Anode Spike Model - A Case Study of Challenges and Future Directions

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Abstract

In 2020, Emirates Global Aluminium (EGA) leveraged Industry 4.0 technologies to develop a predictive model using big data and machine learning for detecting anode spikes, a critical aspect of aluminium production. Despite its innovative approach, the implementation faced significant challenges, including variability in adherence to model predictions by potroom employees, and a noticeable degradation in model accuracy and model drift over time due to changing operating conditions and operational parameters, such as amperage fluctuations. Model drift, a common issue in machine learning, occurs when the predictive performance degrades as the underlying data patterns change, necessitating continuous model evaluation and updating.

Addressing these challenges, this paper underscores the importance of adaptive change management strategies in the era of digital transformation, particularly within the context of Industry 4.0 technology integration. Through a comprehensive case study of EGA's technological adoption of anode spike models in Al Taweelah DX and Jebel Ali D20 technologies, we explore the impact of model drift and the essential role of iterative model recalibration and employee engagement in maintaining the efficacy of such digital solutions.

Key to our findings is the application of a dynamic adaptation strategy to manage model drift, ensuring that predictive models remain accurate and sustainable amidst evolving operational conditions. This approach facilitated smoother transitions and significantly mitigated resistance among potroom employees, enhancing overall acceptance and effectiveness of the deployed Industry 4.0 solutions.

Keywords: Industry 4.0, Anode spike prediction model, Change management, Model drift, Sustainability.

1. Introduction

Emirates Global Aluminium (EGA) stands as the globe's foremost producer of 'premium aluminium' and holds the distinction of being the largest industrial entity in the United Arab Emirates, excluding the oil and gas sector. This study delves into the challenges and reservations encountered during the integration of Anode Spike Soft Sensors by personnel in the potroom, coupled with the issue of model inaccuracy over time. These obstacles are examined within the framework of addressing crucial operational issues associated with the timely identification of anode spikes as they occur.

The Anode Spike Model was seamlessly integrated with state-of-the-art technology in EGA as presented in ICSOBA 2022 [1]. However, the evaluation of its performance and efficacy lacked comprehensive monitoring. This deficiency persisted as the model effectiveness remained contingent on the proactive engagement of shop floor employees. The graph below illustrates the impact of checking compliance on detection accuracy for D20 technology. Notably, a single model was utilised for two potlines, both equipped with the same technology. While the model performance showed similarity during the initial deployment phase, it gradually diverged across both potlines in distinct manners. In Potline 7 (L7), initial checking compliance experienced a decline, mirroring the subsequent decrease in model detection accuracy. However, the model performance began to fluctuate again (Figure 1), despite checking compliance maintaining a consistent level of around 60 %, falling short of the target of 80 %.

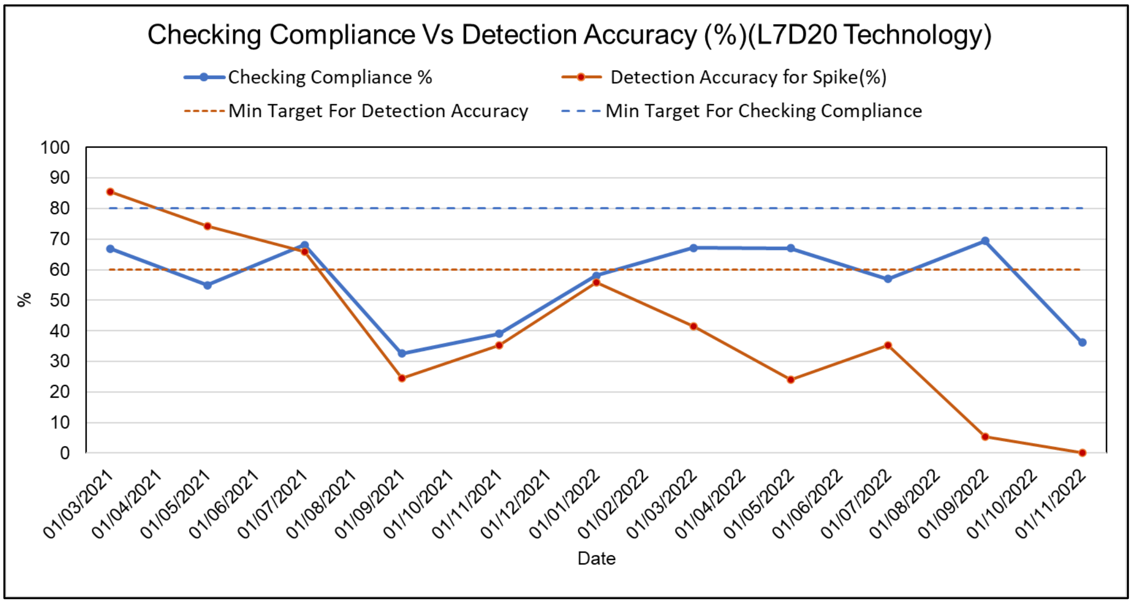

Figure 1. Line7 (D20) potline checking and detection accuracy.

During October-November 2021, Potline 9 (L9) witnessed a decline in checking compliance, which corresponded to a subsequent decrease in model detection accuracy. Nevertheless, the model performance started to show signs of improvement as the checking compliance level reached around 75 % (Figure 2).

The graph depicted in Figure 3 shows the accuracy trend for DX potlines, exemplifying a typical case of model degradation over time, despite never meeting the established target for checking accuracy.

As we delve deeper into understanding why employees are not complying with the checking procedures, it becomes evident that their reluctance stems from doubts about the accuracy and reliability of modern technology. They harbour concerns about potential errors or inaccuracies in predictive models or automated systems, which breeds scepticism and resistance to adopting change. Moreover, there is apprehension about the additional workload and potential for rework that comes with early flags or alerts generated by these models. Such interruptions could disrupt established workflows, necessitating extra time and effort to resolve issues, so it was decided to do an analysis which will clarify the reason for checking noncompliance and enhance customer satisfaction.

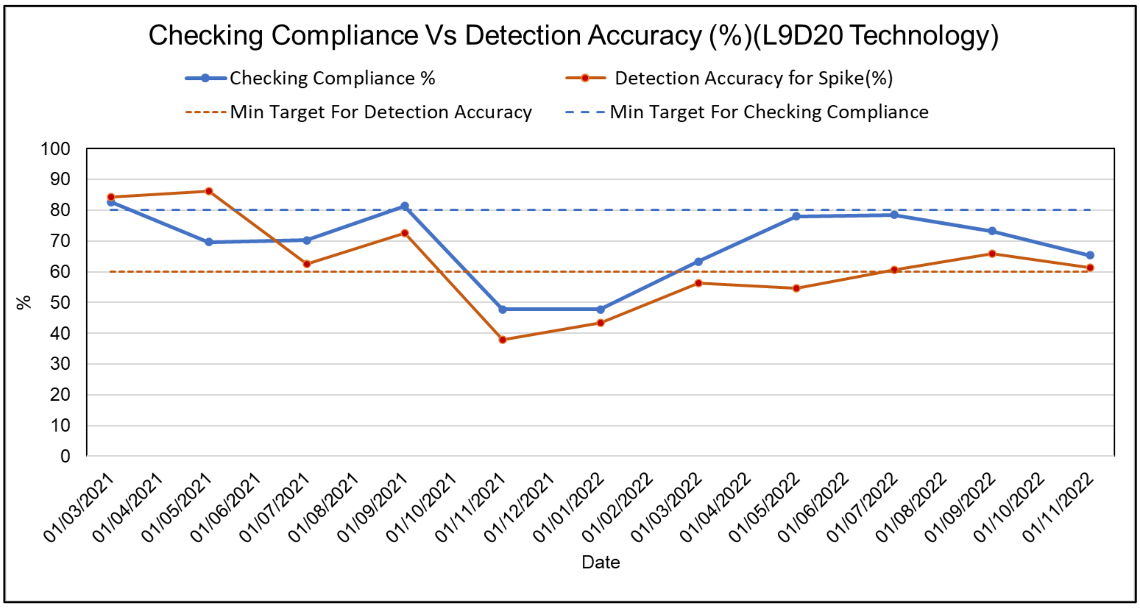

Figure 2. Line 9 (D20) potline checking and detection accuracy.

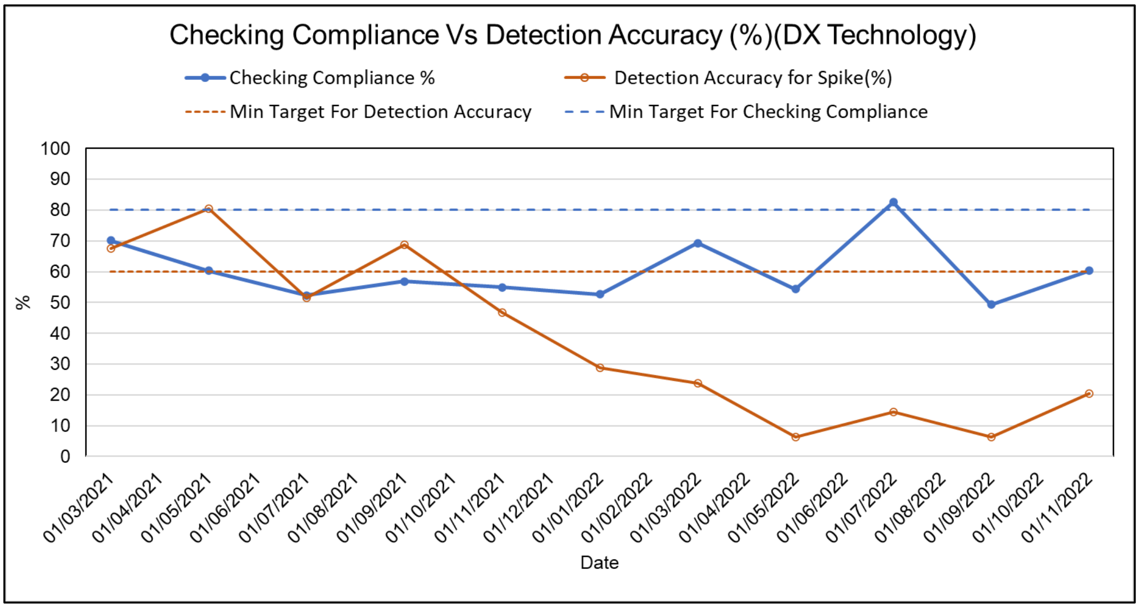

Figure 3. DX potline checking and detection accuracy.

One shocking fact about change management in the context of Industry 4.0 (I4.0) is that despite the transformative potential of technology, approximately 70 % of digital transformation initiatives fail due to resistance to change and inadequate change management strategies [2]. After extensive brainstorming sessions and data analysis involving the potroom, process control, and I4.0 teams, the primary four challenges faced by I4.0 at EGA are:

1) Addressing model performance affected by data drift.
2) Executing change management strategies.
3) Performance tracking systems are challenging to monitor.
4) The clarity of the work effort at baseline was lacking.

EGA initiated efforts to address the aforementioned issues in a sustainable manner, aiming to provide long-term solutions.

2. Model Retraining

Model retraining proves crucial in machine learning, exemplified by the experience of EGA. As the model evolves over time, certain potlines exhibit a drift in accuracy following any alteration in potline parameters. Upon analysis, potential reasons for the model inaccuracy included amperage increase, anode size change, and variations in anode properties. These changes detrimentally impacted on the model accuracy due to its lack of training on data representing these updated conditions.

The primary aim was to construct a model with a long-term solution, ensuring that any adjustments to parameters would not affect its performance. Additionally, there was a focus on implementing continuous retraining of the model with new datasets periodically, thus enabling the model to always incorporate the latest metrics, which may not have been available during the initial training phase.

It was decided to test a different approach in two technologies.

1) Tweak in parameters according to amperage change (D20 technology).
2) Right data labelling to handle problem of observation bias and engineer new features stable to data drift (DX technology).
3) Periodic model retraining to prevent model drift (DX technology).

2.1 Data Drift

Models are trained on historical data and the potline amperage and other critical metrics related to amperage may vary depending on the line target, which is subject to process and management decisions.

- Examples of the magnitude of parameters change causing data drift for D20 and DX technology are shown in Figures 4-7.

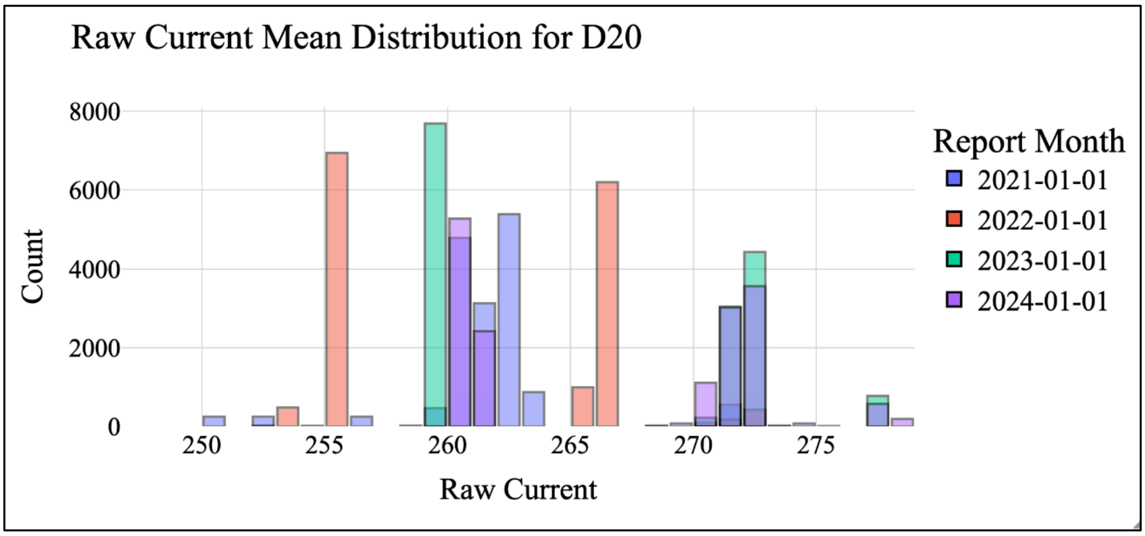

Figure 4. D20 amperage distribution with timeline.

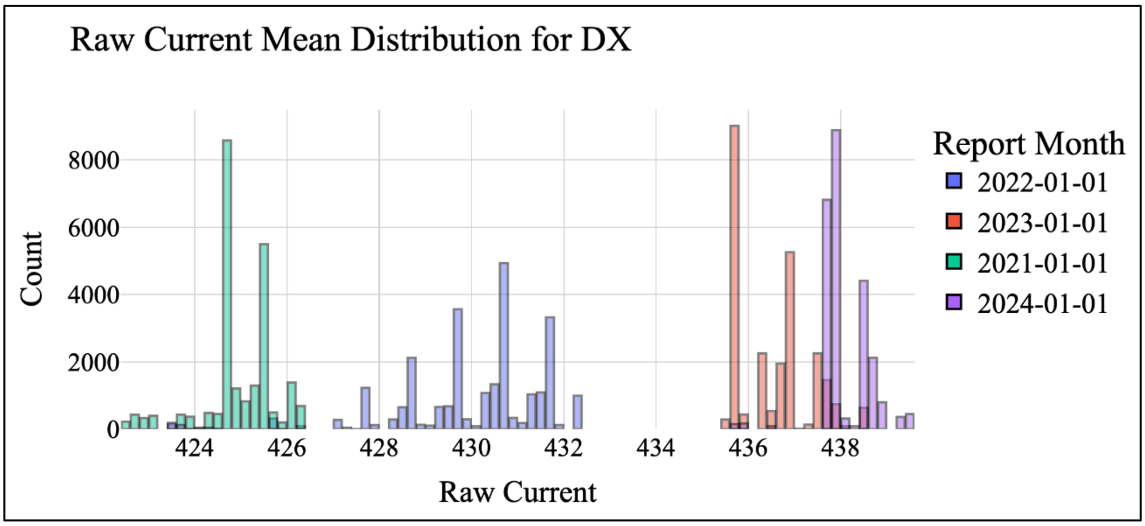

Figure 5. DX amperage distribution with timeline.

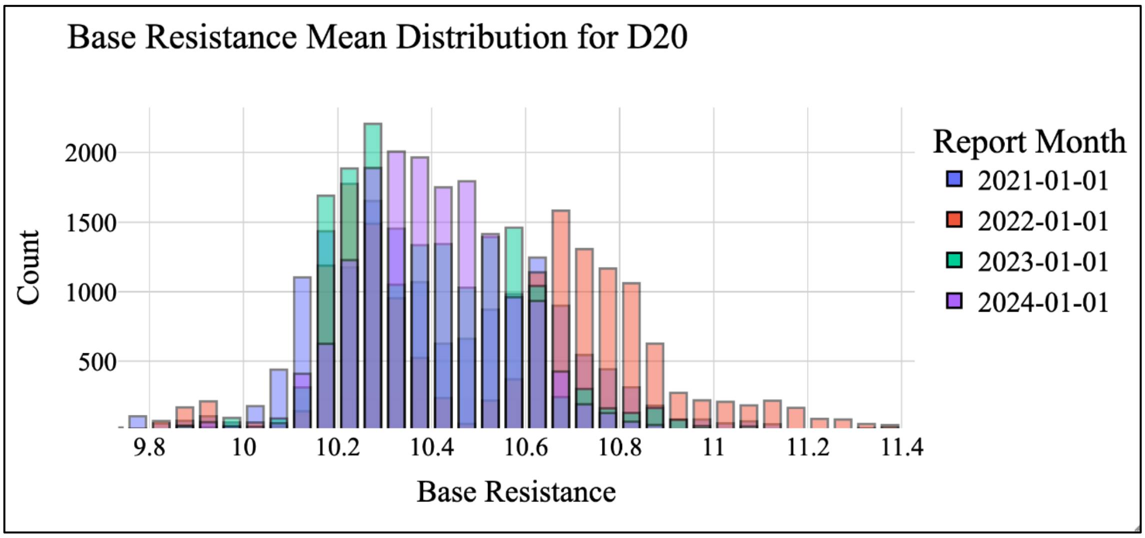

Figure 6. D20 cell resistance distribution with timeline.

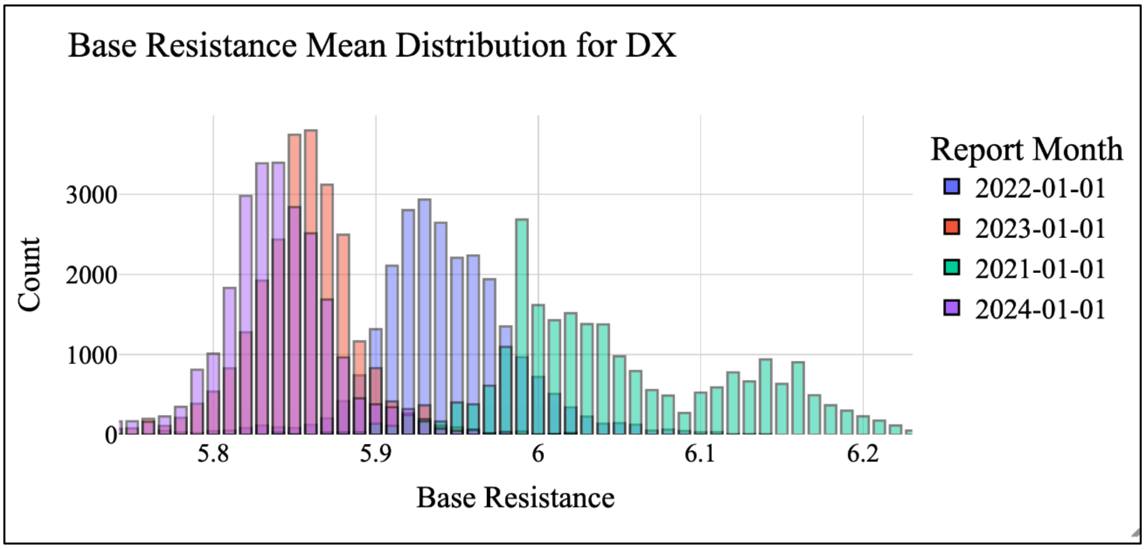

Figure 7. DX cell resistance distribution with timeline.

2.2 Retraining Approach in D20 Technology

EGA D20 technology consists of two lines: L7 and L9, the initial goal was to understand the differences in spike model performance between the two lines. Figure 8 illustrates the accuracy of spike detection model in D20 technology between two lines, with each line showing distinct performance characteristics. L9 model consistently detected spikes, whereas L7 model showed gradual decline in performance over several months, ultimately resulting in zero spike detection.

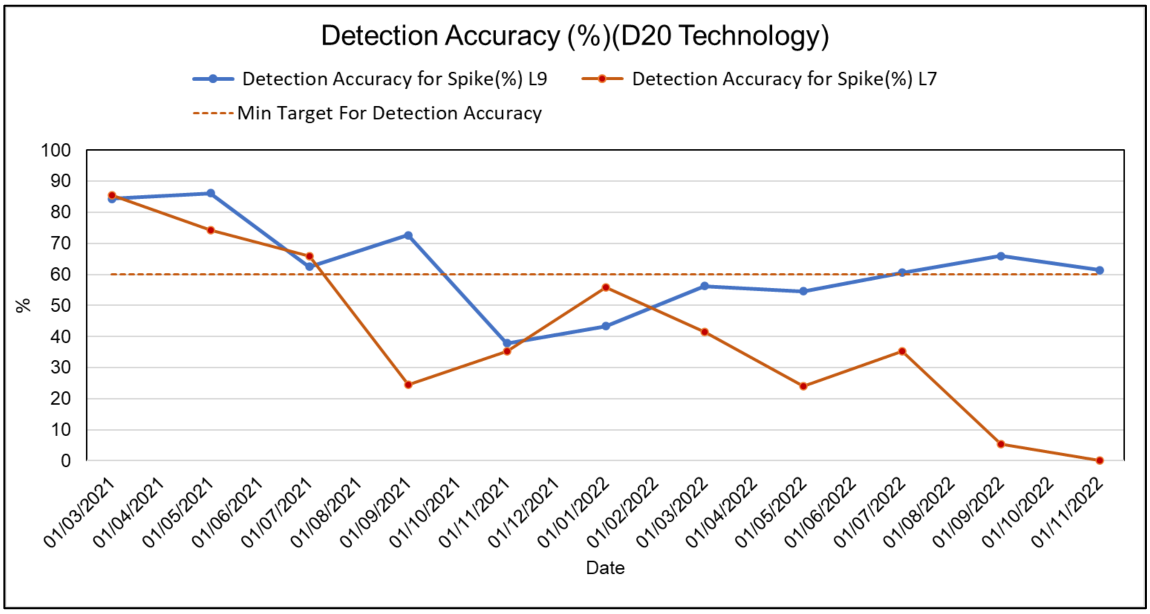

Figure 8. D20 potline detection accuracy.

Initially, the data indicates that the D20 technology model performed comparably in both lines during the initial months following its deployment from April 2021 to July 2021. After performing root cause analyses, the main factors that caused the performance gaps were identified as follows:

A) Anode quality in L7 was different than in L9.
B) There was an anode size change in L7.
C) Amperage was increased by approximately 4 % in L7, accompanied by adjustments in related parameters.

Therefore, it was decided to enhance the model resilience against parameter and raw material variations by retraining it.

2.3 Data Engineering

The inputs to the model were reassessed and data engineering done to ensure robust performance despite changes in operating parameters and raw materials.

An example of this data engineering technique involves the association of parameters in the model. For instance, the absolute value of alumina input in the cell is directly influenced by the amperage. Consequently, instead of solely relying on the number of dumps, the model was adjusted to consider the number of dumps per amperage. Table 1 shows the actual data for L7 with respect to amperage and normalisation.

Table 1. Example of data engineering.

Line	Date	Amperage (kA)	Alumina quantity (Dumps)	Alumina quantity per amperage (Dumps/kA)
L7	12/11/2021	265.1	2191	8.3
L7	19/11/2021	266	2185	8.2
L7	26/11/2021	266	2199	8.3
L7	03/12/2021	266	2184	8.2
L7	10/12/2021	266	2180	8.2
L7	17/12/2021	266	2188	8.2
L7	24/12/2021	265.5	2191	8.3
L7	31/12/2021	266	2185	8.2
L7	07/01/2022	266.4	2199	8.3
L7	14/01/2022	261.3	2144	8.2
L7	21/01/2022	267	2180	8.2
L7	28/01/2022	267	2188	8.2
L7	04/02/2022	267.3	2199	8.2
L7	11/02/2022	268.2	2228	8.3
L7	18/02/2022	269	2263	8.4
L7	25/02/2022	269.5	2272	8.4
L7	04/03/2022	270	2263	8.4
L7	11/03/2022	270	2244	8.3

Figure 9 illustrates the relationship between amperage and alumina. As amperage ramp-up occurs, the number of alumina dumps increases proportionally. Consequently, it was determined that this feature needed to be engineered more robustly to accommodate such changes. This adjustment ensures that variations in amperage will not adversely affect the model performance.

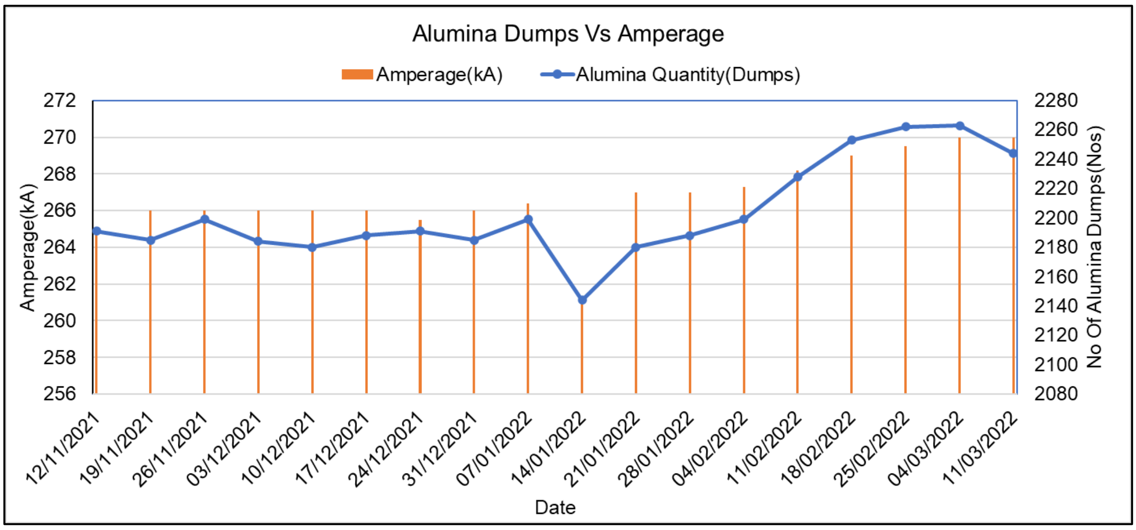

Figure 9. Alumina dumps trend vs amperage with timeline.

Following normalisation, the data shows a much closer resemblance, with the impact of amperage effectively neutralised. Likewise, the quality of the material, including its physical and chemical properties (e.g., bulk density, % F), was utilised in the normalisation process, further enhancing the consistency and reliability of the data. Additionally, anode size and anode current density are added as features. The new, enhanced model is built by retraining (time frame: January 2021 to December 2022) as shown in figure 10.

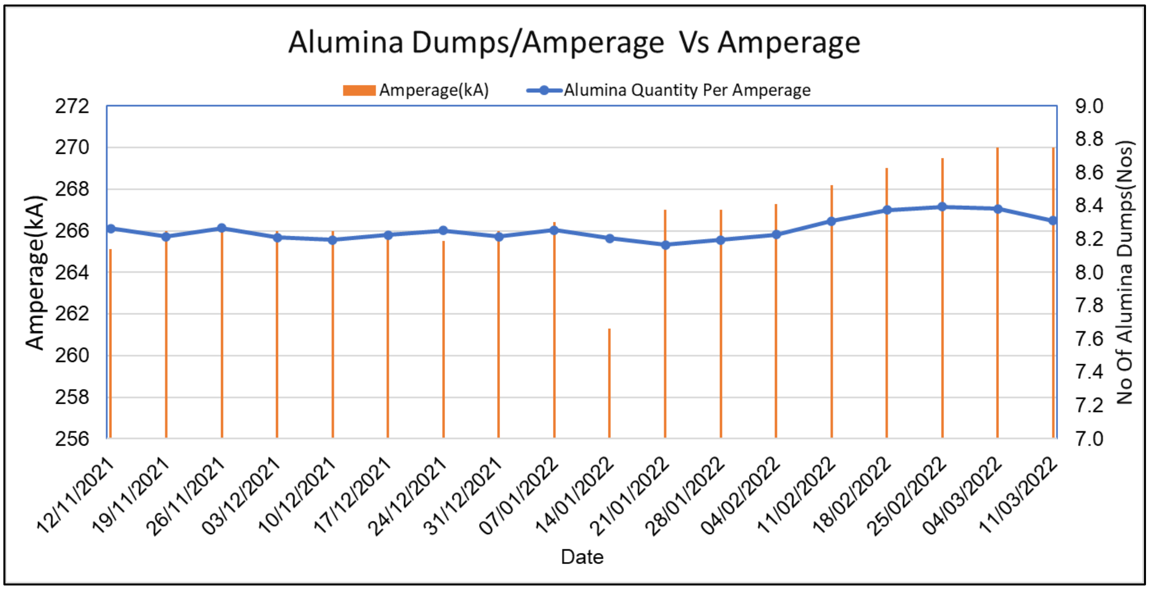

Figure 10. Alumina dumps/kA trend vs amperage with timeline.

2.4 Model Approach:

A comprehensive model was developed to address the challenge of forecasting anode spikes, leveraging feature engineering to mitigate model drift and ensure long-term stability. The examination of L7 spike data indicated that most spikes were scheduled occurrences, resulting in ambiguity regarding the relevant metrics. As a result, the model predictive accuracy was compromised. Moreover, the lower spike frequency in L7, in contrast to L9, presented difficulties in achieving precise predictions. To overcome this hurdle, an auxiliary model incorporating measured bath temperature as a feature was trained. Both models were then integrated into a stacked model framework to enhance anode spike prediction performance.

2.4.1 Results

Table 2 presents results for both the testing and the validation datasets. For L9, the recall was 77 % with a precision of 40 %. For L7, the recall was 76 % with a precision of 31 %, slightly lower than in L9.

Note: In data science, recall represents the ability to accurately detect positive cases, while precision reflects the accuracy of positive case identifications.

Table 2. Model performance during training and testing.

Potline	Total spikes	Model predicted	Recall (%)	Total flags	Precision (%)
L9	1282	982	77	2478	40
L7	512	389	76	1242	31

Following the retraining, utilising the previously outlined data engineering approach, the model demonstrates consistent performance throughout its deployment period, as shown in Figure 11.

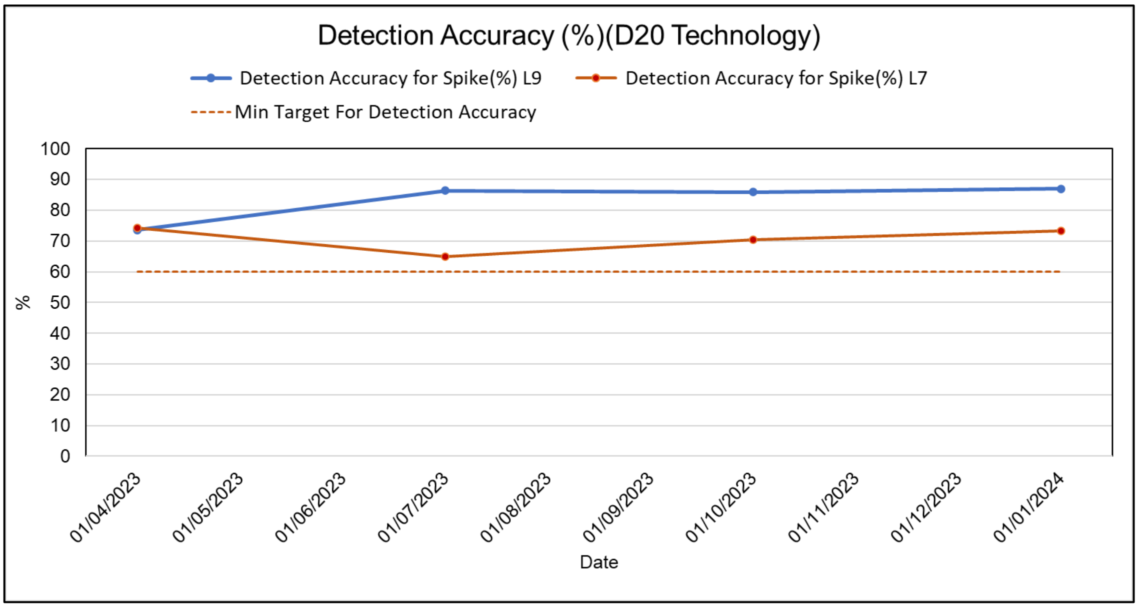

Figure 11. D20 model performance after retraining.

3. Retraining Approach for DX Technology

The development of an accurate anode spike prediction model relies heavily on three key aspects: data labelling, machine learning model selection, and data engineering. In the following sections, we will explore each of these areas in detail, discussing the challenges faced, the solutions implemented, and the results achieved. We will also examine the way forward, proposing steps to further improve the model performance and its impact on the aluminium production process.

3.1 Data Labelling

3.1.1 Reasons for Labelling

The need for data labelling arose from the necessity to improve the quality of existing models. Accurate labelling requires a deep understanding of the smelting process inside the cell. To enhance the labelling process, the team automated heuristic rules to calculate metrics and generate features for improving machine learning models. These rules were implemented using Databricks, as illustrated in Figures 12-13.

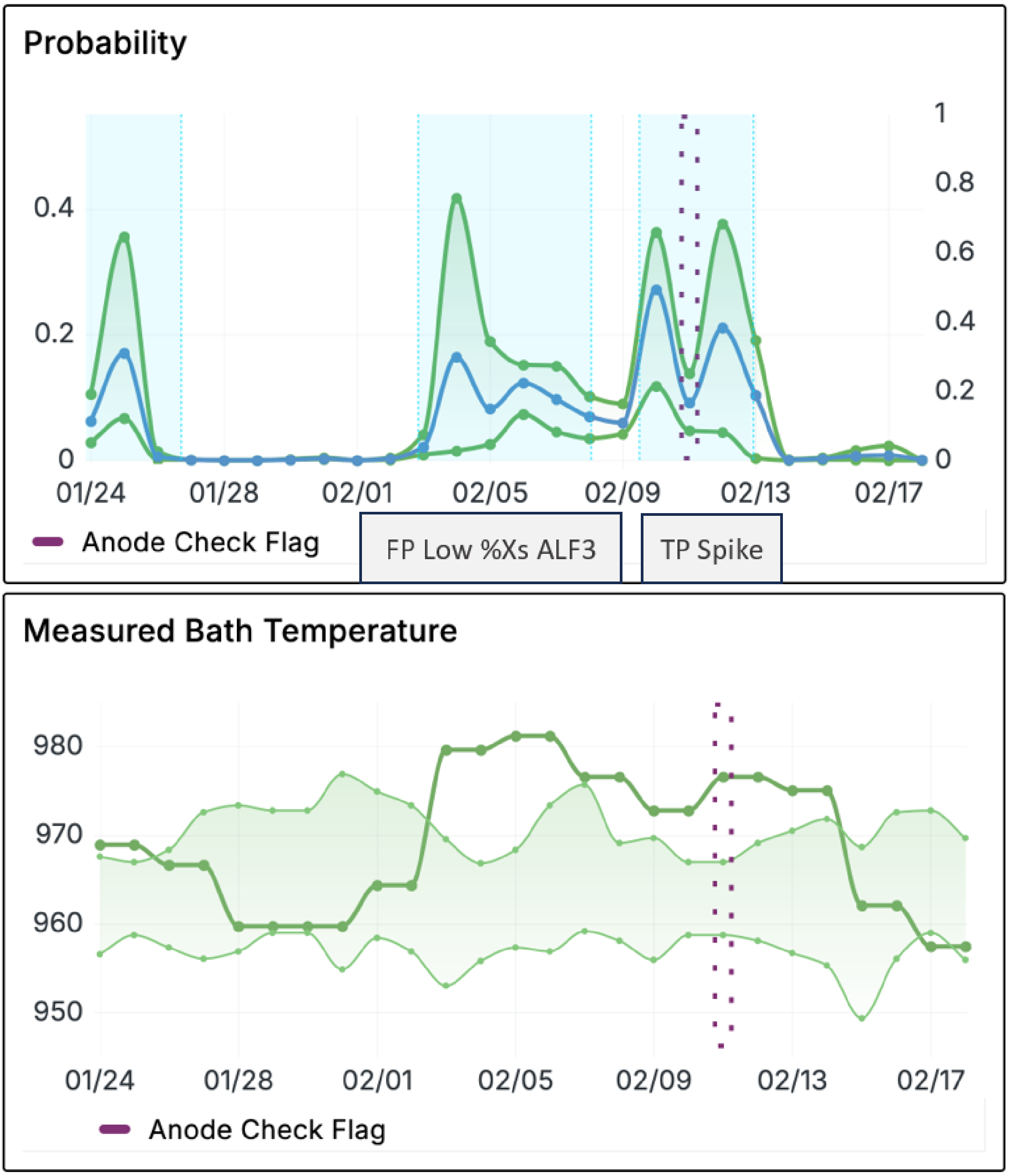

Figure 12. Example of data labelling.

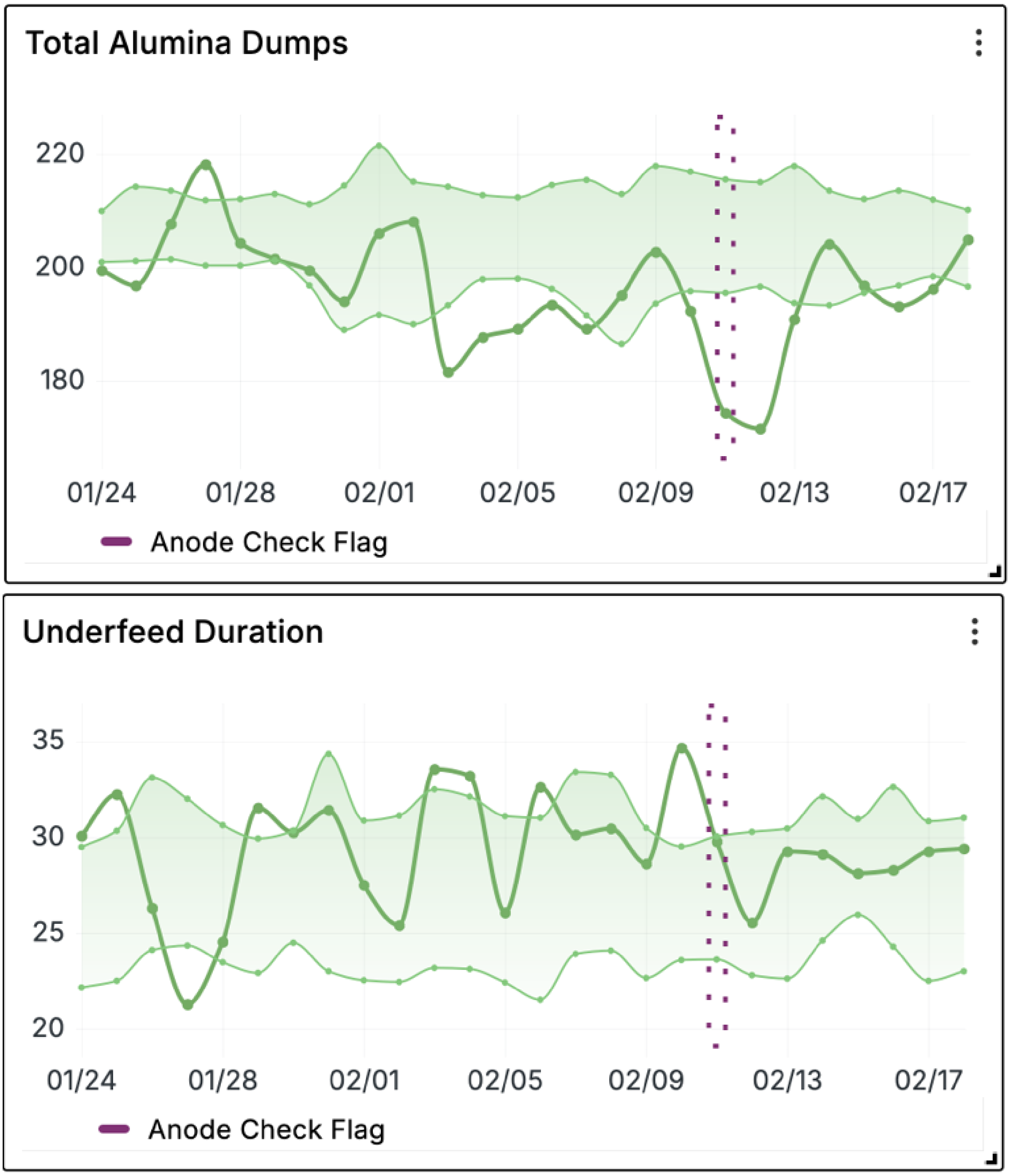

Figure 13. Trend of important features.

3.1.2 Example of Labelling Results

- The labelling process revealed that for 11 % of the cells, there were no visible signals that could be used to predict spikes.
- The baseline model achieved a 70 % precision and recall on the labelled dataset, indicating areas for improvement in the dataset.

3.1.3 Challenges

Formulating requirements for the labelling process proved to be challenging, as there were no tools available that combined rich visualisation capabilities with time series labelling. Additionally, the heuristic rules formulated during the labelling activity required visual pattern recognition, which was difficult to implement using explicit algorithms, thus necessitating the use of machine learning models.

4. Machine Learning Models

4.1 Results

An end-to-end model was developed to address the anode spike prediction problem. Regular retraining was implemented to mitigate the issue of model drift, ensuring the model performance remained stable over time. The team also established monitoring processes for model quality and data drift to maintain the model effectiveness.

4.2 Challenges

One of the main challenges encountered was the inherent bias in the models towards the strategy of the operations team for checking cells. The dataset was also imbalanced, which required careful handling during model development. Implementing distributed machine learning posed additional challenges, as the baseline model developed in low code ML platform did not meet the required performance standards. Furthermore, process parameters changed monthly, causing data to drift, and requiring regular model updates.

Feature engineering proved to be a complex task, demanding a deep understanding of the feeding logic and extensive data processing. The sheer amount of data, spanning four years of minute-level sensor data for thousands of cells and dozens of sensors, added to the complexity. Most of the sensor data was derived from voltage, leading to high cross-correlation between features.

5. Data Engineering

5.1 Results

To streamline data transformation from the cell, a medallion architecture was implemented. The transformations required a deep understanding of the process, and more than one hundred tasks were orchestrated in Databricks to create the dataset for the model.

5.2 Way Forward

To further improve the anode spike prediction model, several steps are proposed. Performing random checks and using the data from scheduled spikes to train the model can enhance its performance.

The dataset quality and model performance should be validated manually by experts to ensure reliability. To demonstrate the new model’s impact on actual business metrics, blind A/B tests on selected control and test groups of cells will be conducted. In this context, A/B testing involves comparing the performance of two different versions of the anode spike prediction model to determine which one yields better results.

Two groups of cells (sets of reduction cells) are selected: the control group continues to use the existing anode spike prediction model (Model 1), while the test group uses the new model developed (Model 2). Cells are randomly assigned to either the control or test group to ensure that any differences in performance are due to the models themselves and not to external factors. The experts evaluating the results do not know which group is using which model, preventing bias in the assessment of the model performance.

Performance is measured using specific business metrics, such as the frequency and severity of anode spikes, the accuracy of spike predictions, and operational efficiency. After a period of testing, the results from both groups are compared. If the test group shows a statistically significant improvement over the control group, it indicates that the new model (Model 2) is more effective.

By conducting A/B testing in this manner, the impact of the new anode spike prediction model on real-world operations can be reliably determined, ensuring that any improvements observed are genuinely due to the new model and no other variables.

New models will require complex feature engineering on large amounts of data. In Figure 14, you can find the results of model improvement through feature engineering. The model with additional feature engineering shows better performance in terms ROC AUC metric. In machine learning, ROC stands for Receiver Operating Characteristic (ROC) curve and AUC for Area Under ROC curve. The ROC AUC metric was used here since it is independent of the score threshold and has an explainable interpretation as the probability that a case with a spike will have a higher score than a case without a spike.

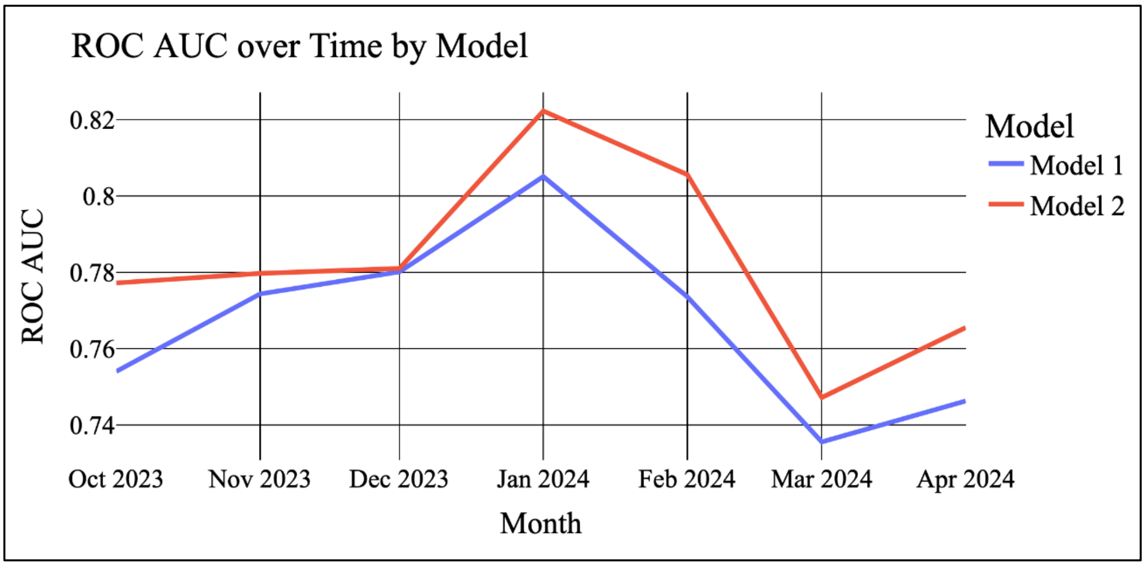

Figure 3. Model with additional feature engineering shows better performance.

6. Change Management

Change management is indispensable for the growth and advancement of any organisation, particularly in a competitive marketplace. While the nature of changes varies, the need for individuals to adapt to new strategies and changes underscores the critical importance of effective change management [3]. This process delves into three key aspects: the competency of individuals, their mindsets, and their behavioural patterns [4].

Figure 15 shows the challenges associate with shop floor employee during the change management activity.

Figure 15. Challenges encountered.

Considering both the psychological factors and technical requirements, the team devised an innovative change management plan tailored for seamless adoption by the shop floor employee.

To ensure successful change management, a systematic plan was meticulously followed. The change management strategy adhered to the sequential steps outlined in Figure 16.

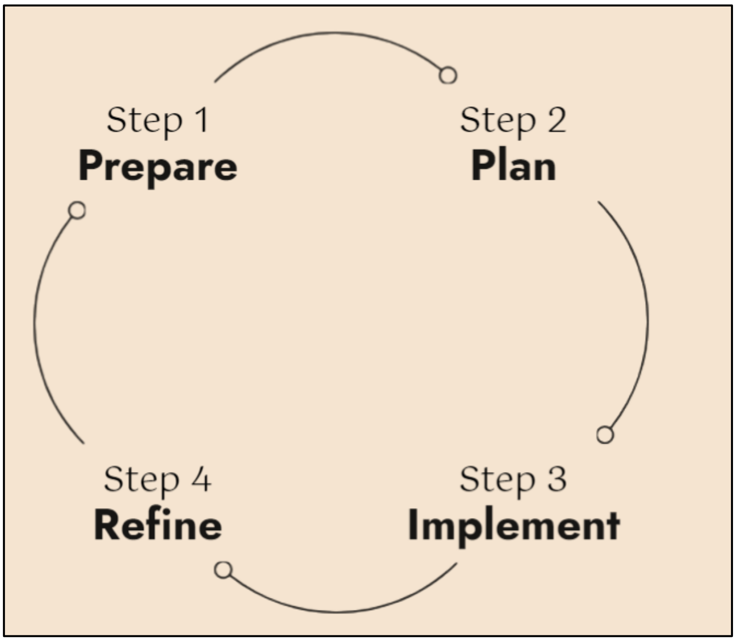

Figure 16. Change management strategy.

6.1 Prepare (Identify the Issues and Prepare)

The original plan entailed assembling a package for swift access to flagged cells requiring attention. This was accomplished by setting up an automated SMS system to transmit a roster of cells exhibiting the highest likelihood of anode spikes to the shift supervisor at the onset of each shift. Additionally, an announcement system was implemented in the potline to signal the presence of flagged cells. Moreover, the list of flagged cells was integrated into the shift work schedule, which encompasses details on routine tasks, shift handovers, and a roster of cells requiring attention.

6.2 Plan (Design and Customise)

Initially, the task handover process was manual, overseen by the shift supervisor. However, a decision was made to automate the generation of the schedule. With the assistance of EGA digital office team, we devised a report linked to various operational logics (such as beam raising, metal tapping, anode setting, etc.) and system entries (including bath temperature, metal sample, metal height, etc.) to identify tasks completed by the preceding shift. Leveraging this data alongside the routine task schedule, we automated the generation of the shift work schedule, incorporating the flagged cells list.

Furthermore, to track the actioned cells, we developed a screen within Reduction Plant Data Management System (iRPMS) where supervisors can manually input the list of cells that have been required attendance (Figure 17). In this interface, "DBDS" denotes cells flagged by the spike model, while "AUTO" signifies routine tasks where abnormalities in the anode were detected and addressed (via logic activation), thus indicating action taken. If a cell is probed but not acted upon, the relevant information must be manually recorded.

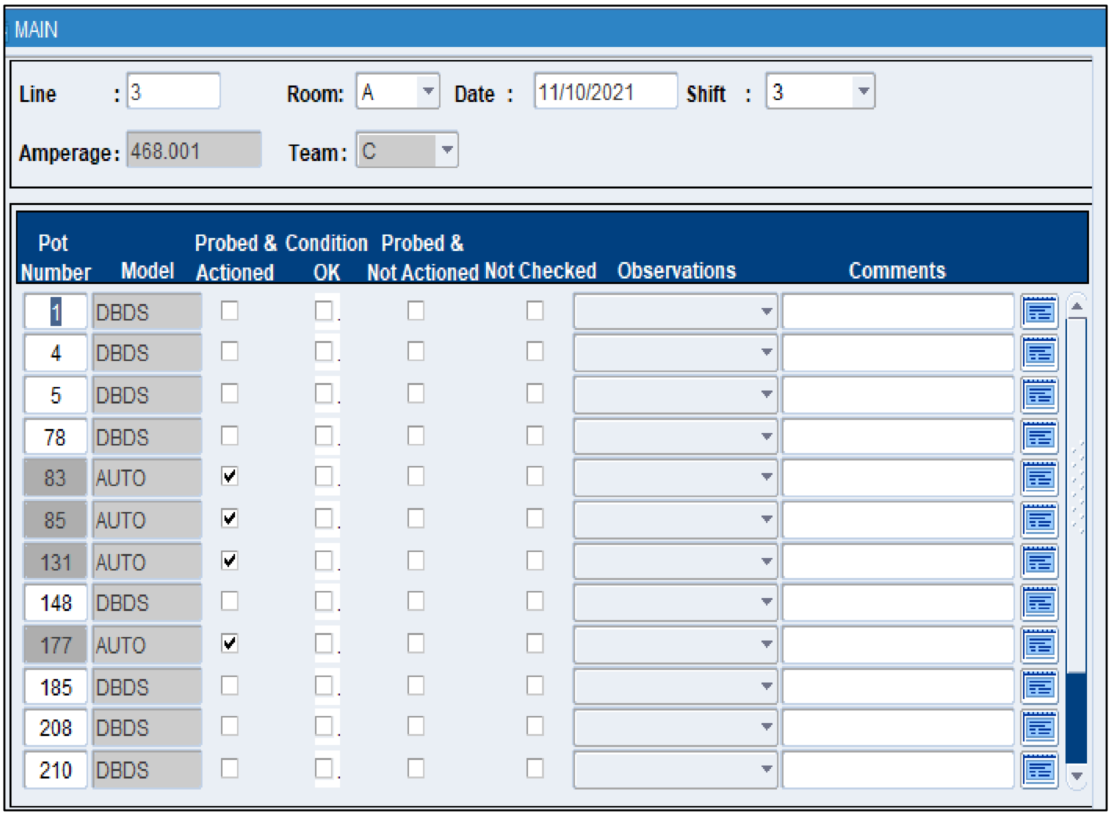

Figure 17. Full cell entry screen in iRPMS.

Additionally, it's aimed to provide monitoring and visualization tools, primarily designed for shift supervisors and shop floor employees for easy navigation and simple to understand, this goal was realised by implementing a red triangle indicator beneath the cell number within iPOTS (Scada system), iPOTS stands out as one of the most practical and frequently utilised tools by shop floor personnel, prominently displayed on screens for continuous monitoring.

Furthermore, we sought to introduce an additional layer of monitoring tailored for higher-level employees, particularly superintendents, via a Power BI dashboard. This dashboard presents historical data, unattended cells, and statistics concerning the trend and frequency of flagged occurrences, along with insights into the types of anode problems addressed (Figure 18).

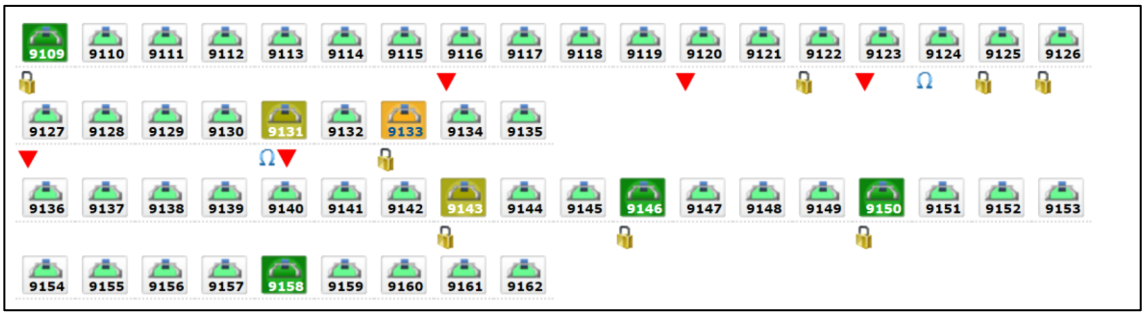

Figure 18. iPOTS flagging cells with predicted spikes.

6.3 Implement

Spreading awareness was a key pillar for the success of the change management initiative. Since employees work in shifts on the shop floor, the most effective way to reach everyone simultaneously was through Toolbox Talks. These sessions, where supervisors meet with the current shift to discuss important topics—ranging from performance and safety to new technologies—were essential.

To ensure all technicians, supervisors, and operators could attend, these sessions were scheduled during the general shift, covering all teams over a span of approximately 3-4 weeks for each potline.

During the Toolbox Talks, the current methods for detecting spikes were explained, which involve observing bath temperature, cell noise, alumina dumps, and visual signs such as yellow flames, red stubs, and high temperatures. The concept of using data science to create a model that could detect these anode problems earlier without manual analysis by the process control team.

While some shop floor employees were intrigued by the new technology, same time few asked many questions, the Toolbox Talks alone were insufficient for fully conveying the message. As a result, compliance and usage of the new tools fell below the targets, as shown in the accompanying graphs. To address this, additional tools were introduced to support change management and enhance the adoption and effectiveness of the new model (Figure 19).

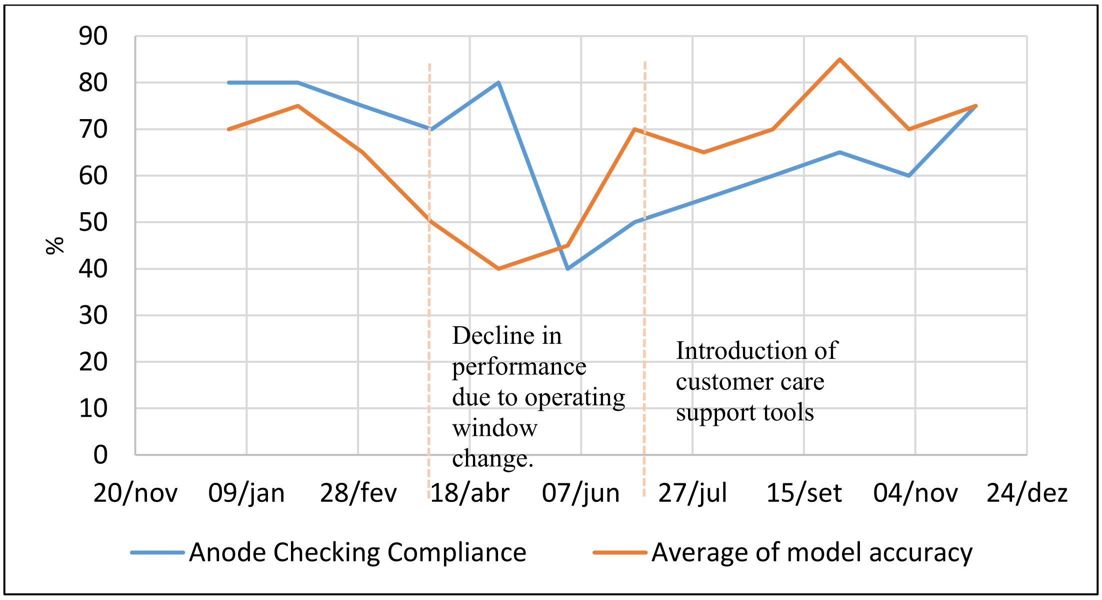

Figure 19. Team performance timeline.

6.4 Refine (Sustain and Monitor)

Efforts were spent on implementing the above plan; however, the level of awareness and actual actioning using the spike model was not satisfactory. Our team was persistent and eager to deploy this new technology in the smelter, in order to do that we had to understand what is causing the non-compliance, were conducted therefore multiple brainstorming session internally, and several meetings with shop floor employees including the superintendent to understand the issue and the following was suggested as shown in Figure 20:

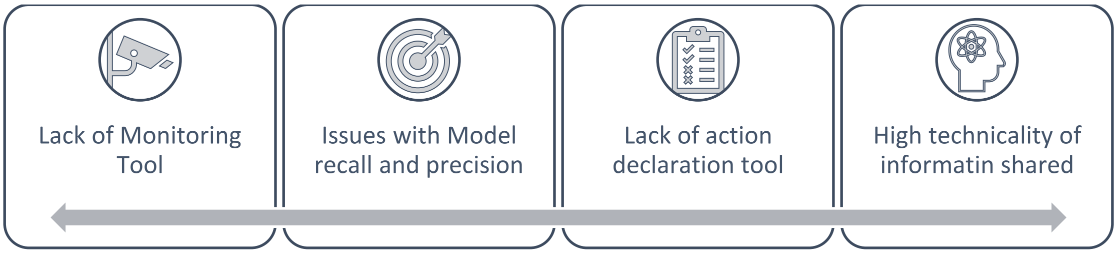

Figure 20. Results of brainstorming sessions (rephrase).

One of the major issues contributing to low compliance was the absence of a monitoring and actioning tool. Although teams were physically checking the cells by probing them, the gathered information was only recorded on the cell board in the shop floor. Additionally, line superintendents expressed the need for a monitoring tool to oversee the compliance and response of different teams to flagged cells, and to differentiate between issues caused by model performance and those resulting from low compliance.

As a result, in collaboration with EGA's digital office team a comprehensive report was created which covers all relevant aspects. Prior to constructing the report, given the absence of an actioning tool, a request was made for a data entry screen to be installed on the shop floor. This screen allows technicians to declare the status of the probed cells directly—whether they were found "OK" or "Not OK". Unlike the previous entry system in iRPMS data base, this new process eliminates the need to visit the office, enabling declarations to be made directly on the shop floor (Figure 21).

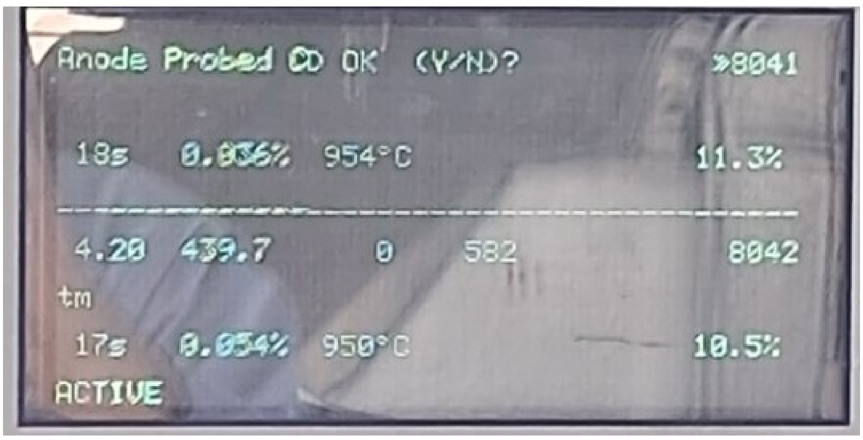

Figure 21. Full cell current distribution (CD) entry screen in shop floor.

Figure 22 illustrates the total number of flags recorded on weekly basis, alongside the count of anode problems detected and addressed from both flagged and non-flagged cells. This breakdown provides insights into the accuracy of identifying various types of anode issues, including spikes and other variants. By making this comprehensive dashboard accessible to all users, transparency regarding the model performance is ensured, fostering a culture of empowerment and motivation. Notably, when a high volume of checks aligns with a notable accuracy rate, it reinforces confidence and acknowledges achievements.

Conversely, in instances where the model's performance is impacted by changes in material quality or operating parameters, it becomes essential to maintain trust with users. This highlights the necessity of imparting knowledge about the functioning of machine learning models. When users grasp the principles underlying these models, they can better anticipate and adapt to shifts, preserving trust and facilitating collective progress towards enhanced and more reliable solutions.

	DBDS Generated Alert (flag)	Anp. Removed from DBDS list	Anp. Removed out of DBDS list	Detection Accuracy of Spikes	Checking Compliance %	Response Time (days)
24-Jun-2023	36	35	17	68.18	75.0	2.0
01-Jul-2023	47	45	13	81.13	78.7	1.8
08-Jul-2023	54	46	13	78.85	77.8	1.3
15-Jul-2023	36	33	18	69.05	75.0	1.5

Figure 22. Overall team efficiency dashboard.

Additionally, the dashboard was made accessible online to all users, and an automatic email was generated to distribute the weekly report to shift supervisors, line managers, and superintendents.

Furthermore, recognising the complexity and technical nature of the information shared earlier, efforts were made to address this issue. One-page lessons (OPL) were developed to provide clear and concise information for shop floor employees, enabling them to effectively utilise the model and associated tools (Figure 23). Refreshment sessions were also integrated into toolbox talks, focusing on feedback from technicians and operators. Similarly, OPLs were shared with the team upon request from potline management. To facilitate understanding and action, a video was created specifically for shop floor employees.

Technical- Process Effciancy Potrooms
EGA
Teams OTE Report
the Teams's OTE report dashboard enables supervisors and Team leaders to monitor their teams performance against Spike Flags checking and anode problem removal
1 Dashboard Location
to access the dashboard you can use the following pathway :
First : go to: https://egasmelteranalytics.ega.a
Second : from the top menu choose Dashboards and choose DBDS Reports
2 Features
The dashboard provides weekly average shift level data associated with the team in charge . The dashboard provides graphs and bar chart for quick visualization .
3 Importance
Monitoring the teams performance showcases the importance of team work in the job moreover it highlights the main aspects for anode problems mitigations Consistency , and Comprehensive & Timely checking

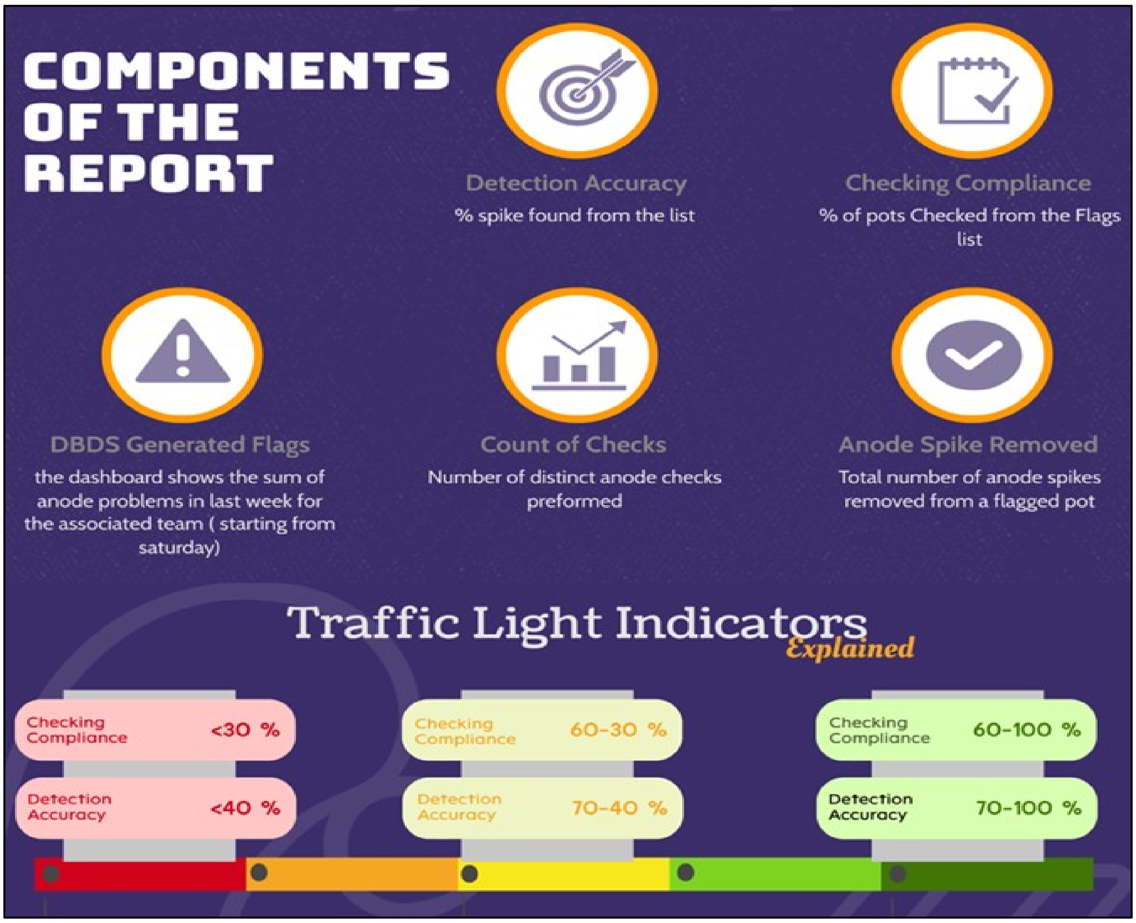

Figure 23. OPL on OTE report.

7. Conclusions

- The implementation of Industry 4.0 technologies for anode spike prediction at EGA has yielded promising results, with the new model outperforming the previous one. However, the process has also highlighted various challenges, such as data labelling, model drift, and complex data engineering requirements.
- The lessons learned from this study can be valuable for the aluminium production industry, as it demonstrates the potential of machine learning in optimising processes and improving product quality. Further research should focus on refining the labelling process, exploring advanced feature engineering techniques, and developing more robust models that can adapt to changing process parameters.
- By addressing these challenges and continuously improving the anode spike prediction model, EGA can set a benchmark for the industry in leveraging Industry 4.0 technologies for enhanced process efficiency and product quality.
- EGA change management for data science project has been a testament to the power of perseverance and strategic adaptation.
- As we reflect on the hurdles overcome and the triumphs achieved, it is evident that our concerted efforts have not only driven successful implementation but have also fostered a culture of data-driven decision-making within our organisation.
- Prioritising communication, collaboration, and continuous learning, we have navigated through complexities and emerged with a refined approach that maximises the value of data science in driving business outcomes.

8. References

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