

AL30 - The Role of New Sensors for Hall-Héroult Process Control, Optimization and Advanced Analytics

Jayson Tessier¹, Pascal Lavoie² and Albert Mulder³

1. Director Casting and Smelting Technology
2. Director Smelting Manufacturing Excellence
3. Principal Consultant Smelting Process Control

Alcoa, Continuous Improvement Center of Excellence, Deschambault-Grondines, QC, Canada
Corresponding author: jayson.tessier@alcoa.com

Abstract

The Hall-Héroult process is controlled using individual cell voltage and line current as the only continuous online signals. Other variables such as bath characteristics, liquid levels or metallic impurities are only periodically measured, normally every few days. Other visual observations are also performed by operators but generally not entered within databases and can have questionable reliability. This limited amount of process data constrains the extent of process control and hinders capability to identify common faulty conditions that require manual intervention from operators such as anode spikes, collapsed crust, bad hooding position, etc. Over the last decade, aluminium producers started to test big data, or advanced statistical techniques, to better diagnose and intervene on reduction cells. Yet, such techniques are also limited by the restricted amount and limited quality of data available to properly train data driven algorithms. On the other hand, the industry is developing new sensors to enrich the information available around the reduction cells. This will pave the way for real time alarms for some process faults and increase effectiveness of advanced statistical techniques to identify other process upsets not easily detectable with common process control schemes. This paper reviews big data initiatives tried at Alcoa within the smelting process and discusses factors preventing success. It also presents an update on sensors, developed internally and off-the-shelf, aiming to improve process control by providing better process insights for advanced analytics initiatives.

Keywords: Process control, Big data, Sensors, Hall-Héroult, On-line measurement.

1. Introduction

Until further development of the inert anode process or other alternative routes, aluminium will continue to be industrially produced using the Hall-Héroult process. In this process, alumina (Al₂O₃) powder is electrolysed into aluminium (Al) and oxygen (O), based on the following overall reaction:



This reaction happens inside metallurgical reactors, called reduction cells or pots, where high continuous electrical current flows between carbon anodes and cathodes. The carbon anodes (C) react with the oxygen and produce gaseous carbon dioxide (CO₂). Molten aluminium, which accumulates at the bottom of the pot, is periodically siphoned and delivered to the cast house. The alumina powder is dissolved within a molten electrolyte, called bath, which is a mixture of cryolite (Na₃AlF₆), aluminium fluoride (AlF₃), calcium fluoride (CaF₂) and some other additives. This process typically operates between 950-970 °C.

The cells electrically connected in series (potline), are typically controlled using the potline current and individual cell voltage as on-line signals. High magnetic fields, corrosive molten salts and acidic vapors, high temperature and abrasive dust produce different challenges to develop

and deploy cost efficient on-line sensors to measure other key variables to improve process monitoring and control. Therefore, other measurements such as electrolyte condition, liquid levels or metallic impurities are periodically measured manually to complement the information available for process control.

The bath chemistry, temperature and superheat are periodically monitored using samples and thermocouples or using in-situ measurements such as STARprobe™ [1]. These variables are controlled to maintain heat and mass balance to achieve high productivity and extended pot life. They also provide great insights on the pot state.

Liquid levels are monitored using a dip stick and a ruler [2]. Metal level is maintained to a specific height range to control magnetic stability and thermal balance. Metal pad height can be used to determine the amount of metal to be tapped from a given cell. The electrolyte level is also maintained to a specific height range to prevent liquid bath dissolving the steel part of the anode assembly while ensuring sufficient bath volume for alumina dissolution. Bath can be added or tapped from a given cell to adjust its level.

Metal pad metallic impurities are measured using samples poured and frozen into molds. The samples are later analysed using spectrometer analysis [3] to determine chemical elements present in each cell. This is required to monitor the cell condition and to determine how to blend metal from different cells to fulfill casthouse orders. Metallic impurities are also used to determine various cell conditions [4].

Other routine measurements are carried-out by operators to diagnose the pot condition and process faults. Those measurements are not typically used as inputs for process control and are not systematically collected within databases. Anode rod voltage drop are measured to detect anodes carrying too much or too little current [5]. Side ledge or heat flux are measured to assess the sidewall condition and the general heat balance of the cells [6]. Sludge (undissolved alumina) surveys or cathode voltage drops are performed to assess the cathode condition and dust surveys [7] can be performed to assess anode performance within the pots.

So far, no on-line real-time sensors are available to monitor alumina concentration within the electrolyte, which control is of prime importance to avoid PFC gas evolution and sludge formation. Instead, it is controlled using an overfeed/underfeed strategy, relative to the nominal alumina consumption rate, based on the time derivative of the cell pseudo-resistance or voltage drop [8]. The same pseudo-resistance or voltage is also used to control the power input to the cell and the anode-cathode distance (ACD) that is critical to the cell magnetic stability and productivity [8].

Aiming to get the most out of the collected data and to better understand their processes, aluminium producers have used advanced analytics, big data, machine learning and digital twins to study the large amount of collected data. Recent examples have been published within the literature. Moreover, technology development teams have pursued the development of new sensors to monitor other parameters around the reduction cells.

This paper reviews some published and in-house advanced analytics initiatives, pertaining to the smelting process, and discusses factors preventing success. It also presents an update on in-house developed and off-the-shelf new sensors, aiming to improve process control and to provide better process insights for advanced analytics initiatives.

2. Advanced Analytics

Over the last decade, thanks to improved computer memory and speed, the use of different advanced statistical methods such as latent variables [9], neural networks [10], deep learning [11] or other techniques became more popular to analyze and improve the knowledge of industrial processes. Those techniques were also applied to aluminium smelting by academics and practitioners and different applications have been published in conference or journal papers.

In [12], Principal Component Analysis (PCA) and flowcharts were used to identify anode spike formation. In [13], latent variables methods were trained on good operating pots and used to detect and diagnose the onset of an abnormal situation at Alcoa Fjarðaál. In [14], a multiblock latent variable approach was used to predict potlife based on pot preheating and early operation data. In [15], changes in baked anode properties were properly identified using latent variable methods using process data.

Moreover, bigger efforts were also presented by Aluminium of Greece and RUSAL, aiming to globally monitor reduction cells from complete potlines, to predict process upsets and to prescribe operating parameters.

In 2017, Aluminium of Greece [16] announced a 10-year breakthrough collaboration between Aluminium of Greece and General Electric (GE) to optimize productivity and reduce energy costs. The developed digital smelter solution is expected to enable new and improved methods to monitor smelters, leading to improved energy efficiency, to use less aluminium fluoride, and to predict pot leakages [17].

In 2019, RUSAL [18] announced the launch of a potroom control system based on big data. The approach developed with Mechanica AI [19] was targeted to decrease the abnormalities throughout the process and to improve the reduction cell control quality.

Internally, Alcoa also conducted advanced analytics projects either independently or jointly with third parties specialised in the matter. Different projects, aimed at optimising overall cell health (stability, throughput, efficiency, etc...) were performed with well-known consulting companies having renowned mathematicians, statisticians, and computer scientists. The approach was to train algorithms based on cells consistently operating well over time, and to use those algorithms to predict the operating pot health. Specifically, the objective was to predict pot temperature, to prescribe operating targets (resistance and bath chemistry) and to predict process faults such as anode problems, instability, and feeder problems.

Despite the considerable knowledgeable resources dedicated to those projects and the availability of massive training datasets, the projects failed to meet the objectives. The following outcomes were derived from the projects post-mortem:

1. The project durations and complexities were severely underestimated on the front end by the third parties.
2. The learning curve for the third-parties' scientists was significantly steeper and longer than anticipated, both on the smelting process expertise and on data understanding, consuming resources at two to three times the initial estimates. The algorithm training phase took more than double the planned time.
3. The smelting process is constantly evolving due to different raw materials properties not necessarily well measured and not easy to account for with the available data. This required frequent model adjustment or limited the model precision.

Several items required to be solved were also identified to increase the chance of success for future large, advanced analytics projects:

1. The smelting process performance metrics are not well measured. It is hence not easy to train algorithms with good and bad performing cells. For instance, current efficiency and energy consumption cannot be precisely estimated daily on an individual pot basis. Hence, algorithms are facing low signal to noise ratio on the performance metrics. Due to the large and rapid fluctuations of those metrics the algorithms may struggle to detect anything.
2. It is difficult to identify when the initiation of process faults occurs. An operator can find an anode spike or a faulty feeder and even if it is properly reported and stored in historians, it is rather difficult or impossible to know when the fault started. This brings challenge when training an algorithm to detect such faults since the initiation can be many days before being otherwise identified. This disturbance can hence be hidden in a time deemed to be associated with good operation, also resulting in a low signal to noise ratio.
3. The smelting process is always in transient mode. Different raw materials blends are used throughout the year and large seasonal variations can be present. Smelters are also actively increasing the line current, and many operating targets must be adjusted frequently to cope with those varying conditions. This requires frequent model tuning and might not even provide a stable period that is long enough to extract a sufficient data set for training and validating the algorithm. Moreover, the model applicability would only be valid for a short period of time due to the transient nature of the process.
4. Many observed variables are lagging indicators of the pot condition and performance. Hence, relying on those variables is not conducive to rapidly solving the actionable cause.
5. The different process control loops are heavily coupled. E.g., Reducing the operating resistance target may help to reduce the heat generated within the ACD but may have an impact on the cell stability, to which the noise control loop would increase resistance, nullifying the reduction in base resistance target,
6. Many manual interventions such as green poling, pot tending or adjusting anode height are not captured properly in databases. Hence, the algorithm can not differentiate those manual interventions from normal or abnormal process variations.
7. Data scientists need to have a solid process understanding to work efficiently with the smelting process team.

Therefore, there is a need to better monitor the reduction cells. Such monitoring should enable to precisely detect in time when a faulty condition is initiated. These sensors would enable to optimize the actual process control and would help to dispatch operators to fix the pots at the right time, with a low false positive rate. There is also a need to better monitor raw materials quality delivered to the cells. A 400 kA cell consumes almost 6000 kg of alumina and 1200 kg of anodes daily. However, not much is known about the quality of those raw materials at the pot level. This also limit the ability to account for raw materials variations when developing statistical models.

3. New Sensors

To cope with this lack of information primary aluminum producers, universities and equipment suppliers have worked on different sensors to collect more data around the reduction cells. These were tested and developed at different levels within the industry and have yet to be the new standard for process monitoring and control applications. Leaving aside soft sensors, which leverage process data to predict a variable that can not be measured, new sensors can be divided in two different categories, enhanced manual measurements or on-line sensors.

3.1 Enhanced Manual Measurements

Enhanced manual measurements are the logical step to improve the information gathered around the reduction cells. These measurements consist in some level of automated measurement and data transfer to the plant data historian, while still involving some manual intervention. This

enables to gather and store the measured parameters precisely in time, while limiting manual data entry errors often seen in potrooms such as wrong pot identification, mixing metal and bath level or just wrong data entry. Such measurement devices are based on Bluetooth, Wi-Fi or other remote data transfer and enable to reduce the time between the measurement and the data availability for process control.

3.1.1 STARProbe™/ FiberLab™

Bath properties such as temperature, superheat and chemistry can now be precisely measured with automatic data transfer to the plant historian. Industrial devices such as STARprobe™ [20] and FiberLab™ [21] are available although not yet deployed in all smelters. On top of providing the bath temperature and superheat, these devices replace the need for laboratory analysis of collected bath samples, thus shortening the time to get the analysis, and also limiting possible errors. The values are available a few seconds after the measurements and can already provide insights to the operators on which interventions to perform on a pot and can be sent to the process control loop for rapid action.

3.1.2 LIBS

Molten aluminium impurities can be measured using Laser Induced Breakdown Spectroscopy (LIBS). Instead of collecting a sample and sending it to spectrometer, portable LIBS [22], are available. These can be mounted on a small potroom vehicle and can provide aluminum chemistry analysis within a few minutes. This reduces the time between sampling and analysis and can greatly help to intervene rapidly on a sick pot or to rapidly determine which pots should be tapped together for cast house orders.

3.1.3 Anode Rod Metering

Anode rod metering is performed frequently to determine how much current flows within a given anode. Measuring the voltage drop of a given length of the anode stem provides an indication of the current flowing through this given anode. These measurements have been done historically without manually recording the measurement due to the time required to do that and the limited capability to process the data in a meaningful way. Modern rod meters [5] enable to record, transfer, and store the individual measurements. This saves time for the operators, but also reduces possible errors and paves the way for advanced data analysis.

3.1.4 Human Feedback

One underestimated sensor are the observations made by floor operators and technicians. Their observations are often written on pieces of paper and if lucky entered within the control system. This helps to understand the condition of a reduction cell. These observations are prone to error, but if handled well, they can be used by the control system or the technical team to make better decisions. In some plants, measurement of temperature and other bath related properties are preprocessed, and some feedback is requested from the operators.

However, there is a need to use well defined comments, so the information can be categorized and used properly. Controlled fields or drop-down menus on smart tablets are a must. Voice recognition algorithms and technologies are now well developed and can be a game changer for this interaction as the operators just have to say what they see. The algorithm can digest the content and combine it with process data for advanced diagnosis.

3.2 On-line Sensors

Development and availability of on-line sensors is paving the way to monitor new features, independent of pot voltage and line current, providing the ability to increase the information available for process control and advanced analytics. Although not widely spread within the industry, these sensors are gaining a lot of interest and many efforts are underway to develop them. Some of those sensors are described below.

3.2.1 Anode Current Sensor

Anode current sensing has probably benefited from the greatest development effort towards new sensors for the Hall-Héroult process. Such sensors enable to monitor in real time the current flowing into each individual anode, allowing to monitor each anode independently, as opposed to the actual average cell behavior. Different ways have been proposed to measure the current, from on-line voltage drop measurement embedded within the stem [23], to Hall effect sensors [24] to current balance on the anode beam [25]. Yet, to the authors knowledge, this has not been deployed globally within a smelter.

Over the last decade, different research was published based on these sensors. In [26], it is shown that anode current signals can detect anode problems using Markov Hidden chains statistical techniques. In [27], individual anode currents are used as inputs to detect feeding problems. Anode current signals are used within a discretized model of the cell where each anode is a sub-part of the whole cell, interconnected to the other anode sub-systems through mass and energy balance. These are just two examples of what can be achieved with those signals. A thorough review of this topic is presented in [28].

3.2.2 Excursion Sensor

Recently, Alcoa started to develop sensors to monitor pot shell, or cathode collector bars conditions, aiming to prevent cell tap-out. Such sensors aim to monitor temperatures at specific locations and generate alarms when given thresholds are reached. Figure 1 presents an example of potshell health monitoring using the developed system on pot B111 shell temperature at anode 15. The shell temperature was stable at about 280 °C for a long time and started to increase to 310 °C over 7 hours and remained stable for a few hours. It then started to increase rapidly to 620 °C in only 16 minutes. Chances for operators to monitor and detect this rapid increase would likely not be possible using manual measurement. At this temperature increase rate, a side tap-out was imminent. Side ledge has melted, and it was just a matter of time for the brick and shell containment to fail. However, using the continuous monitoring system, an alarm was sent, and operators were dispatched to address the situation and prevent the tap-out. Compressed air was locally applied to the shell and temperature quickly dropped to 200 °C. The few temperature increases at a later time are related to anode setting and intervention on anode problems on anode pairs 15-16 and 17-18. Operators had to remove the compressed air systems for the duration of their intervention.

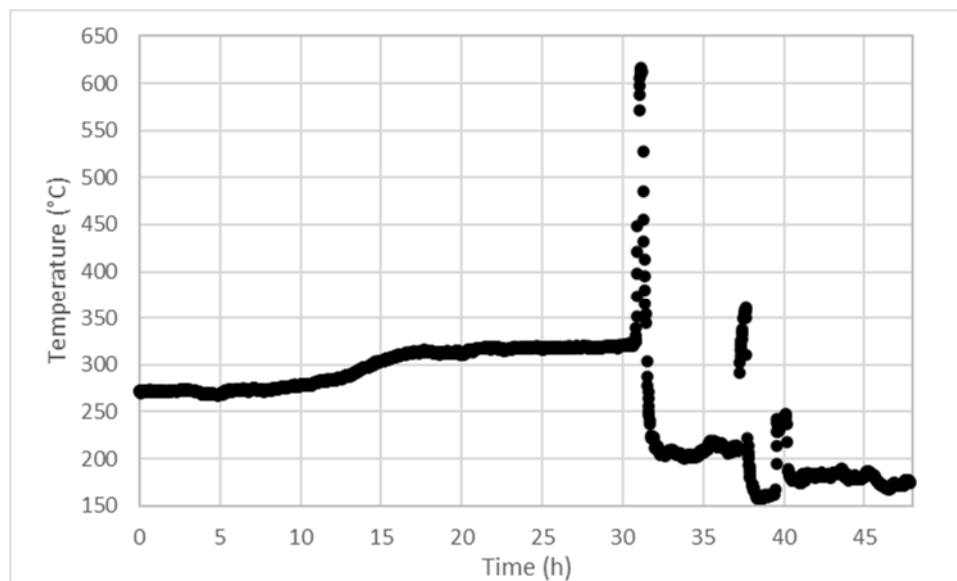


Figure 1. Pot B111, anode 15, shell temperature monitoring using Alcoa's monitoring system.

Moreover, such system can provide additional information when trying to assess the overall pot condition. For example, slow trends, uncorrelated with external temperature or wind conditions, can indicate ledge growing or melting. Once combined to other metrics, this can greatly help tuning set points and prevent conditions leading to side tap-out.

3.2.3 Alumina Properties Sensor

Alumina is the primary raw material used within the Hall-Héroult process and yet, little is known about its properties before it is being fed to the pot. Alumina distribution systems are prone to time delays and segregation, up to the point where it's rather difficult to know the alumina properties at the pot level. For example, maintenance performed on silos or valves can deliver more fines to some pots for a few hours or days. Those fines have different dissolution properties and sodium content, which creates a disturbance to the feeding control loop. Aiming to improve alumina feeding control, Alcoa developed methods and systems to monitor alumina properties related to alumina dissolution rate [29]. This system monitors alumina flowability, which is highly correlated to its dissolution rate, and is used to adjust the feed control parameters. This system is now deployed industrially and providing good impact on pot stability and performance.

3.2.4 Alumina Feeding Abnormality Detection

Other important sensors are related to alumina feeder and breaker systems. Detecting faulty condition is of prime importance for a rapid intervention. This helps to prevent anode effects, sludge formation and to disturb the overall cell condition. Different means to detect those faults can be from using anode signals [27] or through improved feeding systems where plungers can detect contact with bath and other devices can ensure the breaker-feeder are functioning properly [30].

3.2.5 Anode Bridge Position

Anode bridge position can be measured using different techniques. A potentiometer attached to the anode beam and a reference point (Figure 2) is a good way to monitor the beam movement and position and was tried at Alcoa during the last decade. This could be useful for pot

technologies having separate anode beam and motors on upstream and downstream but also for conventional anode bridges equipped with crossovers.



Figure 2. Potentiometer installed on anode beam on cell B114.

As seen in Figure 3, such sensors can help to monitor the beam position and hence improve metal pad level control and monitoring during metal tapping. Moreover, such systems can help to compute the anode cathode distance and the bath electrical resistivity [31].

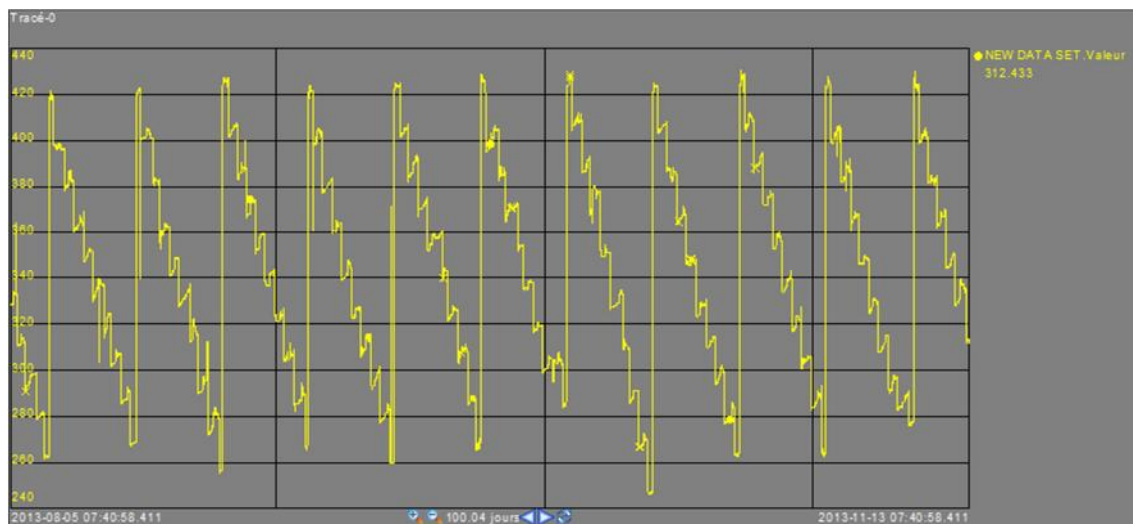


Figure 3. Bridge position of cell B114 over 100 days.

4. Possible Outcome

Aiming to improve the monitoring and process control of reduction cells, combining new sensors presented above and advanced statistical techniques can deliver a lot of potential to improve cell performance. New sensors can on their own deliver value as they provide new insights to the process. However, they pave the way for a new generation of control systems or digital twins, which can deliver even more benefits.

4.1 New Generation Control System

Most, if not all actual cell control systems try to detect abnormalities, or their outcome, and fix them. This works well to get the pot back in control over the long run, but it does not necessarily address the problem. The problems are in fact hidden by the lack of diagnosis and by the actions performed by the control system to correct the disturbance.

Hence, there's a need for a new type of process control system, not only relying on information coming from sensors, but also including feedback from operators and their decision-making process. A system like this was initially built and deployed by LMRC [32] in 2012. The use of new sensors described in this paper can aid to detect and monitor problems. Combined with the feedback from operator interventions, the control system can learn and adapt to changes. It is believed that such a system should give better performance than actual simple control loops.

Soft sensors will benefit from the addition of new sensors and will provide a better precision. Adding information on shell temperature, liquid level fluctuations or anode performance can only improve already useful soft sensors, based on actual data, for predicting bath temperature and excess of AlF_3 .

4.2 Digital Twin

Digital twin, a digital representation of a reduction cell, is still under development and not yet widely spread amongst aluminium producers. Due to complexity of the aluminium reduction process and the variability of operations and raw materials properties, digital twins are generally focussed on a subset of the process. For example, prediction of the MHD state, prediction of temperature. This will change with new sensors providing a different view of the cell health.

5. Conclusions

The Hall-Héroult process is probably controlled as best as possible with available signals. Lots of improvements were made during the last decades due to the advances in computer hardware for process control and computer capability. Still, most of the control scheme relies on basic volts and amperage on-line signals, while other variables such as bath characteristics, liquid levels or metallic impurities are only periodically measured, normally every few days.

Advanced analytics based on actual data can help to improve monitoring or control of sub-sets of the process but don't provide true breakthrough in process control unless new sensors are added to supplement the information.

New sensors will help to properly monitor the process and to rapidly identify process faults, not relying on the human interpretation. Coupled with at the pot monitoring of raw material properties, this will greatly increase the process control performance and the effectiveness of operators' interventions. Sensors must be low cost and robust to enable mass deployment across the industry.

Such systems will help the aluminium smelting process to improve its energy efficiency while also providing greater flexibility to raw material properties fluctuations and to amperage modulation.

6. References

1. Xiangwen Wang, Robert Hosler and Gary Tarcy. Alcoa STARprobe™, *Light Metals* 2011, 483-489.
2. K. Viumdal and S. Mylvaganam, Beyond the dip stick: level measurements in aluminium electrolysis, *JOM*, Vol. 62, No. 11, 2010, 18-25.
3. ASTM E1251-17a, Standard Test Method for Analysis of Aluminum and Aluminum Alloys by Spark Atomic Emission Spectrometry.
4. Steve J. Lindsay, Metallic impurities from the mine to metal products. *Light Metals* 2013, 177-181.
5. Benoit Verreault and Renaud Santerre, Millivolt Anodes - New Technology Opportunities for Better Pot Control, *Proceedings of 35th International Symposium ICSOBA*, Hamburg, Germany, 2 – 5 October, 2017, Paper AL06, *TRAVAUX* 46, 823-834.
6. Mark P. Taylor, Barry J. Welch and R. McKibbin, Effect of convective heat transfer and phase change on the stability of aluminium smelting cells. *AIChE journal*, Vol. 32, No. 9, 1986, 1459-1465.
7. Matthias Dechent, Carbon dust metrics for cell and plant process audits, *Proceedings of 39th International Symposium ICSOBA*, Virtual Conference, 22 – 24 November, 2021, Paper AL10, *TRAVAUX* 50, 727-732.
8. Geoff P. Bearne, The development of aluminum reduction cell process control. *JOM*, Vol. 51, No. 5, 1999, 16–22.
9. Svent Wold, Kim Esbensen and Paul Geladi, Principal component analysis, *Chemometrics and Intelligent Laboratory Systems*, Vol. 2, 1987, 37-52.
10. Derry, A., Krzywinski, M. & Altman, N. Neural networks primer, *Nat Methods*, Vol. 20, 2023, 165–167.
11. Amit Gupta, Introduction to deep learning: Part 1, *CEP*, June 2018, 2018, 22-29.
12. Nazatul Aini Abd Majid et al., Aluminium process fault detection by multiway principal component analysis, *Control Engineering Practice*, Vol. 19, Issue 4, 2011, 367-379.
13. Petre Manolescu, Carl Duchesne, Jayson Tessier and Gudrun Saevarsdottir, On the use of multivariate statistical methods to detect, diagnose and mitigate abnormal events in aluminium smelters. *Light Metals* 2018, 475-484
14. Jayson Tessier et al., Increasing potlife of Hall–Héroult reduction cells through multivariate on-line monitoring of preheating, start-up, and early operation. *Metallurgical and Materials Transactions B*, Vol. 41, 2010, 612–624.
15. Julien Lauzon-Gauthier, Carl Duchesne, Jayson Tessier, Diagnosing Changes in Baked Anode Properties using a Multivariate Data-driven Approach, *Light Metals* 2013, 1219-1223.
16. Breakthrough collaboration between Aluminium of Greece and General Electric (GE) to optimize productivity and reduce energy costs, https://www.mytilneos.gr/media/12zlfxns/mytilneos_announcement_14022017_en.pdf, (accessed on 15 July 2023).
17. Ioannis Karnachoritis, Laith Al-Hindawi, An example of applying 4.0 on Aluminium Potlines : The Digital Smelter, Future Aluminium Forum, 22 May 2019, <https://futurealuminiumforum.com/content-images/speakers/S4P6-2019-FAF-ICSOBA-presentation-AoG-GE-fin4.pdf> (accessed on 15 July 2023).
18. RUSAL is implementing a ‘BigData’ aluminium production management project at several of its Siberian smelters, https://rusal.ru/en/press-center/press-releases/rusal_is_implementing_a_bigdata_aluminium_production_management_project_at_several_of_its_siberian_s/, (accessed on 15 July 2023).
19. Emili Dral, Optimizing Aluminium Production with Machine Learning, Future Aluminium Forum, 22 May 2019, <https://futurealuminiumforum.com/content-images/speakers/Emeli-Dral-Mechanica-AI.pdf>, (accessed on 15 July 2023).

20. STARprobe: STARprobe™ | STAS, <https://www.stas.com/produits/electrolyse/starprobetm/> (accessed on 15 July 2023)
21. Hereaus website: Bath Temperature & Chemistry Measurement (hereaus.com), (accessed on 15 July 2023).
22. DTS: DTE – Metals Intelligence – Metals Intelligence, <https://dte.ai/> (accessed on 15 July 2023).
23. Hans Erik Vatne, Smelter of the future, keynote presentation at TMS 2019, March 10-14 2019, San Antonio, USA, https://www.tms.org/tms2019/downloads/lmkeynote/FINAL_Vatne.pdf , (access on 15 July 2023).
24. Daniel A. Steingart, James W. Evans, Paul K. Wright and Donald P. Ziegler, Experiments on wireless measurement of anode currents in Hall cells, *Light Metals* 2008, 333-338.
25. Li Jie, Yang Shuai, Zou Zhong and Zhang Hongliang, Experiments on measurement of online anode current at anode beam in aluminum reduction cells, *Light Metals* 2015, 741-745.
26. Arthur Martel, Anode spike detection using advanced analytics and data analysis, *Proceedings of 35th International Symposium ICSOBA*, Hamburg, Germany, 2 – 5 October, 2017, Paper AL05, *TRAVAUX* 46, 815-822.
27. Yuchen Yao et al., Fault detection and diagnosis of alumina feeding system using individual anode current measurement, *Light Metals* 2020, 543-549.
28. Jayson Tessier, Gary P. Tarcy, Eliezer Batista and Xiangwen Wang, towards on-line monitoring of alumina properties at a pot level, *Light Metals* 2012, 633-638.
29. Choon-Jie Wong et al., A smart individual anode current measurement system and its applications, *Light Metals* 2023, 43-51.
30. Bo Hong et al., The application of intelligent breaking and feeding technology for aluminium reduction pot, *Light Metals* 2020, 719-725.
31. Louis Bugnion and Jean-Claude Fischer, Effect of carbon dust on the electrical resistivity of cryolite bath, *Light Metals* 2016, 587-591.
32. Yashuang Gao, Mark P. Taylor, John J.J. Chen and Albert Mulder, Aspects of change management and process management at some smelters, *Light Metals* 2015, 763-768.