Multiblock Monitoring of Aluminum Reduction Cells Performance

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Keywords: Process Monitoring, Reduction Cells, Process Control, Multivariate Statistics

Abstract

Aluminum reduction cells performance are affected by many factors. In order to efficiently understand possible causes of performance upsets, all major sources of variations have to be monitored. This implies monitoring all anode and alumina properties, as well as pot state and manipulated variables, while also taking into account pot design or integrity after start-up. Considering the high number of variables involved in such a task, this is practically impossible using typical statistical process control tools. The problem is even worst when applied on a pot basis. This paper proposes the use of multiblock PLS (MBPLS) to build a monitoring scheme on a pot basis, simultaneously taking into account the influence of alumina and anode properties, of pot state and manipulated variables, as well as the pot state following its start-up. Derived from a regression model, the monitoring policy ensures that only variations relevant to pot performance variations are highlighted.

Introduction

Aluminum reduction smelters typically operate a hundred to a thousand metallurgical reactors known as reduction cells or pots. Although each cell process variables are followed by process engineers on a daily or a weekly basis, key performance indicators (KPI) are typically followed on a weekly or a monthly basis. Hence, reports on current efficiency (CE) and energy consumption (EC) are investigated by process engineers and feedback corrective actions are taken, aiming at keeping cells in an optimal productive state.

However, it is generally not easy for process engineers to determine what might have been the cause of a process excursion leading to low CE or high EC. The reason is that reduction cells performance are simultaneously affected by the behavior of variables of different nature that could be grouped in different blocks. This is illustrated in Figure 1.

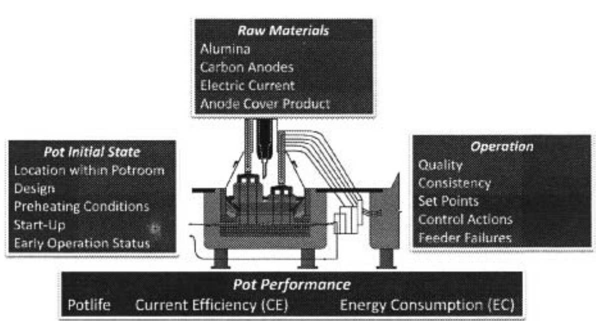

Figure 1: Variables typically involved in reduction cells performance variations.

Hence, following a pot excursion on CE or EC, engineers have to look at the behavior of many variables before taking corrective actions. Typically, this is achieved through the investigation of each variable using univariate statistical methods (i.e.: computation of variables average and standard-deviation or through the investigation of univariate Shewart control charts). This is time consuming and suboptimal as it does not account for the fact that reduction cells performance are resulting, from the simultaneous interaction of all these variables. Reduction cells are multivariate processes. Unfortunately, through the use of univariate statistical methods, it is impossible to capture the combined effect of these variables.

A better approach for investigating a process upset would consist of looking at the pot status based on all variables at the same time. This is advantageous as it captures the structure or the interactions between process variables and pot performance. This is achieved through the use of multivariate statistical methods such as principal components analysis (PCA) or partial least squares (PLS). These methods enable the construction of multivariate monitoring charts and diagnosis tools while accounting for the multivariate nature of processes.

This work proposes the use of these methods to develop a pot overall status or health monitoring scheme based on all available information aiming at explaining pot performance variations. Hence, the proposed monitoring strategy includes alumina and anode properties, pot state and manipulated variables, the pot initial state following its start-up and different binary variables arising from process knowledge. Doing so, a single monitoring strategy would enable to easily and efficiently monitor pot status based on all variables leading to its performance variations. Moreover, this strategy would also help diagnosing process upsets through the use of contribution plots.

This paper is divided as follows. First, the drawbacks of univariate statistics and advantages of multivariate statistical analysis are illustrated. The dataset used for the model development is presented and the construction of the monitoring strategy is discussed. Finally, a case study illustrating how contributions plots can be used for upset investigation is presented. This is followed by a conclusion.

Multivariate Process Monitoring

Over the last decades, multivariate process monitoring has started to find its place in chemical and pharmaceutical industries, as well as within the food or the metallurgical industries. This is mainly due to the fact that more sensors, collecting data at a fast sampling rate, are now available. This resulted in the availability of massive databases for process monitoring and upsets diagnosis.

Nevertheless, the information enclosed in industrial databases encloses some noise and many variables are highly collinear (i.e.: correlated or dependent).

Multivariate statistical methods such as PCA or PLS become handy as they are well suited to the analysis of thousands of correlated noisy variables, even possibly enclosing some missing values arising from different sampling rate or defective sensors. These methods have been used for different Multivariate Statistical Process Control (MSPC) applications [1, 2, 3].

Recently, multivariate statistics have been used to develop different monitoring strategies for reduction cells. Majid *et al.* [4] used PCA on 5 minutes pot data for early detection of anode spikes and anode effect. Tessier *et al.* [5] also used PCA to develop a daily multivariate monitoring tool for reduction cells based on 65 variables. This later approach was used for detecting cells behaving abnormally as well as for troubleshooting.

Limitation of Univariate Process Monitoring

A limitation of univariate process monitoring can easily be illustrated using a simple case study. Daily bath temperature and excess of AlF_3 were gathered for a pot over two years. These are presented in Figure 2 and 3 with their respective +/- 1, 2 and 3 standard-deviations limits (std).

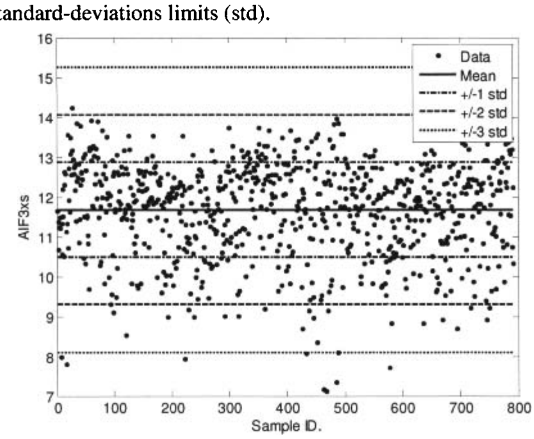

Figure 2. Univariate SPC for bath excess AlF3.

An engineer can inspect these two graphs on a daily basis to determine if a pot is in control, based on bath temperature and excess AlF_3. Engineers would flag observations based on some SPC rules [6]. However, this would not account for the fact that these two variables have a correlation coefficient -0.71. Hence, the underlying assumption for univariate SPC that variables must be independent is not met. This consequence is well illustrated in Figure 4. This figure presents bath temperature as a function of excess AlF_3. The +/- 2 standard-deviations limits are illustrated by dotted lines for both variables. Independent variables would have filled the gray square formed by the dotted lines and univariate SPC would have been an efficient tool for process improvement. However, it is evident that these observations only move along a defined axis. Monitoring the behaviour of a cell based on the joint confidence interval of these two variables would be much more appropriated. This is highlighted in Figure 4 through the +/-2 standard-deviation joint confidence interval marked by the ellipse. It is seen that the joint confidence interval captures the correlation structure between the two variables and thus enable monitoring cell behaviour with respect to its bivariate nature, assuming that only bath temperature and excess of AlF_3 are of importance.

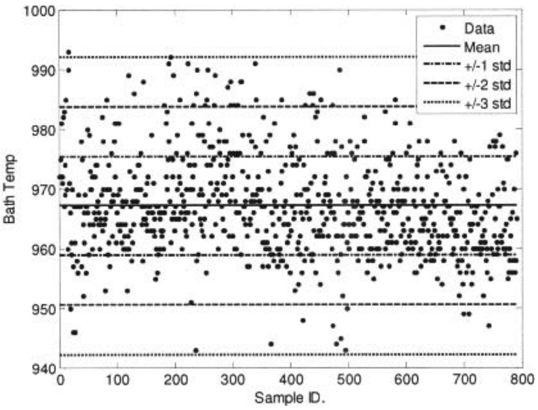

Figure 3: Univariate SPC for bath temperature.

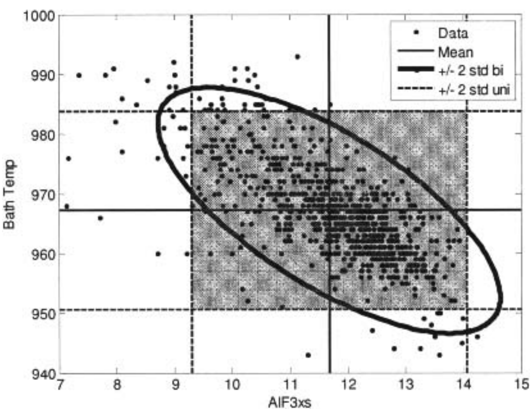

Figure 4. Bivariate SPC chart for bath excess AlF_3 and temperature.

This procedure is easily extended to more than two variables and allows the computation of a single metric indicating how far a pot daily observation is from the control space. This is computed using the Hotelling's T^2 statistics, which is χ^2 distributed.

$$T_i^2 = (x_i - x)\, \mathbf{S}^{-1} (x_i - x)^T \qquad [1]$$

where x_i is a row vector enclosing process measurements, x is a row vector enclosing process variables means or target, **S** is the process variables variance-covariance matrix and T_i^2, a scalar, is the Hotelling's T^2 statistics for the i^{th} observation. However, due to correlations among process variables, **S** is often ill-conditioned and leads to poor monitoring tools.

PCA/PLS Based Monitoring

In a way to overcome the ill-conditioned problem, it is advantageous to use PCA or PLS to compute the Hotelling's T^2 metric. PCA and PLS methods simply project process data into a sub-space (i.e.: the latent space) consisting of less variables that the original process data space. PCA aims at finding *A* latent variables **P** (*JxA*), each one explaining the greatest amount of variance of the original data **X** (IxJ) that is unexplained by the previous latent variables. On the other hand, PLS aims at finding A latent variables (**P**), each one explaining the greatest amount of the covariance between **X** and a response matrix **Y** (IxH). The latent variables are computed in such a way that they are independent, or uncorrelated, of each other, ensuring that each latent variable captures new information unexplained by the previous latent variables. Mathematical details of PCA and PLS are presented in the literature [1, 2, 3, 7].

The structure of the PLS model is given by:

$$\mathbf{X} = \mathbf{T}\,\mathbf{P}^{\mathrm{T}} + \mathbf{E} \quad (2)$$
$$\mathbf{Y} = \mathbf{T}\,\mathbf{Q}^{\mathrm{T}} + \mathbf{E} \quad (3)$$
$$\mathbf{T} = \mathbf{X}\,\mathbf{W}^* \quad (4)$$
$$\mathbf{W}^* = \mathbf{W}(\mathbf{P}^{\mathrm{T}}\,\mathbf{W})^{-1} \quad (5)$$

where **T** ($I \times A$) is the common latent variable space defined by the weight matrix **W*** ($J \times A$) and capturing the information in **X** that is the most highly correlated with **Y**. The **P** ($J \times A$) and **Q** ($H \times A$) matrices contain the orthogonal loading vectors mapping the common latent variable space in the space of **X** and **Y** (models of these blocks). The PLS model residuals for **X** and **Y** are stored in **E** ($I \times J$) and **F** ($I \times H$), respectively.

Dataset

The dataset for this work comes from the Alcoa Deschambault smelter, operating 264 AP-30 reduction cells above its nominal capacity. Data were collected over the complete life cycle of 31 cells. For each cell, a total of 209 preheating, start-up and early operation data, as well as alumina and anode properties and pot operating data were retrieved for complete pot life cycles. The pot related variables were retrieved on a daily basis, from the plant database while the other variables were stored as available. These data, the process descriptor data, are enclosed in the **X** matrix.

Developing the Monitoring Strategy

A PLS based monitoring strategy was selected for this application. On this basis, it is possible to link variations enclosed in the process descriptor matrix **X** with different response variables (**Y**). Here, the objective is mainly to track reduction cells production metrics. Hence, CE and EC are used as response variables. Therefore, these metrics were computed on a daily basis from daily tap metal weights, line current and pots volts.

The assumption is that, if a good statistical model can be built, it would be possible to assess pot status by simultaneously taking into account alumina and anode properties, of pot state and manipulated variables and also based on some pot specific parameters.

Time Basis Considerations

However, it is known that CE and EC computed through metal production, on a daily basis, are noisy metrics. One reason for that is coming from the use of metal tapping tables. This particular smelter uses a tapping table, similar to the one presented in Figure 5, to determine the amount of metal that should be tapped from a pot. As an operator measures the metal pad level, the metal height indicating the quantity of metal in the pot is converted into a tap weight that will be used for the next tapping operation. As seen in Figure 5, small differences in metal height may lead to large differences in CE. Another source of perturbation arises from bath carryover. As an operator taps metal, a variable quantity of molten bath is tapped from the pot. As this bath is tapped instead of metal, some metal is left in the pot. Hence, this artificially boosts the metal height and affects CE. Unfortunately, it is not possible to quantify the amount of bath that is carried over through the metal tapping operation on a pot basis. At best, it is possible to determine the amount of bath that has frozen on the crucible lining for some group of pots. Finally, sideledge freezing and thawing also induce some artificial variations on CE. For a defined quantity of metal inventory, sideledge freezing will boost the metal height and hence artificially increase CE as the metal level will be higher. Conversely, sideledge thawing will negatively affect daily CE. These sources of noise or error will also affect EC as it is a function of CE.

Hence, daily CE and EC computed from metal tap weights, on a pot basis are irrelevant for performance assessment. Typically, plant operator will average CE and EC on a monthly basis in order to smooth out variations created by the tapping table, bath carryover and sideledge freezing/thawing.

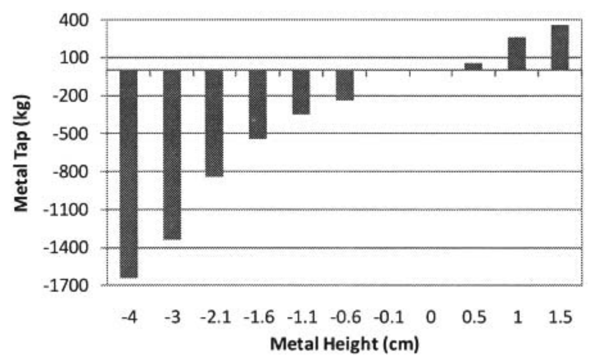

Figure 5: One of the metal tapping tables used at Alcoa Deschambault.

Hence, data gathered over the life cycle of the 31 cells were averaged on a monthly basis, leading to 2271 observations. Therefore, **X** contains 2271 observations and 209 variables and **Y** encloses 2271 observations and 2 variables. A schematic of the data structure is presented in Figure 6. The *Al2O3* and *Anodes* blocks enclose alumina and anode properties, respectively. The *MV* and the *SV* blocks encloses pot manipulated and state variables, while the *PSE* encloses pots start-up and early operation information. Finally, the *PLV* block encloses some logical (i.e.: binary) information with respect to the pot location within the potrooms.

Process Lag and Dynamics Considerations

In order to cope with process dynamics, lagged version of data blocks were used. The idea was that a pot processing bad alumina or anodes, for example, for an extended period of time may be more negatively affected than a pot processing such raw materials for a short period of time.

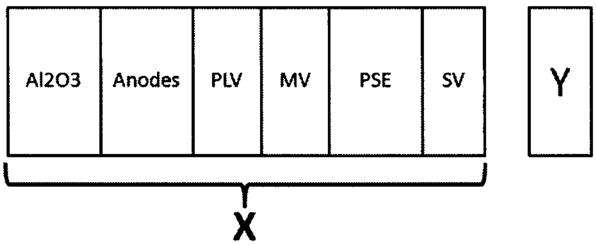

Figure 6: Schematic of the available data structure.

Therefore, PLS models using different lags were developed and assessed. Table 1 presents statistical details of three PLS models developed for different lags. The first model (*No Lag*) includes only present month data, while the *One Month* and *Two Months* models include present monthly values as well as one and two months lagged versions, respectively, of the data for the *Al2O3*, the *Anodes*, the *MV* and *SV*. The *PSE* and the *PLV* blocks are not lagged as they do not evolve over time. This table includes; the number of variables included in **X**, the number of principal components used in the different PLS models, the amount of variance of **X** accounted by the model (R^2X), the root mean squared error in calibration (RMSEC) for CE and EC and the amount of variance explained for CE and EC (R^2Y).

Table 1: Statistical details of PLS models.

	No Lag	*One Month*	*Two Months*
Nbr. **X** Variables	209	345	481
A	5	4	5
R^2X (%)	23	19	24
RMSEC CE (%)	2.21	2.21	2.14
RMSEC EC (kWh/kg)	0.38	0.37	0.38
R^2Y CE (%)	51	51	54
R^2Y EC (%)	51	50	51

From these results, it could be said that 19 to 24% of the variance of **X** (R^2X) explains about 50% of the CE and EC variance (R^2Y), indicating that most of the variance enclosed in **X** is not used for explaining variations in CE and EC. As seen from these results, including three months (present month and last two months) of data slightly improves the model performance as opposed to only using the present month data. The R^2Y CE slightly improves from 0.51 to 0.54, while it stays constant for EC. On the other hand, the RMSEC diminishes from 2.21 to 2.14 for CE and stays unchanged for EC. Hence, it was decided to use the *Two Months* model. Even if this model includes more variables, while leading to slightly better prediction performances, these are data collected in the present and last two months of the pot operations and are easy to extract from the plant historian while not causing any problems for the PLS algorithm. Still, it has the advantage of highlighting recurrent problems leading to CE or EC drifts while troubleshooting.

A considerable amount of efforts were made to improve predictive ability (R^2Y and RMSEC) using other ways to pre-process the data, but with no significant gain. Data quality may help explain some of the difficulties in capturing a greater percentage of variations (R^2Y) in CE and EC. Alumina and anode quality variables are not measured on a pot-to-pot basis. Alumina properties are rather estimated from suppliers COA and blending data, and weekly population averages are used to describe anode quality based on a limited number of analyzed core samples. A better traceability of these raw materials would certainly help explain additional variance. Furthermore, the uncertainties involved in computing, the CE and EC values due to the tapping tables and errors, as discussed earlier, may very well limit the theoretically explainable performance fluctuations.

Figure 7 presents predicted against measured autoscaled CE values for the 2271 observations. This figure demonstrates that most of the predictions follow the prefect prediction line and that the prediction errors are distributed along the complete scale of measured CE. The reader should keep in mind that 2271 observations are plotted on this figure and that most of the observations are close to the prefect diagonal prediction line.

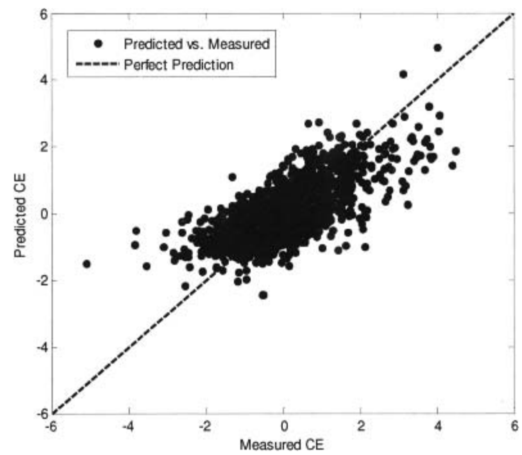

Figure 7: Predicted autoscaled CE as a function of measured CE.

Figure 8 presents the actual and predicted autoscaled CE values over the complete life cycle of four pots. From these plots, it is possible to conclude that the model can follow or describe most of the CE variations over the four pots life cycles. For example, the model almost perfectly matches some CE peaks for pot B102 at months 13, 50 to 53 and 63 to 66, demonstrating good predictive performance, but also indicating that the model structure (**P**, **W**, **W*** and **Q**) reproduces typical pot behaviour. However, the model does not capture all peaks as seen for pot A003 at months 6, 12, 17 to 19 and 25, for example. This indicates that either not enough information was included in the data to capture these peaks and that they are driven by different behaviour not accounted using the analyzed variables or they are arising from noise (i.e. tapping tables or measurement errors).

Case Study

As a statistical model enclosing most of the systematic interactions between pot process variables and performance is available, it is possible to use this model for process monitoring and diagnosis. The methodology is illustrated here using a case study.

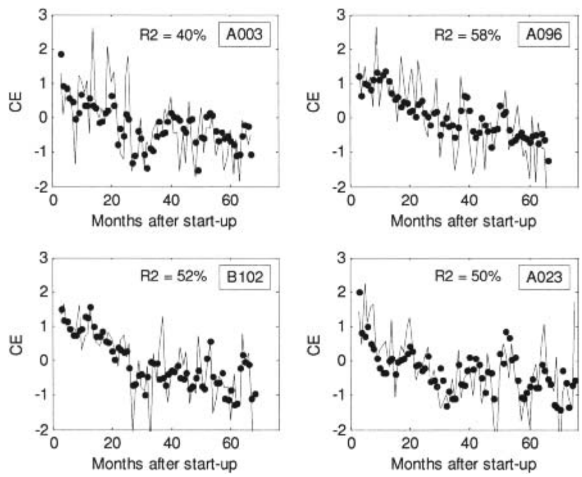

Figure 8: Actual (solid line) and predicted (dots) autoscaled CE over the complete life cycle of four pots.

After the first three months of operation, the monitoring strategy was applied to pot A003. Over time, on a monthly basis, process engineers follow predicted and computed autoscaled CE as presented in Figure 9. It is seen that the predicted CE does not exactly match the computed values, mainly arising from the different points discussed in the previous section. However, predictions follow the major trends and at least indicate if CE is improving or degrading. This figure illustrates a CE drop from observations (months) 26 and 27. The computed CE indicates a CE drop of 10%, probably greater than what the pot experienced as the computed CE were suspiciously high for months 24 and 25, while the predicted values indicate a drop of 4.5%, which is about twice the magnitude of the RMSECV. At ~350 kA, a 4.5 % CE drop equals ~4 tons of metal and is a significant drop. After highlighting this drop, the engineer can interrogate the variables contributions [3] in order to determine which variables played a role in this significant CE drop.

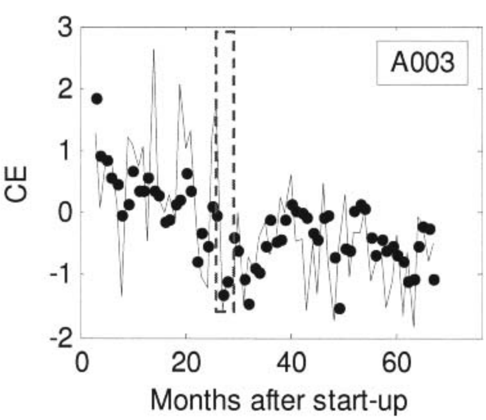

Figure 9: Actual (solid line) and predicted (dots) autoscaled CE over the complete life cycle of four pots.

The contribution of variable *j*, to the overall movement between two consecutive observations, *i* and *i-1*, within the latent space of *A* dimensions is computed using the following expression:

$$C_{i,j} = \sum_{a=1}^{A} \frac{[(x_{i,j} - x_{i-1,j}) * w^*_{a,j}]^2}{S^2_{t_a}} \tag{6}$$

where $x_{i,j}$ and $x_{i-1,j}$ are values of the j^{th} variable for observations *i* and *i-1*; $w^*_{a,j}$ is the weight associated to the j^{th} variable in the a^{th} latent space and S^2_{ta} is the variance of the a^{th} score. It basically consists of the difference between two observations of variable *j*, weighted by its importance in the model (w*). Dividing by the score variance gives an equal chance to each latent variable to influence the variable contribution. Note that the weights and variances in the above expression are taken from the regular PLS model with block scaling. To obtain the contribution of the variables in a particular block, one only needs to use the appropriate variables within that block ($x_{i,j}$'s). Variables contribution to the difference in predicted CE from observations 26 to 27 are presented in Figure 10.

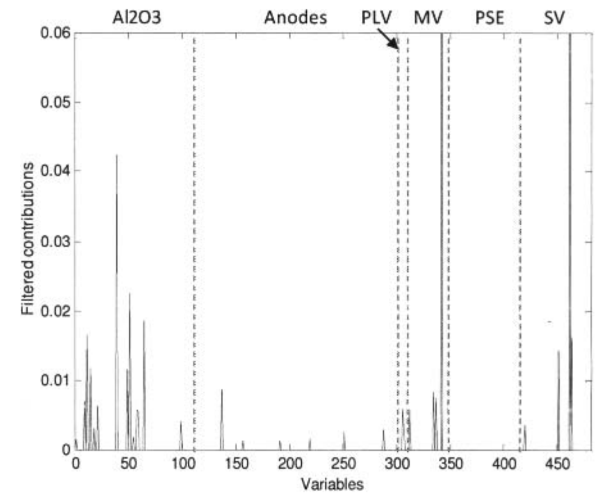

Figure 10: Variables contribution to the CE drop between observations 26 and 27 for pot A003

Following the inspection of this plot, smelter operators found that various alumina properties and pot state variables were strong contributors to the CE drift. Furthermore, bath height level and its target as well as the number of anode effects were flagged using the contribution plot. These correspond to variables 18, 22, 420, 462 and 464, respectively. During this period, the bath level dropped by more than 2.2cm, further reducing alumina dissolution capacity due to a smaller bath volume. This, in turn, increased the frequency of anode effects since less alumina was dissolved in the bath. Hence, it is easier to deplete alumina below the concentration leading to an anode effect. As a matter of fact, the anode effect frequency was three times greater than usual for pot A003 at observation 27 (i.e. monthly average corresponding to observation 27). Finally, the CE drop was most probably the result of degrading alumina quality and low bath level. Together, these variables increased anode effect frequency which, in turn, had a negative impact on current efficiency.

Conclusion

In this paper, an efficient monitoring tool based on all variables collected around reduction cells has been proposed. This methodology, based on multiblock PLS can efficiently cope with hundreds or thousands of correlated and noisy variables as it projects the pot information into a latent variable space of much lower dimensions than the original data space, while capturing most of the systematic variations.

Such a model was developed based on data collected over the complete life cycle of 31 reduction cells. Information on alumina and anode properties, on pot state and manipulated variables, on pot integrity after start-up and some logical information indicating pot position in the potroom was included. The resulting model accounts for 54% of the CE variance and 51% of the EC variance. Since different sources of variations may create added noise to computed CE and EC values, the model is judged useful and enables to predict CE and EC monthly values, on a pot basis, based on process data.

Following a drop of CE, or an increase of EC, for two consecutive months, it is possible to compute variables contributions and investigate what may have caused the performance upset. The reader should keep in mind that the model was built upon happenstance data (correlations) and not from a design of experiment. Hence, the model can not indicate causation. However, the lack of correlation indicates no causation. Therefore, process engineers have to use their knowledge and judgements, combined with the information arising from contribution plots, to identify possible root causes.

References

1. Kourti, T., MacGregor, J.F. (1995). Process analysis, monitoring and diagnosis, using multivariate projection methods, *Chemometrics and Intelligent Laboratory Systems*, Vol. 28, pp. 3-21.

2. Kourti, T. (2002). Process analysis and abnormal situation detection: From theory to practice, IEEE Control Systems Magazine, October 2002, pp.10-25.

3. Kourti, T. (2005). Application of latent variable methods to process control and multivariate statistical process control in industry, International Journal of Adaptive Control and Signal Processing, Vol. 19, No. 4, pp.213-246.

4. Majid, N.A.A., Young, B.R., Taylor, M.P., Chen, J.J.J., 2009, Detecting abnormalities in aluminium reduction cells based on process events using multi-way principal component analysis (MPCA), Light Metals 2009, pp. 589-593.

5. Tessier, J., Zwirz, T.G., Tarcy, G.P., Manzini, R.A., 2009, Multivariate statistical process monitoring of reduction cells, Light Metals 2009, pp. 305-310.

6. Ostle, B., Turner Jr., K.V., Hicks, C., McElrath, G.W., (1996), Engineering Statistics: The Industrial Experience, Duxbury Press, 568 p.

7. Tessier, J., Duchesne, C., Tarcy, G.P., Gauthier, C., Dufour, G., 2008, Analysis of a potroom performance drift, from a multivariate point of view, Light Metals 2008, pp. 319-324.