Light Metals 2009 *Edited by xxx* ***TMS (The Minerals, Metals & Materials Society), 2009***

DEVELOPMENT OF A MULTIVARIATE PROCESS CONTROL STRATEGY FOR ALUMINIUM REDUCTION CELLS

Marco A. Stam[1)], Mark P. Taylor[2)], John J.J. Chen[2)], Albert Mulder[1)], Renuka Rodrigo[3)]

[1)] Aluminium Delfzijl B.V., P.O. Box 133, 9930 AC Delfzijl, the Netherlands
[2)] The Light Metals Research Centre, University of Auckland, Private Bag 92019, New Zealand
[3)] Heraeus Electro-Nite Company LLC., One Summit Square, Langhorne, PA 19047, USA

Keywords: Multivariate Process Control, Cell Behaviour, Root Cause Analysis

Abstract

Process intensification is used worldwide to maximize economic as well as sustainable operation of existing chemical plants. The aluminium reduction process has strong interactive multivariate characteristics with limited process observability and responses which are non-linear and vary over a wide range of time scales. Instead of applying compensatory single input-single output loops, this paper describes a process control strategy based on passivated responses to common cell behaviours, advanced detection of abnormalities and cause-specific corrective or preventative control actions.

Statistical multivariate control surfaces are identified for alumina feed, bath and liquidus temperature measurements. Online root cause analysis and subsequent quality of decision-making have been improved through soft sensors which fingerprint individual failure mechanisms. Cells are brought back to their natural behaviour envelope and this envelope is constantly updated and improved. A module-based approach allows flexible configuration of the overall control philosophy, which has now been tested on industrial scale resulting in significantly higher current efficiency and reduced energy consumption.

Introduction

There is a strong pressure to push aluminium smelters towards maximum value for all stakeholders, but both pathway and final destination are continuously under discussion and are strongly influenced by rapid changes in economical and environmental circumstances. Although the development of cell technology has been through an incremental approach with cell dimensions and line amperage increasing, the controllability of the aluminium reduction process hasn't improved much over the last thirty years [1]. For example the rate of decrease of energy as well as carbon usage has dampened considerable. This indicates that the same or even more causes of variation are still embedded in the process. Drivers of variation are actually building, not reducing due to power modulation and raw material deterioration. The need of new control strategies is linked to the necessity to reduce the energy usage and to increase the flexibility of energy use. Beside this smelter footprints in many communities will not be tolerated because it is seen as cost and environmental burden on the community.

In particular process intensification through amperage increase has exacerbated the interactions of the various parameters due to the cell dynamics, and imbalances must be sensed quickly and their causes corrected or removed to maintain cells in their most efficient operating zone, or move them quickly to a new economic operating point. Advanced control of a type not previous employed is necessary in order to run smelters at these new heat dissipation and alumina dissolution intensities continuously. Much as Edwards Deming advocated decades ago for the manufacturing industries, causes of variation must be continually removed every day in processing industries such as aluminium production using a new control strategy - if the cost and energy intensity of production is to be reduced to sustainable levels in the carbon-sensitive, global economy.

In the present collaborative research between Aluminium Delfzijl, the Light Metals Research Centre at the University of Auckland and Heraeus Electro-Nite, the development of such a control strategy has been undertaken and tested at Aldel. In this work the interactive multivariate nature of the aluminium reduction process is incorporated into the new control philosophy to improve the quality of decision-making, automated control decisions and also human decisions.

Control Theory

Classical control theory advocates manipulation of inputs in order to bring the outputs of a system to their targets, in order to maintain the desired process conditions. Single input-single output control systems are usually simple feedback loops which recalculate process settings based on sensor measurements. For more complex processes multiple input-multiple output control systems have been implemented and for both SISO and MIMO systems proportional-integral-derivative (PID) loops are commonly used in many process industries. These controllers regulate inputs in a systematic, but empirical manner using the deviation between measured and target sensor values. Therefore an aggressive control action is produced at a large deviation from the target, whereas a limited action occurs close to the target in order to avoid overshoot of the control model.

This traditional control approach results in the response of manipulating control variables or inputs being repeated over and over thousands of times for every control loop, until the limits of manipulation are reached or the controller is disabled. Surveys of PID control loops in USA and Australia have found that only 31-36% of these controllers are operating as intended. The basic problem here is that the systems assume the cause of the variation and compensate for it, rather than diagnosing and trying to remove the cause in each case. Further variation is induced through this compensatory behaviour of inputs and these are not considered in the control philosophy. The fact that the real causes of the variation are not removed in this control paradigm means that apparently successfully automated processes deteriorate over time as more causes of variation are introduced.

In order to avoid under- and overreaction of a controller, and action when no statistically significant variation exists, systematic or common process behaviours should be taken into account - for example alumina feeding/sludging, anode setting and bath/ledge induced variation. These events influence both temperature and composition/volume of the bath and therefore the variation in these parameters and others is strongly interrelated (Figure 1). Without understanding the relationship between bath and liquidus temperature in the multivariate operating space, control actions based on fixed targets and deviations, quickly lead to incorrect responses [2]. Specification limits or 'dead bands' for these variables (eg. yellow region in Figure 1) illustrate the fallacy of univariate or 'deviation from target' based strategies in this complex process. In fact the natural behaviour of the system in Figure 1 is well outside the specification region and is actually defined by a multi-variate, elliptical control surface as shown by the red dotted line.

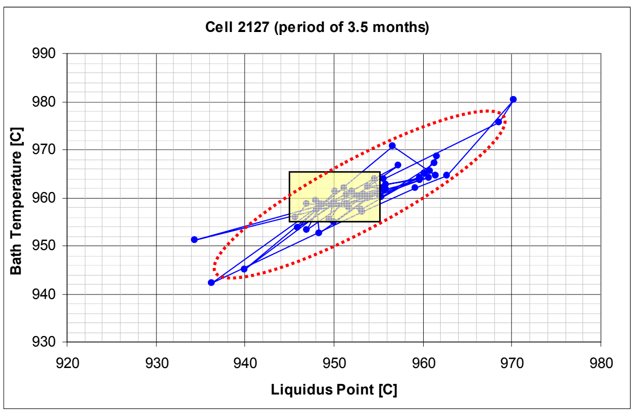

Figure 1: Temperature-liquidus control ellipse

Despite being a continuous electrolysis process, most sub-processes in a smelting cell like alumina feeding, anode setting, anode covering, metal tapping and liquid level control are conducted batchwise and controlled by univariate control loops. Maximum efficiency in such a system can only be achieved by stabilizing all individual input variables - rather than manipulating them continually.

In addition, control should incorporate root cause identification and analysis within its daily function as an intermediate step between measurements and control actions to avoid treatment of symptoms. By correction or elimination of abnormalities during the control function, process variability will be continually removed and optimum control settings can be determined. Continuous improvement is then able to be achieved by an iterative approach of systematic elimination of these problems, day by day.

Control Model

The underlying strategy here is based on the statistical definition of common cell behaviours and the detection of abnormalities which lie outside the control surfaces defining these natural behaviour envelopes. To do this the cyclic thermal behaviours driven by alumina feeding, sludge formation and dissolution and the associated bath volume changes had to be investigated since they were found to play a crucial role in the instability of these thermal cycles [2, 3]. A thermal self-regulation mechanism between mass and energy balance had been derived earlier and involved melting or freezing of side-ledge only [4]. In this case changes in liquid bath volume are limited and the process is self-damping - therefore able to be controlled automatically by small adjustments to ordinary process settings like cell voltage and/or AlF_3 additions [5].

However in most reduction cells today the mass of alumina fed to a cell per day is almost equal to the amount of liquid mass available for dissolution. Combined with the batch feeding technology still being used, this huge energy demand for dissolution means that sludge formation is almost inevitable in aluminium smelting and, if allowed to continue over a sustained period of time, sludge build-up can de-stabilize the overall process conditions significantly. Additional energy is needed to heat up and dissolve extra alumina added to the cell and large, fast variations in liquid bath volume and composition can occur as a mixture of alumina and cryolite in the sludge is precipitated onto the cathode. Under these conditions Cry-O-Therm measurements detect a fast drop in liquidus temperature (sometimes into the 930's) indicating a rapid increase in AlF_3 concentration due to sludge formation.

Finally, the thermal and physical stability of anode cover can also lead to large disturbances in cell mass and energy balance control [6, 7]. Both sludge and anode cover mechanisms have self-accelerating characteristics which are distinctly more dangerous than the bath/ledge self regulation. These mechanisms are shown in red in the overall Mass/Energy Balance diagram in Figure 2 and require early detection in operation followed possibly by intervention at the cell in order to correct a physical problem there.

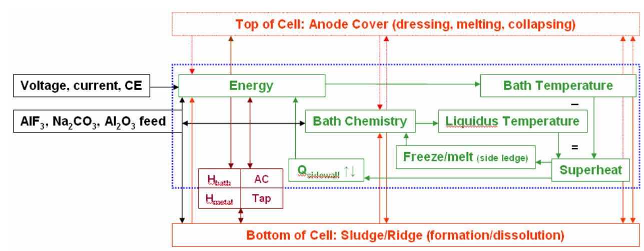

Figure 2: Overall interaction between mass and energy balance

The Hotelling T^2 statistic is an appropriate multivariate control charting and analysis method to use in these interrelated, multivariate process conditions [8]. A three-dimension control envelope is calculated for every cell based on historical data of alumina feed, bath and liquidus temperature measurements. In order to take line current variations into account, alumina feed is transformed to a ratio which is calculated by the amount of alumina fed by point feeders divided by the theoretical amount related to average line current and current efficiency. Bath and liquidus temperatures are measured every two days.

The resulting operating ellipsoid represents the limits of common behaviour for each cell (Figure 3). If the trajectory through the control envelope stays within these given surface limits and the ensuing vector length doesn't exceed a predefined threshold value ("pinballing") the cell is statistically in-control [3, 9]. Under these circumstances normal control can be used to optimize process settings. Otherwise the reduction cell is out-of-control statistically and additional data and control actions are needed to address the cause. In these out of control situations, over-reaction of the control system is avoided by resetting process settings to the basic set points or a long-term average value. The sensitivity of the Hotelling T^2 statistic will be increased as abnormal process variations are reduced because the natural behaviour envelope of the cell shrinks. This leads to earlier warning signal of abnormal behaviour over time.

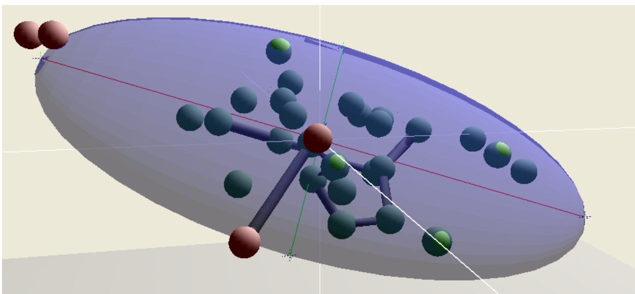

Figure 3: Natural behaviour envelope of a reduction cell

The second part of the underlying process control philosophy is an advanced method of detection of abnormalities. Hotelling T^2 statistic and "pinballing" detect and signal out-of-control behaviour, but it does not give information about the origin of abnormalities. Detailed root cause analyses within the control system are used online to diagnose a wide range of individual failure mechanisms. Soft sensors have been developed in order to detect specific failures as early as possible, while smart combinations of different information sources distinguish real problems from false alarms, or separate individual problems, as discussed in subsequent sections of this paper. Due to the origin, speed and potential impact on the cell stability of some failure mechanisms, especially around alumina feeding and anode spike formation, this online sensing approach is justified. Better understanding and documentation of the underlying cell dynamics in Figures 2 and 3 are providing recognition of repeat conditions and aiding process decision making on shift, as a result of which the process variability in the test cell group has been reduced.

Control Architecture

A module-based approach has been developed which allows flexible configuration of the underlying control philosophy. Every module is designed for a specific task. Parameters or targets used in the module logic are defined as variables and can easily be adjusted. All modules have the same IT-program structure which enables simple modification based on additional knowledge from test programs or adjustments in process conditions like raw materials, line current increase and power modulation. New modules can easily be added to the control model and old modules can be switched off.

The control architecture is based on three different types of modules. The first category of module calculates all statistical information. The outcomes are real numbers such as Hotelling T^2 values, "pinballing", cusums of different process parameters like alumina feed and AlF_3 additions. The second module type is for the detection of abnormalities in which every potential failure mechanism has its own detection module. If a problem has been detected, a cause-specific event with binary characteristics will be set. Then a decision-tree will be activated to initiate root cause analysis (RCA). In this case an intervention by an operator or process engineer might be triggered if necessary. Feedback from measurements and observations into the system create better understanding and further possibilities to improve the detection modules.

The third module type calculates new process settings like cell voltage, AlF_3 additions or alumina feeding. The optimization of set points is only allowed when no abnormalities have been found. Figure 4 shows the philosophy and architecture of the control model which follows the loop of determination of cell behaviour, using statistical calculations (1), detection of abnormalities (2) and root cause analysis or automatic control actions (3). Over a period of time, statistical analysis of frequently detected abnormalities leading to similar disturbances in the ensuing cell dynamics are pareto'd leading to structural improvements as re-design of people's work, cell/smelter hardware, or control modules (4), as shown in Figure 4. For example maintaining heat balance at higher amperages will need adjustments to anode cover (thickness and/or composition), anode changing and tapping, as well as adjustments inside existing control modules (e.g. targets, limits) or even the development of new modules (for current modulation as a recent example).

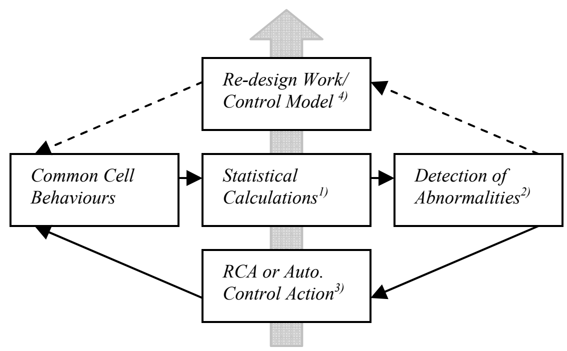

Figure 4: Control Philosophy and Architecture

Operation of the Control System

As an outcome of detection modules different events will be set. The pot controller unit generates digital outputs which are recognized by the Supervisory software as 64 events at level 1. On a higher level, soft sensors can identify more complex failure mechanisms by a smart combination of these different events and other measurements and signals. For example a bath temperature rise and a reduction of the cusum of alumina feed simultaneously is an indication of an anode spike [3]. In total approximately 100 events are defined. In order to judge individual cell stability the number of critical events is registered and traced over time. To focus the strategy on continual process improvement, Pareto analysis of the events on a group of cells or potline over a given period of time can be carried out. The combination of number and duration of individual causes gives information about dominant causes of variation input into project planning and control module development in the future.

Module management is ordered by predefined sequences based on three individual steps within every module and activated by a process trigger (Figure 5). This trigger can be a timer (once per 1, 5, 60 minutes or once per day), an activity (beam raising, anode changing, metal tapping, anode effects or process measurements) or new calculated statistical signals (abnormality detection) or process settings. After this trigger the activated sequence will pass through individual modules. Every module starts with a check whether this module is applicable to a particular cell. Modules can be connected to potlines, group of cells or individual cells. If a module is not valid for that cell, the system will step further to the next module (A1).

The second step is a check whether this module is "active" or "blocked" by the control system. Modules can only be blocked by events and the system will step on to the next module (A2). For example a problem in respect to alumina feed detected by more than 2 anode effects within the last 48 hours can be blocked after a current outage. A blocked module can be activated due to the absence of that particular event or by a module-specific timer. In this case 2 days after the current outage the described module is activated automatically. Finally the module function will run and depending on the type of module, statistical calculations will be carried out, cause-specific events will be set or new process settings will be calculated. After that the system will step further to the next module (A3).

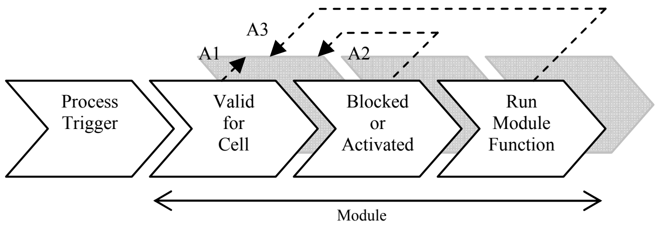

Figure 5: Sequence of Modules

Results and Discussion

The multivariate process control strategy has been tested on a group of 10 industrial cells on Potline 2 at Aldel and compared with 10 reference cells located in the same row in same potline to ensure similar process conditions and operational circumstances. Figure 6 demonstrates the average and uncertainty for the test and reference groups respectively, over a test period of 8 months. A 95% confidential test has been carried out and parameters with a significant difference between the groups have been marked*).

	Trial Group	Reference Group	
Bath Temperature	966.7±0.6	967.5±0.5	°C
Liquidus Temperature	953.5±0.5	952.6±0.5	°C
Superheat*)	13.1±0.2	14.9±0.2	°C
Cell Voltage*)	4.501±0.001	4.465±0.002	V
Cathode Voltage Drop	1.54±0.00	1.68±0.02	µΩ
Noise	0.071±0.001	0.071±0.001	µΩ
Bath Height*)	19.5±0.1	18.8±0.1	cm
Number of Overfeeds*)	14.0±0.1	12.3±0.1	1/day
Al_2O_3 via Point feeders*)	1996±2.0	1970±2.1	kg/day
Number of Anode Effects*)	0.23±0.01	0.12±0.01	1/potday
Iron Content	0.150±0.002	0.158±0.003	%
Silicon Content	0.056±0.000	0.059±0.000	%

Figure 6: Test Group versus Reference Group for 8 months

The above listed parameters, including ellipsoid volume (-34%) and vector length of "pinballing" (-11%), give a clear indication of significantly lower process variability on the test cells. A detailed investigation of the data gives strong evidence for the existence of a prevailing sludge cycle on the reference group. This is supported by a crosscheck of the variation over the test period in a number of different process parameters. Specifically, lower liquidus temperatures, lower bath heights and higher cathode voltages are an indication of higher sludge formation and sludge levels in the reference cells. These parameter ranges are summarized in Figure 6.

The higher number of anode effects indicates leaner operation (lower average alumina concentration) on the test cells. The number of overfeeds of alumina per day and the total amount of alumina fed via the point feeders to the reference cells are significantly lower, over the eight months of the trial. These parameters show not only higher averages on the test cells, but also lower variability over time. In the case of long term variations across the whole potline due to raw material changes for example, the test cells were kept longer at normal process conditions and the drop in performance is not as large as on the reference cells.

Sludge formation can induce rapid thermal and compositional changes as discussed earlier, with correspondingly large drops in liquidus temperature due to preferential precipitation of cryolite out of liquid bath. In this case the superheat actually rises, because the reaction in bath temperature is much slower than the drop in liquidus point. Contrary to previous thinking a low liquidus temperature is connected with high superheat in this situation and an increase of cell voltage, either/or in combination with reduction of AlF_3 additions, will hide the root cause of the underlying mass and energy imbalance. Over the long run, higher sludge levels lead to higher cathode voltage drop and higher ensuing temperatures, while over-reactions of the control system may result in periods of lower temperature and lower anode-cathode distance (ACD) operation leading to poorer alumina solubility and increased re-oxidation of metal, respectively.

The average bath temperature is lower for the test cells, whereas the liquidus temperature is higher. The superheat shows a significantly lower average and a lower number of spikes (-11%) was found. The distribution for the test cells demonstrates a 10% higher number of cells running ≤10°C and 6% less cells with superheat excursions above 20°C. Of course it's questionable whether bath temperature is a reliable key performance indicator, being the outcome of very complex interrelated process dynamics. For example a stable temperature over time can be found at low current efficiency due to re-oxidation of aluminium and without increased noise levels. However there is now little doubt that sustained period of low temperature on cells lead to a deterioration in their performance - both current and energy efficiency being adversely affected.

In order to determine long term effects both bath and metal mass were followed over a period of 2 anode rotas for a cell. Last year an average bath mass of 4.7 tonnes was found with a standard deviation of 0.7 tonnes [3]. Measurements carried out over the last 2 months of the underlying test period show an average bath mass of 4.3 tonnes and a standard deviation of 0.5 tonnes. With respect to the overall cell dynamics it can be concluded that a more stable mass balance and bath volume has been achieved due to the new control system.

Although the average bath height is higher for the test cells, the ensuing iron and silicon levels are considerable lower, showing that the variation in bath height is better. Most of the iron contamination can be related to stub-attack, caused either by high bath levels and/or by local air burn of anodes around tapping and point feeder holes. The higher silicon level on the reference group can be directly linked to the combination of higher cell superheats and more variation in the superheat.

Both current efficiency and energy consumption for the test group are better, the current efficiency substantially so (Figure 7). One of the main control strategy effects has been the extra check prior to automatic control actions about whether the cell is within its natural behaviour envelope. On the test cells 30% of ordinary control actions have been blocked by a number of different events like Hotelling, “pinballing”, spike detection, anode effect error or sludge detection. After this blockage the voltage will be set to a long term average and AlF_3 additions will be adjusted to the base feed rate. From these decisions, unwanted variation of the anode-cathode distance has been prevented.

For the reference cells, a comparative reduction in the amount of alumina dumps via the point feeders was found in combination with a strong reduction of the cell voltage (and ACD), both of which match the lower current efficiency of these cells. Due to higher current efficiency of the test cells, extra energy is needed to maintain the overall energy balance. Of course this energy could be supplied more profitably and at better energy efficiency in the future using higher line amperage. The higher current efficiency has been confirmed by copper dilution measurements.

	Current Efficiency [%]	Energy Consumption [kWh/kg]
Test Cells	95.2	14.09
Reference	93.9	14.17
Difference	1.3	-0.08

Figure 7: Current Efficiency and Energy Consumption

Conclusions

A multivariate process control strategy has been developed and successfully tested on 10 industrial reduction cells. The focus of the strategy is the determination of natural behaviour envelopes according to the strong interactive multivariate characteristics in combination with an advanced detection of abnormalities resulting in cause-specific corrective or preventative control actions. A significant increase in current efficiency of 1.3% and a reduction of energy consumption of 0.08 kWh per kg aluminium has been achieved. As a side-effect an increase of the predicted failure age of the cells is projected due to tighter superheat control.

Depending on rapidly varying economic circumstances and the technological limits of a given technology, control decision-making itself is situation-specific. Therefore the control philosophy is built upon a module-based structure leading to maximum flexibility in the configuration of the underlying control strategy. The sequence of the control system starts with a statistical investigation of individual cell status followed by a detailed detection of potential abnormalities. Finally, root cause analysis and/or automatic control actions are applied in order to bring the cell back to its natural behaviour envelop as soon as possible. Frequently detected abnormalities based on Pareto analysis are leading to re-design of work procedures and/or adjustments to the control model. Continuous improvement is accelerated by an increased sensitivity of the Hotelling T^2 statistic due to continual shrinking of the multivariate control envelope.

References

1. B.J. Welch and J.T. Keniry, “Advancing the Hall Heroult Electrolytic Process”, Light Metals 2000.
2. M.A. Stam, M.P Taylor, J.J.J. Chen, S. van Dellen, “Operational and Control Improvements in Reduction Lines at Aluminium Delfzijl”, Light Metals 2007
3. M.A. Stam, M.P Taylor, J.J.J. Chen, A. Mulder, R. Rodrigo, “Common Behaviour and Abnormalities in Aluminium Reduction Cells”, Light Metals 2008
4. Taylor, M.P., 1997, Challenges in Optimising and Controlling the Electrolyte in Aluminium Smelters, *Molten Slags, Fluxes and Salts ’97 Conference*, 659-674.
5. M.A. Stam, K.R. Kloetstra, “Development of an Advanced Process Control Strategy at Aluminium Delfzijl”, Proceedings 8th Australasian Aluminium Smelting Workshop, 2004
6. M.P. Taylor, G.L. Johnson, E.W. Andrews, B.J. Welch, “The Impact of Anode Cover Control and Anode Assembly Design on Reduction Cell Performance”, Light Metals 2004.
7. E.W. Andrews, M.P. Taylor, G.L. Johnson, I. Coad, “The Impact of Anode Cover Control and Anode Assembly Design on Reduction Cell Performance - Part 2”, Light Metals 2005.
8. J.J.J. Chen, M.P. Taylor, “Control of Temperature and Aluminium Fluoride in Aluminium Reduction”, Aluminium, 2005.
9. Y.S. Gao, M. Gustafsson, M.P Taylor, J.J.J. Chen, “The Control Ellipse as a Decision Making Tool to Control Temperature and Aluminium Fluoride in Aluminium Reduction”, Proceedings 9th Australasian Aluminium Smelting Workshop, 2007.