AL32 - Maintaining Optimal Setpoint Voltage in Smelter Pots Using Digital Technologies and ML Algorithms

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Abstract

The voltage/resistance setpoint (VRsp) of a smelter pot is an important design setpoint at which the pot is meant to ideally operate. The setpoint is a function of the pot design and is an optimized trade-off between pot operating conditions such as instability, bath temperature, metal production, energy consumption, etc. Although a pot is initialized into service at its design setpoint, this value usually changes during pot operation due to daily procedures such as metal tapping, anode change, instability treatment, etc., as well as long-term aging of the pot. Continuously determining and operating at the optimal VRsp for a pot over the course of its life can yield best production and energy benefits in a potline. The population of pots in a potline typically tend to fall into the following categories:

(Type A) Pots operating within a small acceptable band of design V/R setpoint,
(Type B) Pots operating well above design V/R setpoint,
(Type C) Pots operating well below design V/R setpoint.

Pots of Type B are identified using modern data analytics techniques and machine learning (ML) algorithms which are ideal candidates for setpoint reduction and energy saving if they are otherwise good pots in terms of noise, instability, bath temperature and metal production. Such pots are recommended for squeezing into Type A to save on energy consumption without sacrificing their good characteristics. Although the recommended squeezing is by a tiny amount it can provide significant energy savings aggregated over time over a whole potline. Pots of Type B that are squeezed into Type A can over weeks and months drift into Type C operation and become cold, sludgy, noisy and unstable with poor metal production. The same analytics are used to identify such pots as well for un-squeezing by a tiny amount to correct them back into Type A operation and rectify their metal production.

Keywords: Smelter analytics, Data science, Predictive analytics, Voltage setpoint, Industry 4.0.

1. Introduction

Process decisions and optimizations driven by data analytics solutions present a huge opportunity for enhanced business outcome for a wide range of industrial domains. These digital solutions represent the crux of the digital transformation in Industrial Internet of Things (IIoT) and can be profitably applied in the aluminum smelting industry to achieve increased business value. This paper specifically discusses one such solution implementation by General Electric Digital (GED) in collaboration with the Mytilineos Group at their AoG aluminum smelter site in Greece. We first provide an overview of the scope of such digital solutions and their application to exploit the wealth of operational data at a smelter plant to achieve both bottom-line (energy and material cost savings) and top-line benefits (increased metal production). We describe these solutions briefly and indicate how they are enabled and delivered to a smelter plant using cognitive and cloud computing technologies.

2. Digital Solutions and Smelter Analytics

2.1 Aluminum Smelter Opportunity

An Aluminum Smelter plant represents a large and complex industrial ecosystem. In addition to the core metal production process in the electrolytic cells of the potlines, there are important operational adjacencies upstream and downstream such as the alumina refinery, the carbon plant, the metal cast house, the gas treatment centers, power rectification and transmission, etc. In some cases, the plant derives its energy from a captive or dedicated power plant that requires a large power-generation and grid infrastructure also to be in place.

The above ecosystem can derive benefits from data analytics based digital solutions both for the physical assets (reduced equipment downtime, predictive maintenance strategies, etc.) as well as for the process (energy and material cost savings, increased production). In this paper we discuss only process targeted digital solutions for the process heart of a smelter plant, namely the electrolytic potline where the most energy consumption takes place.

Digital solutions for the potline aim to maintain as close as possible to ideal equilibrium conditions in the potline with stable voltage operation and minimal noise and instability. Such solutions combine metallurgical principles with machine-learning algorithms that exploit historical plant data to identify patterns and behaviors unique to the potline to provide advisories and alerts for optimal potline operation. In this manner they provide long-term data based holistic “wisdom” on the pots, which perfectly complements the installed potline control system that dictates real-time operational settings over a shorter-term time horizon.

Furthermore, the nature of digital solutions is such that they are most effective when deployed in close partnership with the smelter plant thereby creating a fundamental cultural change in the plant workforce to align with and adapt to modern Industry 4.0 operations and practices. In the AoG plant in Greece which already has a strong data driven culture, these digital solutions have further empowered the plant operators and given them the confidence to look to these solutions daily to help them prioritize their tasks and get the best outcomes.

2.2 Plant Data and Solution Philosophy

The potline in a smelter plant generates vast amounts of data. The data comes from various sources at varying frequencies and is stored in various forms. For instance, we can have everything ranging from fundamental sensor-based voltage and resistance data measured and recorded at a per-second level, to per-minute instability data, to per-hour dosing data, to per-shift temperature data, to per-day tapping data, to per 2-3-day bath chemistry data (as examples). In addition, we have event data that record say anode effects, anode changes, beam movement, pot leaks/stoppages, etc. Some of this data exists in electronic form while others are in manual logs. A well digitalized plant like AoG has all its historical data digitized and aggregated in an organized fashion, and ideally stored electronically on servers in an easily accessible manner going back in time as far as possible.

All the above potline data represents a treasure trove of wisdom at the disposal of the plant. Typically, a plant consists of multiple potlines with a total of hundreds of pots which represent assets which are nearly identical in make-up/build, even though each pot in fact has its own unique character. However, the data they generate is too vast and complex to be humanly assimilated and exploited and the operational wisdom they have to offer is unfortunately not fully exploited. The smelter analytics solutions use modern algorithms and computing power to take advantage that the pots are near clones to build a common solution framework as a foundation which is customized with the historical behavior of each pot to capture its unique identity. In this manner historical process knowledge is used to develop digital replicas of the physical pots and applied with real-time live data, without the need for installing any new hardware sensors or infrastructure.

2.3 Target Business KPIs

The smelter analytics solution for the potline targets different business KPIs through a suite of predictive analytics. The analytics are built on a foundational dashboard that assimilates and presents all the potline data from various sources in a friendly User-Interface that provides clear visibility of operations along with basic trends and insights. The analytics that sit on this foundation target the following KPIs that yield bottom-line cost savings. In addition, these analytics provide top-line benefits through improved current efficiency and increased metal production revenue that of course varies dynamically with the global LME price of aluminum.

A. Energy (Voltage) KPI

Multiple analytics have been developed with the objective of reducing the energy consumption in a potline where small percentage gains can offer significant cost savings. The analytics cover detection and prediction of instabilities, anodic events, poor electrical connections, etc. as well as offer other potline process improvements that can reduce the mean voltage of an individual pot and of the potline as a whole.

B. Material (AlF_3) KPI

Virtual-sensor based analytics are used to predict the thermochemistry of the pot that allows for more accurate AlF_3 dosing decisions and can reduce AlF_3 consumption in the potline. Additionally, maintaining the bath temperature and composition within an optimal window helps to prevent undesired process fluctuations and improve the current efficiency and metal productivity of the potline.

C. Pot Life KPI

Historical pot stoppage data is used to develop algorithms that can predict the health of the pot for remedial action or also raise alerts that warn of impending failure so that a graceful shutdown can be facilitated.

3. The VRsp Analytic

3.1 Overview

The VRsp analytic is a predictive solution that aims to optimize the operating setpoint voltage of a pot. For a given pot amperage the cell voltage has to be at its right value to drive the electrolytic reaction forward and also produce enough energy in the pot to compensate for heat losses from the sidewalls. Too high a voltage will lead to excessive power consumption and higher operating temperatures causing back reactions that reduce production. Too low a voltage will lead to cold sludgy pots that become unstable and result in poor current efficiency. Operating at the right voltage is critical to optimal power consumption and metal production which yields the minimum specific energy consumption (SEC) on a per-tonne production basis.

The voltage of an electrolytic cell has multiple components such as the decomposition voltage, the excess voltage due to polarization and broadly various ohmic voltage drops. Together they combine to give rise to a complex and dynamic variable that is changing on a per-second basis which is measured and monitored continuously. The setpoint value of the voltage is therefore truly reflective of all the conditions in the pot (which also depends on its age) and maintaining at its optimal value yields the best consumption to production ratio. This optimal voltage tends to drift over days as the pot condition changes and requires to be regularly tuned for best results.

3.2 Solution Approach

Most pots in a potline typically operate within a small acceptable voltage band of the optimal setpoint. For the purposes of this paper, we call them Type A pots or just "normal pots". They are normal in the sense that they consume energy and produce metal in near-optimal operation. However, there are other pots that operate outside of this normal range which are the topic of this paper. There are pots we call Type B which have drifted to operate at higher voltages but are otherwise "well-behaved" in terms of instability and temperature and metal production. We have developed a machine learning based analytic that identifies such pots and marks them as candidates for squeezing so that their setpoint voltage can be reduced without sacrificing their good operating behavior. At the other end of the range are pots we call Type C that have drifted to operate at lower voltages and have become cold and noisy and sludgy and poor in metal production. The analytic identifies such pots as well as candidates for un-squeezing so that they can be heated back up to stable operation and production. Overall, the analytic has been developed based on a combination of supervised and unsupervised learning algorithms. It uses several months of historical data, each time it executes, to understand the patterns to identify the pots and make recommendations.

The analytic has been deployed in the cloud and integrated with the overall operational performance monitoring application to give the recommendations as alerts in the application. The analytic is scheduled to run every day currently but can easily be configured to run weekly or monthly depending on the requirement.

3.3 Squeezing Analytic for Type B Pots

Here we identify pots that are operating with good performance but have higher voltages which can be squeezed to reduce voltage and save energy. This analytic was developed using historical data to understand the operating pattern or behavior of each pot vis-à-vis their design code, age, operational history, repairs / reconstruction, instability time and noise, bath properties, production volume and anodic incident history. The analytic uses specially designed and validated heuristics to recommend pots as potential candidates for squeezing.

These recommendations are screened using a set of rules with a combination of measured KPIs to have a final selection of pots for squeezing. Typical performance improvements upwards of 50 % has been observed for many of the squeezing recommendations over time. These recommendation analytics' thresholds and persistence (in time) can be configured at several levels to suit the needs of the operation based on the tradeoff between available resources and outcome requirements.

3.4 Un-Squeezing Analytic for Type C Pots

This analytic applies to pots that have drifted into lower voltages and become cold, noisy, sludgy and low producers of metal. These pots behave with mostly an opposite behavior on most of the KPIs compared to the Type B pots that have potential to be squeezed. The analytic identifies these kinds of pots using a similar approach as described in the previous section but using heuristics on the opposite range of the spectrum with KPIs such as instability time and noise, cryolitic bath properties, history of anodic incidents, repairs and production. Using carefully chosen persistence and KPI thresholds, the analytic identifies and recommends the pots that need an un-squeezing treatment. These could be pots that were earlier on squeeze treatment. The analytic has shown good performance with upwards of 80% accuracy on identification of such pots. As mentioned previously, the heuristics can be configured with thresholds and persistence that suit the available resources and outcome requirements.

3.5 Performance Metrics

The tool that was developed based on this analytic was first evaluated on small groups of pots with validation from AoG on suitability for this treatment. Once confirmed the base resistance of the pot was decreased/increased by a small amount (about 0.1-0.2 μΩ) depending on whether it was a squeezing/un-squeezing operation. After this change in base resistance, the trial pots were carefully monitored based on the following metrics:

(a) Base resistance

All the pots have a setpoint for their base resistance. The selection of the actual value is dependent on the pot design and the materials used to build it. During the pot's lifetime this value needs to be revised due to several factors that including pot's age, thermal history (behavior) and its productivity.

(b) Mean actual resistance of the pot

As the base resistance is a set value, the pot tries to attain it continuously but due to fluctuations caused by operations or the current flow through the potline, the actual resistance of the pot keeps changing. The average resistance of the pot and its deviation from the set point are monitored continuously. The smaller the deviation, the better the pot's function and performance.

(c) Instability

The current flow within an electrolytic cell is crucial for the efficiency of the cell. Instability describes the variations of the current flow and is an undesired state for the pot, since it reduces CE and negatively affects the energy consumption (Having a pot running in a different resistance setpoint than the nominal, increases the electrical consumption of the pot, either due to high instability which reduces the pot's current efficiency or due to higher but not necessary energy offer to the pot.) The target resistance is critical for achieving low levels of instability, without over consumption of electrical energy. Thus, it is important that after the changes in resistance the instability remains inside the optimal operating window.

(d) Voltage

The most crucial KPI that was monitored during the trial was the average operating voltage of the pots before and after changing the base resistance based on the alerts that VRsp analytic has produced. The pot's voltage is mostly affected by most of the operations and events that happen inside a pot and determines the final energy consumption of the pot. Hence the goal is to improve the pot's voltage to conclude if the trial's outcome is successful or not.

(e) Additional resistance

Additional to pots' base resistance, there are supplementary resistances that has to do with the operations, the instability, cathode resistance etc. The pot's base resistance is also regulated due to operations and the pot's cathodic voltage drop. For the pot to operate in a state close to nominal the monitoring system dictates changes in the supplementary resistances for each pot. These changes must be considered during the trials to conclude if the outcome was affected by those changes or by the initial base resistance change that was made for the trial.

(f) Current efficiency

The pot's current efficiency is the most important productivity KPI. The pots that took part in the trial were monitored closely on their current efficiency to make sure that the changes of base resistance would not affect the metal production of the cells. The current efficiency of each pot calculation is based on the actual molten aluminium mass that has been tapped from the pot every 48 hours and the relevant metal height measurements after it compared to the expected one. The pots were tapped separately from the rest group, in order to ensure that there were no variations due to tapping process.

All the above KPIs have to be taken in combination to evaluate if there is an improvement from the change in VRsp. For example, if a Type B pot is squeezed to reduce overall voltage and save energy, it should not come at the cost of increased instability and reduced current efficiency and metal production. Similarly, if a Type C pot is un-squeezed to improve metal production, its performance should not suffer from higher than optimal bath temperatures and increased energy expenditure.

3.6 Implementation Process

The analytic was deployed as a tool that makes recommendations to be implemented by AoG. The plant at AoG has 3 potlines (A, B, C) with 260 pots each. Based on the recommendations from the analytic, 101 pots in the plant were selected for this treatment: 85 for squeezing (Type B) and 16 for un-squeezing (Type C). The remainder majority of the pots were deemed to be operating at nominally optimal conditions (Type A) and not in need of this treatment.

Once selected each pot is kept on trial for 14 days and evaluated based on the above KPIs both on a 7-day and a 14-day basis. Various other heuristics including rolling window averages are used to smooth out daily variations and get a clearer trend in the performance metrics of each pot.

Many such trials have been conducted by AoG in batches over the past 12 months and based on the increased confidence in the tool the recommendations are being implemented across the plant. It is important that the tool provides both squeezing and un-squeezing recommendations and in this manner is self-correcting to make sure that each pot is regularly evaluated to understand if it is in the Type B or Type C regime and if so, how to guide it back into the Type A regime.

The trial of the tool initiated in potline A and at the time the tool was producing alerts only for the pots that needed a reduction of their resistance setpoint. The reverse function of the tool was available and tested in potlines B and C subsequently. The alerts for unsqueeze were tested for their validity separately. For pots whose the resistance setpoint was reduced based on a squeeze recommendation, without beneficial outcome, their resistance setpoint was restored to the initial levels and not increased furthermore whether an alert for unsqueeze was produced or not according to the restrictions that AoG has set for executing a low risk trial.

The success of the tool is measured by the aggregation of the success of each performance monitoring KPI described in section 3.5. For the test pots, each KPI was compared with potlines best pots performance and pots previous performance. The cases for which the majority of the KPIs monitored have improved as a result of the trial with the pot's actual operating voltage mandatorily included are considered successful. The final success rate for each potline is calculated as a weighted average of each separate trial's percentage, multiplied by the number of pots that have participated, divided by the total number of pots participating in the trial. Tables 1 and 2 shows the success rates of the pots in the trial.

Table 1. Squeeze and un-squeeze trial results.

		Squeeze (-0.1 µΩ)			**Un-squeeze (+0.1 µΩ)**		
Potline	**Batch**	**Pots**	**7-days**	**14-days**	**Pots**	**7-days**	**14-days**
A	1	14	36 %	43 %			
	2	3	33 %	67 %			
	3	8	38 %	75 %			
	4	6	67 %	83 %			
B	1	5	40 %	40 %			
	2	1	100 %	100 %			
	3	10	40 %	50 %			
	4	2	50 %	50 %			
	5	6	33 %	50 %	2	50 %	50 %
	6	7	85 %	57 %			
C	1	3	100 %	67 %			
	2	3	67 %	67 %			
	3	2	100 %	50 %			
	4	6	33 %	33 %	4	75 %	100 %
	6	4	50 %	50 %	5	40 %	40 %
	7	5	40 %	80 %	5	80 %	80 %

The average success rates for the potlines for both squeeze and un-squeeze trial results are shown in the Table 2.

Table 2. Squeeze and un-squeeze trial results - average summary.

	Squeeze Ave SR		**Un-squeeze Ave SR**	
Potline	**7-days**	**14-days**	**7-days**	**14-days**
A	42 %	61 %		
B	51 %	51 %	50 %	50 %
C	56 %	57 %	64 %	79 %

4. Conclusions

The results of the first sets of trials that were conducted by AoG with the use of the initial version of the analytic tool were better in terms of accuracy for the duration of 14 days for every potline and for both types of pots (Type B and type C). The tool achieved the highest level of accuracy (reaching 61 %) for Type B pots in the long-term trial for potline A. The highest accuracy percentage for type C pots was 79 % and was achieved in potline C for the 14-day trials. It is safe to conclude that the recommendations of the analytic tool have become more accurate and reliable in the long-term trials.

Due to the analytic tool's ability to provide recommendations for squeeze and un-squeeze, it was observed that squeezing recommendations which were not beneficial for the pot's function were quickly captured by the reverse function of the analytic and a new un-squeeze recommendation was generated for the same pot minimizing the effect of the inaccurate initial prediction.

To summarize, the results of these first sets of trials are encouraging given the maturity of the analytic tool and the constraints that AoG has set to keep track of the trial with minimum risk for the long-term function of the pots on trial. The main constraints were the duration of the implemented actions after the recommendation and the minimum modification of the pot’s base resistance (-0.1 μΩ for type B and +0.1 μΩ for type C pots). These constraints will be fine-tuned in future trials and better results are expected.

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