

Real-Time Cathode Voltage Drop (CVD) Analytics in Aditya Potline

Anish Das¹, Himan Kundu², Anshu Mangal³, Prateek Lath⁴ and Kapil Kumar⁵

1. Head, Potline Process Control

2. Data Analyst

3, 5. Potline Process In-charge

4. Lead Automation, Upstream, Metals

Aditya Aluminium – Hindalco Industries, Lapanga, India

Corresponding author: anish.d@adityabirla.com

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Abstract

Aditya Aluminium, a state-of-the-art AP-30 smelter with a capacity of 370 kt/a, ranks 2nd globally in metal purity among AP-30 smelters. Located in Odisha, India, the smelter emphasizes precise control over various parameters to ensure metal quality and competitiveness in the energy-intensive aluminium smelting process. Any deviations can lead to significant energy and productivity losses.

Aluminium smelting is a highly energy-intensive process, with energy consumption a major driver. Cathode voltage drop (CVD) is the voltage drop across the cathode carbon block to the end of collector bars in the pot. As CVD increases in pots, it may lead to pot voltage increase and squeezed anode-cathode distance (ACD) which decreases current efficiency. ALPSYS process control compensates CVD increase with pot voltage adder, in order to avoid ACD squeezing, which increases energy consumption. This study presents a real-time potline CVD monitoring, Analytics, and Root Cause Analysis (RCA) tool developed for Aditya Smelter, to decrease CVD and energy consumption, and increase pot life.

The proposed solution uses a data-driven approach by creation of digital thread (data pipeline), integrating real-time process monitoring, statistical analysis, and predictive analytics to identify high-CVD pots at an early stage. A five-step methodology was implemented, covering data engineering, multi-linear regression analysis for causal factor identification, and the development of an interactive analytical dashboard using open-source tools like Python NumPy [1] and Streamlit [2] Integrated Development Environment (IDE). Key influencing factors, such as cathode block type, collector bar variations, and process conditions, were analysed to determine their impact on CVD trends over different pot age groups. The deployment of this tool has led to a 30 % reduction in recurring high-CVD pots and energy savings of 78 kWh/t Al. Additionally, automation has resulted in a monthly reduction of over 15 hours of manual work

Keywords: Cathodic voltage drop, Root cause analysis, Multi-linear regression, Energy savings, Data driven decisions.

1. Introduction

In the modern aluminium production, optimizing energy consumption is a critical and continuous operational priority due to its substantial influence on overall production cost and environmental impact. Among the multitude of parameters influencing the efficiency of the aluminium smelting process, CVD stands out as a pivotal indicator. CVD is directly influenced by factors such as cathode wear and contact resistance between carbon and steel collector bars in the cathode blocks.

As aluminium is produced through an energy-intensive electrolytic process (Hall-Héroult process), any increase in electrical resistance in the cathode translates to higher DC energy

consumption. A high CVD thus implies an inefficient energy profile, which not only inflates operational costs but also exacerbates cathode deterioration, accelerates pot failure, and undermines overall process sustainability.

While it is understood that CVD naturally trends upward with pot age due to gradual material degradation and thermal stresses, the occurrence of abnormally high CVD in younger pots (low-age pots) is a matter of significant concern. These sporadic and recurring high-CVD behaviours often point toward latent process inefficiencies, equipment faults, or suboptimal operational practices. If left unaddressed, such anomalies can cascade into larger systemic issues, such as premature pot failure, reduced current efficiency, and heightened maintenance frequency.

Traditionally, CVD monitoring has been conducted through periodic measurements and manual review, often after threshold violations have occurred. This reactive approach lacks precision, timeliness, and context-specific insights required to drive meaningful process interventions. Furthermore, the sheer volume and velocity of production data render manual methods both time-consuming and prone to oversight.

To overcome these challenges, this paper introduces a comprehensive, data-driven digital platform for real-time CVD monitoring and root cause analysis. The manual method of CVD measurement remained in place after the implementation of this project, typically measuring all pots once per week. Developed entirely in-house at Aditya Aluminium, Hindalco Industries, the new system integrates automated data acquisition, statistical analysis, and machine learning techniques within an intuitive Streamlit-based UI. This platform empowers plant personnel with timely alerts, historical trend visualizations, predictive insights, and actionable diagnostics, enabling faster and more informed decision-making.

The objective is not merely to detect high CVD events but to transform the way pot health is understood and managed, shifting from a reactive paradigm to a predictive and preventive approach. By embedding analytics at the core of potline operations, the solution aims to enhance energy efficiency, reduce unplanned downtime, and improve the overall performance of the smelting process.

2. Problem Statement and Objectives

2.1 Challenges

CVD trends are impacted by pot age, making it difficult to distinguish between natural and abnormal rises. Manual reports lead to delays in identifying high-risk pots and existent high CVD in some pots goes unnoticed, affecting efficiency.

2.2 Objectives

The following objectives were set at the start:

- Develop a real-time monitoring tool to track pot-wise CVD.
- Identify young pots (age < 1000 days) with abnormally high CVD.
- Compare recurring vs. non-recurring high-CVD patterns.
- Enable root cause identification and suggest corrective actions.
- Deliver insights to shop floor personnel through automated alerts and intuitive dashboards.

3. Methodology

The solution was structured around a five-step analytical pipeline:

3.1 Data Engineering

Raw data from plant-level systems were ingested and cleaned for consistency. Timestamp synchronization, missing value imputation, and data normalization were key preprocessing steps.

3.2 Analytical Modelling

A combination of statistical models and domain-specific rules were used:

1. Multi-linear regression identified significant predictors of CVD.
2. Time series decomposition analysed long-term trends and seasonal patterns.
3. Correlation matrices helped explore relationships among process parameters.

3.3 Visualization and Dashboards

Using Streamlit, an open-source Python library, a responsive UI was developed. Key features included:

- Cathode block and age-group wise recurring High CVD Pots tracking panel.
- 21-days behaviour tracking window for the recurring pots based on process-based actions
- Comparative reports for same cathode block and age-group-recurring vs non-recurring pots
- Potline process parameters deviation ranges with respect to CVD variations

3.4 User Acceptance Testing (UAT)

UAT was conducted with plant engineers and process in charges. Iterative feedback was incorporated to enhance UI usability and model relevance.

3.5 Adoption and Scale-Up

Automated daily mail-based reports to process in-chargers reporting key identified focus pots and deviations from normal behaviour.

OLS Regression Results			
Dep. Variable:	Cathode_Resistance_Latest	R-squared:	0.656
Model:	OLS	Adj. R-squared:	0.614
Method:	Least Squares	F-statistic:	15.54
Date:	Sat, 18 May 2024	Prob (F-statistic):	1.60e-234
Time:	10:26:28	Log-Likelihood:	3466.4
No. Observations:	1639	ATC:	-6573.
Df Residuals:	1459	BIC:	-5600.
Df Model:	179		
Covariance Type:	nonrobust		

Figure 1. Regression summary report for CVD using multiple linear regression

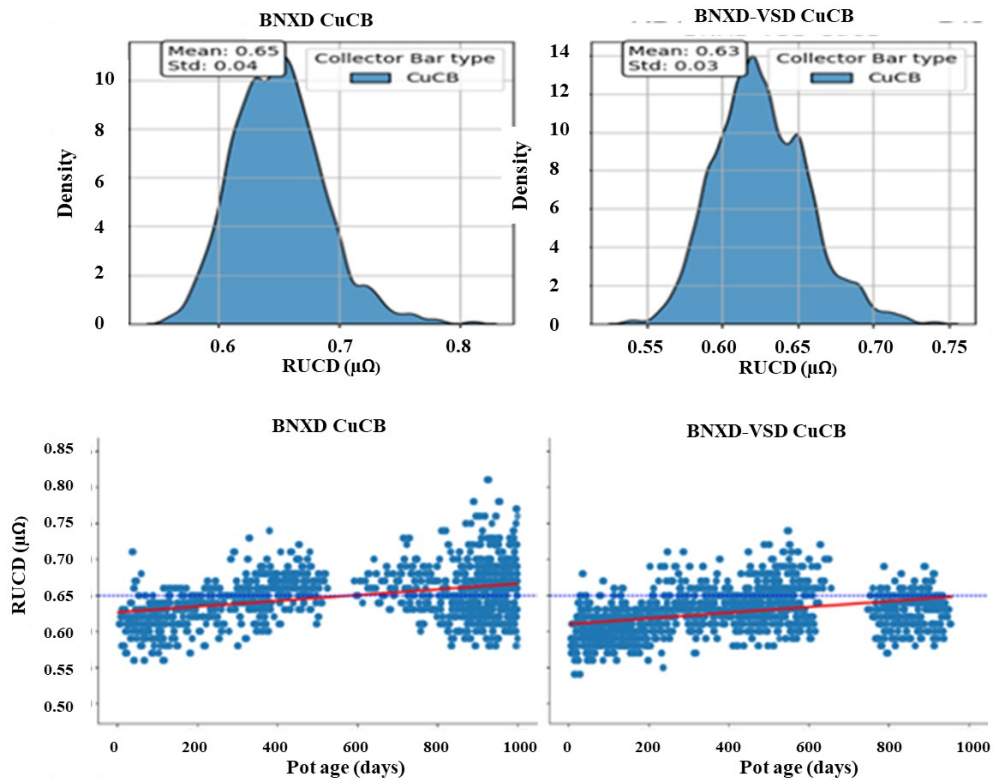


Figure 2. KDE Distribution plots for CVD (RUCD) for different collector bar types (CuCB and VSD) and scatterplot showing the impact of age on cathode resistance (RUCD) for different cathode blocks

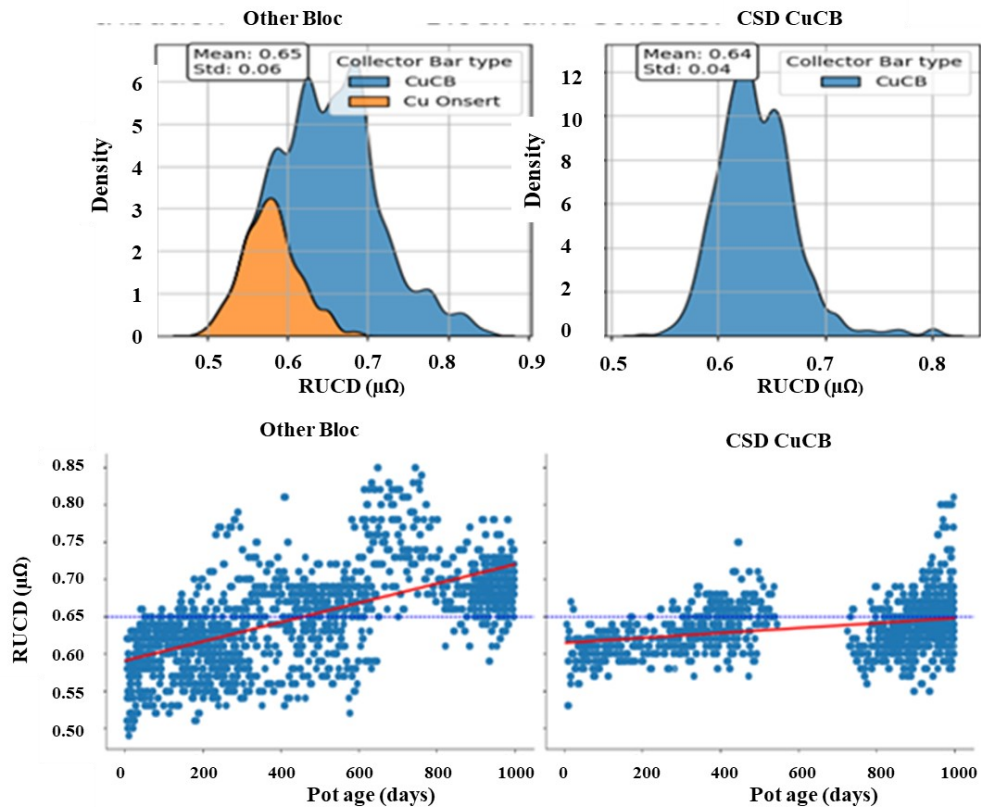


Figure 3. As Figure 1, but here Left: Other Blocks, Right: CSD-CuCB.

4. System Architecture

The system architecture is modular, ensuring scalability and ease of maintenance:

1. **Back-end:** Python scripts for data extraction, preprocessing, and modelling.
2. **Middleware:** Automated job schedulers and alert mailers to relevant stakeholders and end-users.
3. **Front-end:** Streamlit dashboards accessible to-shop floor personnel and supervisors.

The design supports real-time data processing and daily auto-email alerts that highlight high-CVD occurrences and potential root causes.

5. Results and Business Impact

5.1 Quantitative Benefits

The recurring number of high CVD ($\geq 0.7 \mu\Omega$) pots decreased by 30 % (Figure 4). The most important KPIs are shown in Table 1. The average CVD decrease 7 mV but the pot voltage was decreased by 12 mV. Moreover, the current efficiency increased by 0.28 %, so that the specific energy consumption decreased by 78 kWh/t Al. Besides that, 15 man-hours per month of manual work was saved due to higher automation of potline data analysis.

Table 1. Quantitative benefits: Potline KPIs before and after project implementation. The data are average of 3 months before and 3 months after.

KPI	Unit	Before	After	Difference
Current	kA	372.94	373.12	+0.17
Net pot voltage	V	4.229	4.217	-0.012
Current efficiency	%	94.24	94.52	+0.28
Specific DC energy consumption	kWh/t Al	13 373	13 295	-78
CVD	mV	253	246	-7

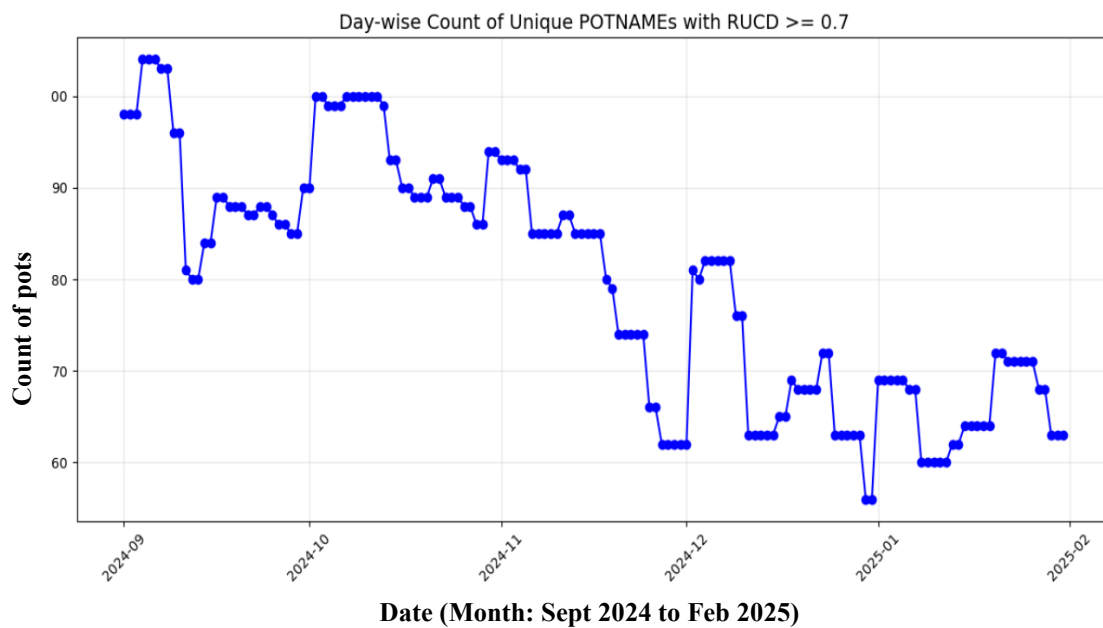


Figure 4. Day-wise number of pots with cathode resistance $\geq 0.7 \mu\Omega$.

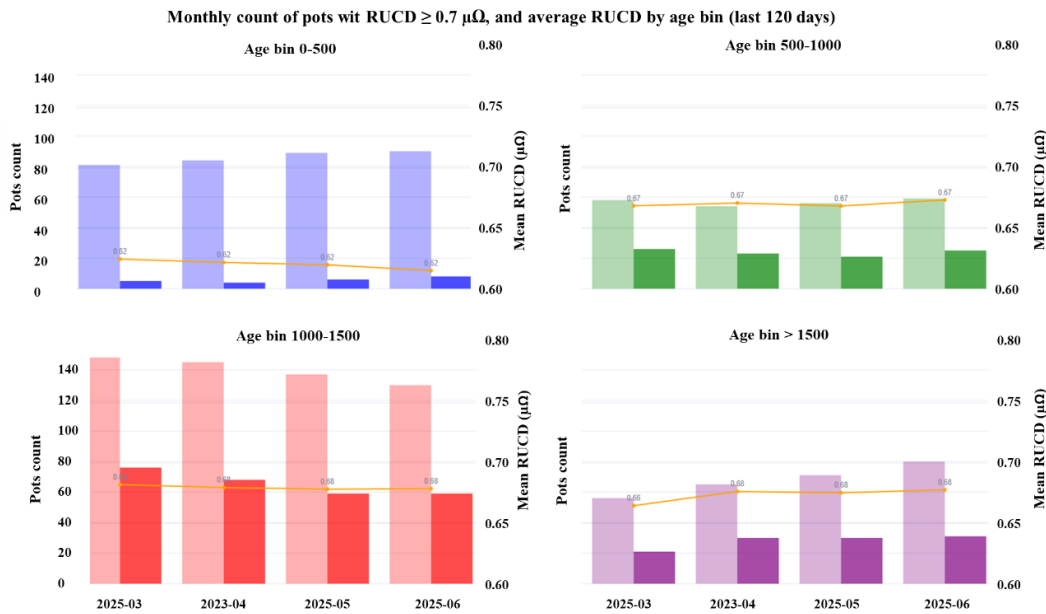


Figure 5. The count of pots in high CVD Zone ($RUCD \geq 0.7 \mu\Omega$) amongst all the operating pots in that age bracket and the trendline shows the mean RUCD monthly average in that age group. Pale colour: before, intense colour: after. The yellow line is RUCD.

5.2 Qualitative Benefits

The following qualitative benefits were achieved:

1. Data democratization through easy-to-use dashboards.
2. Historical trend analysis - improved process transparency.
3. Early identification of at-risk pots enabled timely interventions.

Figures 6 to 9 show examples of program display on the computer screen.

Table: List of all recurring POTs with high CVD and new edits in the table

Cathode Block	POTAGE_Binned	Recurring_Pots_3_W	List_Pots_21_D_Mean	New_Occurrence_15_D	Non_Occurrence_15_D	New_Occurrence_7_D	Non_Occurrence_7_D	Collector Bar type	Collector bar supplier
Alubase CuCB	500-1000	A050(791)	A050(791)	-	-	-	-	CuCB	Chandi
Alubase CuCB	>1500	B126(1583)	B126(1583)	-	-	-	-	CuCB	Tata
BNXD CuCB	1000-1500	A108(1247), B178(1194), A029(1055), B127(1218), B131(1475), A133(1311), B102(1250)	A110(1257), B178(1194), B127(1218), A108(1247), A029(1055), B131(1475), A133(1311), B094(1281), B102(1250), B125(1449)	-	-	-	B094(1281), B125(1449), A110(1257)	CuCB	Chandi, Tata
BNXD CuCB	>1500	A179(1542), B130(1521), B129(1503)	A179(1542), B130(1521), A129(1779), B129(1503), B133(1526)	A122(1538)	A129(1779), B133(1526)	A171(1830)	A122(1538)	CuCB	Chandi, Tata
BNXD-VSD CuCB	>1500	A126(1660)	A126(1660)	-	-	-	-	CuCB	Tata
CSD CuCB	1000-1500	B135(1286), A116(1296), B128(1305), B134(1322), B124(1477), A132(1291), A134(1346)	B135(1286), A116(1296), B128(1305), B134(1322), B124(1477), A125(1428), A132(1291), A134(1346)	-	A125(1428)	-	-	CuCB	Chandi, Tata

Figure 6. Dynamic tracking window of 21-days for identification of the recurring high CVD pots; behaviour tracing of pots based on their occurrence and non-occurrence in the 14- and 7-days windows.

Comparison for Cathode Block: Alubase CuCB, Age Bin: >1500, Pot: All Recurring Pots

Comparison Results for Recurring vs. Non-Recurring POTs in the Same Age-Bin and Cathode Block

Cathode Block	POTAGE Binned	Parameter to Compare	Recurring Pots Mean	Other Pots Mean	Recurring Pots Count	Other Pots Count	Normal Range
Alubase CuCB	>1500	NDAL2O3	4697.409091	5267.500000	1	2	5300-5500
Alubase CuCB	>1500	ALF3D	9.509091	11.736364	1	2	11-12.5
Alubase CuCB	>1500	RKM	6.716182	6.647302	1	2	6.69-6.74
Alubase CuCB	>1500	RUCD	0.728636	0.664773	1	2	0.6-0.7
Alubase CuCB	>1500	SURCH	7.575764	11.825757	1	2	7-12
Alubase CuCB	>1500	TBD	969.772727	963.204545	1	2	960-965
Alubase CuCB	>1500	HBD	12.909091	14.977273	1	2	16.0-18.0
Alubase CuCB	>1500	HMD	20.136364	20.477273	1	2	18.0-20.0
Alubase CuCB	>1500	RS	6.630000	6.585000	1	2	6.55-6.6
Alubase CuCB	>1500	WRMI	50.348432	49.541591	1	2	60-65
Alubase CuCB	>1500	SOUSAL	26.142636	30.139759	1	2	26.5-28.0
Alubase CuCB	>1500	KALIMMT	100.422727	99.550000	1	2	97.0-98.0
Alubase CuCB	>1500	DPFC	11.133333	11.193548	1	2	10.5-11
Alubase CuCB	>1500	DPFP	16.815876	12.968991	1	2	14-16
Alubase CuCB	>1500	NTEA	0.045455	0.204545	1	2	0.0-0.3

Figure 7. The table in the summary provides the end-user a dynamic UI to compare the process parameters for the recurring and non-recurring pots in the same cathode block and pot age group.

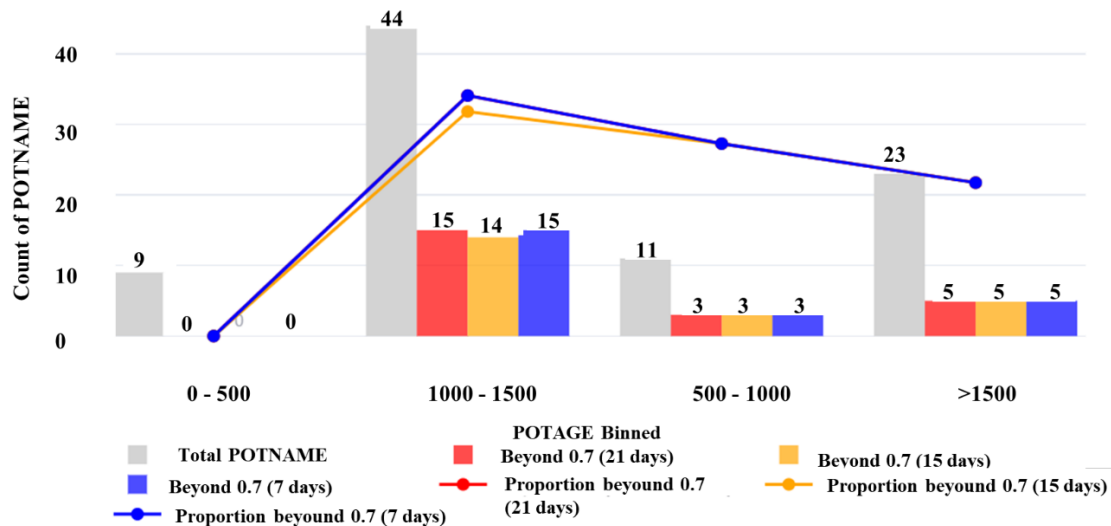


Figure 8. Graphical representation of the 21-days tracking window table for pots behaviour and count in the 7-days, 14-days and 21-days window for different cathode block types. If a pot exists in the high CVD zone ($\geq 0.7 \mu\Omega$) in all the 3 averages, it is counted there. Analysis for BNXD CUCD. Based on block types and age bins: Proportion of pots with CVD beyond $0.7 \mu\Omega$.

Deviation Matrix - Parameter-wise as per Domain Operating Ranges

POTNAME	NDAL2O3	ALF3D	RKM	RUCD	SURCH	TBD	HBD	HMD	RS	WRMI	SOUSAL	KALIMMI	DPFC	DPFP	NTEA
B126	▼ 602.591	▼ 1.491	In-Range	▲ 0.029	In-Range	▲ 4.773	▼ 3.091	▲ 0.136	▲ 0.03	▼ 9.652	▼ 0.357	▲ 2.423	▲ 0.133	▲ 0.816	In-Range

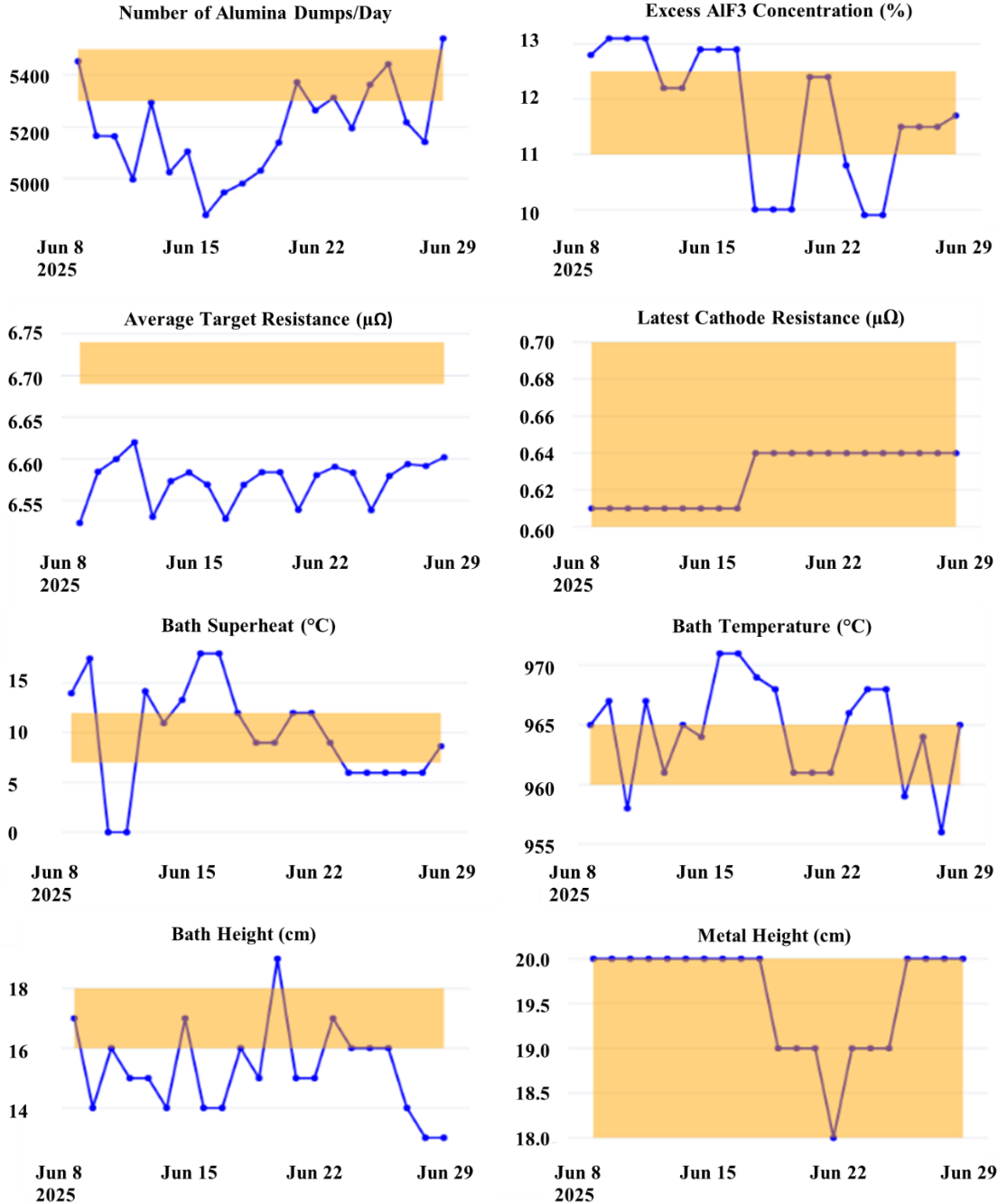


Figure 9. Graphical representation of the last 30 days trend of process parameters and identification of the deviation zones beyond the domain specific operational normal ranges (yellow). Taken from Dashboard.

6. System Adoption and Sustainability

To ensure adoption and sustainability, the following steps were implemented:

- **Training sessions:** Conducted for process in-charges and technical staff.
- **Mailer integration:** Daily alert mails for quick action on anomalies.
- **Scalability:** Architecture designed to be replicated across Hindalco's other smelter locations like Mahan, Hirakud, and Renukoot.

7. Conclusions

The in-house developed real-time CVD analytics tool has demonstrated measurable benefits in energy savings, process transparency, and shop-floor responsiveness. With the integration of analytical logic and user-centric design, the system provides actionable insights, aiding timely decision-making. The platform sets a benchmark for digital transformation in energy-intensive process industries and is now a model for other smelters in Hindalco.

8. Acknowledgements

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9. References

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