environmental challenges, AEs significantly increase specific energy consumption and affect pot life. Aluminium smelter industries are aggressively examining ways to reduce the number of AEs as well as their duration.

To mitigate these challenges, an in-house AI-driven AE prediction model has been developed, utilizing real-time pot data from the control system to forecast AE occurrences up to one hour in advance. This model, seamlessly integrates with an in-house software system, enables proactive control measures, effectively reducing both anode effect frequency (AEF) and anode effect duration (AED). With an accuracy ranging from 85 % to 90 %, the system has significantly minimized manual interventions, reducing workplace hazards, improving operational stability, and enhancing overall energy efficiency. Additionally, by optimizing process control, the model aligns the smelter's performance with global benchmarks, ensuring sustainable aluminium production.

Keywords: AI-driven model, Aluminium smelting, Anode effect prediction, Energy efficiency, PFC emissions reduction.

1. Introduction

The Hall-Héroult Process is used for the extraction of aluminium (Al) from its oxide, alumina (Al_2O_3). In this process, alumina is fed into the system through point feeders, dissolving in molten cryolite (Na_3AlF_6) for electrolysis to liquid aluminium (Al) and carbon dioxide (CO_2). The Hall-Héroult process operates in the temperature range of 940–980 °C and typically produces aluminium with a purity between 99.5 and 99.8 %. Additives such as the fluoride salts AlF_3, MgF_2, CaF_2, and LiF are mixed with cryolite in order to optimize the process. These additives reduce the liquidus temperature and increase the efficiency of the electrolysis of alumina [1].

The Hall-Héroult Process is highly energy-demanding, wherein electricity constitutes 30–40 % of the total cost of production. A schematic showing the process is given in Figure 1. Modern aluminium smelters achieve current efficiencies (CE) nearing 94 %, while best-practice benchmarks go up to 96 % [2]. Maintaining high CE requires strict control of the alumina concentration, keeping it within the optimal range, along with rigorous compliance to standard operating procedures (SOPs).

In earlier days, when automatic feed control systems did not exist, the operator would detect the anode effect (AE) when a spike in the cell voltage occurred. This signal alerted the operator to manually add a certain amount of alumina into the cell. The interval until the next AE occurred allowed calculating the adequate feeding rate. For example, if AE is too early, increase the alumina dosage; if too late, decrease it. Manual termination of AEs usually occurred as either scraping by iron rakes or by green wooden poles. As a result of the above, AEs cause melting of the side ledge and localized sludging. More critically, AEs lead to the emission of perfluorocarbon (PFC) greenhouse gases, mainly CF_4 and C_2F_6 which possess very high global warming potentials [3–7].

With the advent of the computerized automatic feeding systems, computer controlled dosing facilities, and automated AE termination protocols, the aluminium industry has considerably reduced both occurrences and durations of anode effects. Currently, most aluminium smelters have adopted point-feed technology for the alumina introduction into the electrolytic cell. This system is generally provided with a cylinder-type volumetric feeder, which works side by side with a crust breaker. Normally, alumina is added in discrete batches, whereby each feeder delivers its precisely measured quantity of 1 to 2 kilograms into the bath through a designated feeder hole at predetermined time intervals. The initial feed control strategies were based on cell voltage which reflects several factors such as alumina concentration, anode-cathode distance, electrolyte conductivity, and the operating anode current density.

Renukoot Smelter has been in existence since 1962, and over these years, it has continued to modernize pot designs including upgrades of various registers and control systems. Such advancements have ensured the smelter remains competitive with state-of-the-art technologies. Renukoot is producing at 410 kt/a and achieves current and energy efficiencies comparable to modern smelters. The process control systems at the smelter have improved significantly from manual alumina feeding to an automated, resistance-based feeding system, referred to as dynamic feed, which includes hardware and design improvements. The control system is further enhanced by incorporating the AI-based models. This paper is about development of AI-based AE prediction model which enables early detection of AE.

Hindalco Renukoot

- Potline amperage = 70 kA
- Metal production: 530 kg/pot·day
- Number of pots: 2138 in 11 potlines
- Current density: 0.94 A/cm^2
- Metal production: 410 kt/a

Figure 1. Brief overview of aluminium smelter at Hindalco Renukoot.

This AI – led solution boldly heralds a futuristic approach to industrial automation-and it is helping to set a precedent as to what predictive technologies can do in the aluminium world.

9. References

1. George E. Totten et al., *Handbook of aluminum: Volume 2 alloy production and materials manufacturing*, 2003, 736. https://doi.org/10.1201/9780429223259
2. Geir Martin Haarberg, Effects of electrolyte impurities on the current efficiency during aluminium electrolysis, *Proceedings of 33rd International ICSOBA Conference*, Dubai 2015, Paper AL27.
3. Warren Haupin and Edward J. Seger, Aiming for zero anode effects, *Essential Readings in Light Metals* 2016, 767–773. https://doi.org/10.1007/978-3-319-48156-2_114
4. Kai Grjotheim and Halvor Kvande, *Introduction to aluminium electrolysis*, DIN Media GmbH, 1993.
5. J. Thonstad, T.A. Utigard and H. Vogt, On the anode effect in aluminum electrolysis, *Essential Readings in Light Metals* 2016, 131–138. https://doi.org/10.1007/978-3-319-48156-2_18
6. David S. Wong, Alton T. Tabereaux and Pascal M. Lavoie, Anode effect phenomena during conventional AEs, low voltage propagating AEs & non-propagating AEs, *Light Metals* 2014, 529–534. https://doi.org/10.1007/978-3-319-48144-9_90
7. A. Mulder, P. Lavoie and R. Düssel, Effect of early abnormality detection and feed control improvement on reduction cells performance, *Proceedings of the 12th Australasian Aluminium Smelting Technology Conference*, Queenstown, New Zealand, 2018, 2–7 December 2018.
8. Andri Ísak Þórhallsson, Anode effect reduction at Nordural — practical points, *Light Metals* 2015, 539–543. https://doi.org/10.1007/978-3-319-48248-4_90
9. Sylvain Fardeau et al., Statistical evaluation and modeling of the link between anode effects and bath height, and implications for the ALPSYS pot control system, *Light Metals* 2014, 845–850. https://doi.org/10.1002/9781118888438.ch142
10. Ron Kremser et al., Investigation of different measurement techniques for individual anode currents in Hall-Héroult cells, *Proceedings of the 12th Australasian Aluminium Smelting Technology Conference*, Queenstown, New Zealand, 2018, 2–7 December 2018, 2–7 December 2018.
11. Zuguo Chen et al., Anode effect prediction based on collaborative two-dimensional forecast model in aluminum electrolysis production, *Journal of Industrial & Management Optimization* 2019, 15(2), 595–618. https://doi.org/10.3934/jimo.2018060
12. Lukas Dion et al., Preventive treatment of anode effects using on-line individual anode current monitoring, *Light Metals* 2017, 509–517. https://doi.org/10.1007/978-3-319-51541-0_64
13. C. Cheung et al., Frequency response analysis of anode current signals as a diagnostic aid for detecting approaching anode effects in aluminum smelting cells, *Light Metals* 2003, 887–892. https://doi.org/10.1002/9781118663189.ch151
14. Fernando Pestana da Costa et al., Computer algorithm to predict anode effect events, *Light Metals* 2012, 655–656. https://doi.org/10.1007/978-3-319-48179-1_112
15. A. Wilson, M. Illingworth and M. Pearman, Anode effect prediction and pre-emptive treatment at Pacific Aluminium, *Proceedings of the 12th Australasian Aluminium Smelting Technology Conference*, Queenstown, New Zealand, 2018, 2–7 December 2018.
16. Yu Zhang, Study on anode effect prediction of aluminium reduction applying wavelet packet transform, *Proceedings of 6th International Conference on Intelligent Computing*, China, August, 2010, August 18-21, 2010, 477–484. https://doi.org/10.1007/978-3-642-14831-6_62

17. Nazatul Abd Majid, *Cascade fault detection and diagnosis for the aluminium smelting process using multivariate statistical techniques*, PhD Thesis, The University of Auckland, 2011. http://api.digitalnz.org/records/30143110/source
18. Zhixin Zhang et al., Anode effect prediction based on expectation maximization and XGBoost model, *Proceedings of the 2018 IEEE 7th Data Driven Control and Learning Systems Conference*, Enshi, China, 2018, 25–27 May 2018, 560–564. https://doi.org/10.1109/ddcls.2018.8516046
19. Ron Kremser et al., Anode effect prediction in Hall-Héroult cells using time series characteristics, *Applied Sciences* 2020, 10, 9050. https://doi.org/10.3390/app10249050