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# CONTROLLING THE VARIABILITY OF POTS KPVs : THE VARIABILITY MATRIX

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**Abstract**

*Over the course of 30 years the Process Control softwares have narrowed the variations of individual reduction cells. The volume of data available for day-to-day management of the potlines have increased considerably while the number of technical personnel per pot and per potline have been considerably reduced.*

*Combining the tools and principles of Continuous Improvement with in-depth knowledge of Reduction Process Control systems allows for a new generation of Potline Process Optimization techniques. These techniques, powered by new generation data integration software, can breathe a new life in the Energy and Environment Performance of all smelters. They can show their owners a new trend for improvement and demonstrate strong care to the local communities without mobilizing expensive capital resources and additional people. How much can we expect? What does it require in terms of Human and System capabilities? Where do we start and how far can we improve?*

*We will bring an innovative answer by describing a new tool: the Variability Matrix.*

## Introduction

One of the pillars of Continuous Improvement is the control of the process variability and control charts are widely used to follow and control the variability of the Key Process Variables – KPVs.

**JUST A REMINDER...of what could be done**

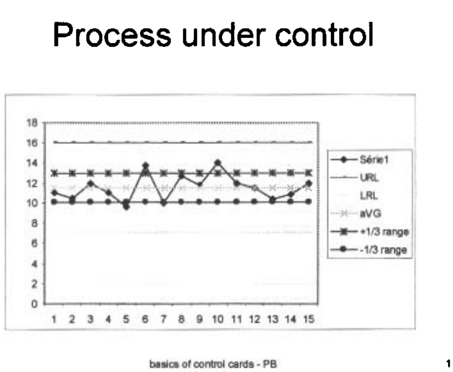


Figure 1: Control chart of a process under control

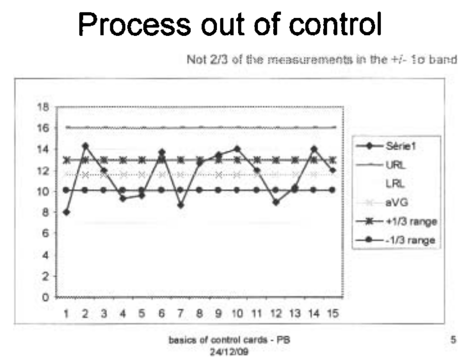


Figure 2: Control chart of a process out of control

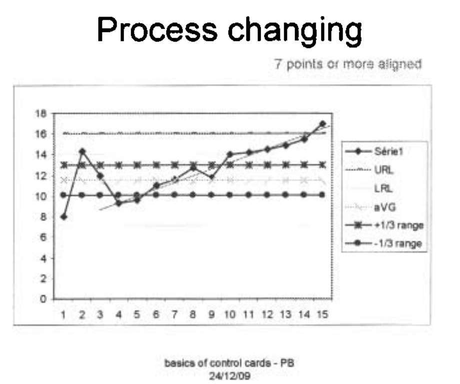


Figure 3: Control chart of a process changing

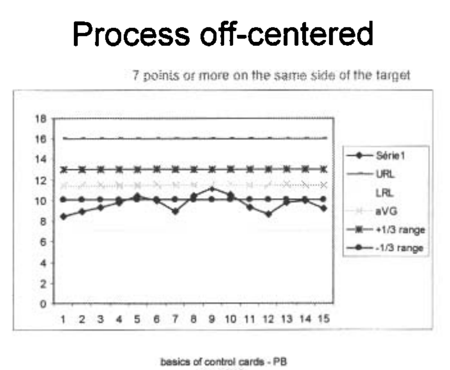


Figure 4: Control chart of a process under control but off centered

## Opening considerations

If these control charts are commonly used for processes with a single flow diagram as complex as it may be (e.g. an alumina refinery or a rolling mill), it is not the case for the potlines where things are significantly complicated by a series of facts:

- the KPVs of each given pot are a mix of KPVs common to all pots (e.g. amperage) and individual KPVs (e.g. metal height, bath composition, temperature…),
- these common and individual KPVs interact significantly over each other (e.g. amperage over bath characteristics)
- certain KPVs are measured and adjusted continuously by real time process controllers (pot resistance), others are measured periodically and controlled by discrete adjustments (e.g. $AlF_3$ excess, bath temperature, metal height)
- furthermore, the adjustment the common KPVs, in the first place the potline amperage depends significantly upon the interpretation of perceived common trends of individual pot data.

The efficient operation of any potline lies before anything in the ability of the operating team to control the variability of individual KPVs to facilitate the reading of the thermal condition of the pots in order to act upon the common KPVs.

If we review two most common pot KPVs, i.e. Aluminium fluoride excess and bath temperature, we see a significant variability, even in modern well operated smelters:

A few examples in real life:

- potlines targeting 11,5% $AlF_3$ excess experiencing a SD of 1,5% means one third of the pots are operating below 10% or above 13%.

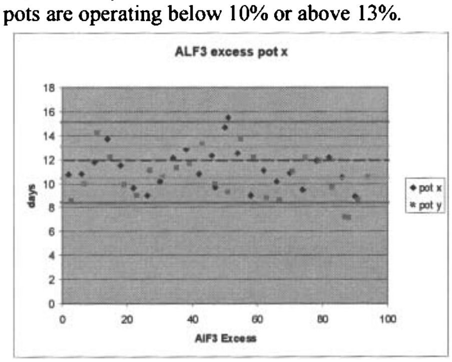


Figure 5: example of the $AlF_3$ control chart of two pots

- potlines targeting a bath temperature of 960°C experiencing a SD of 7°C or more means one third of the pots operate below 953°C or above 967°

The impacts on the Current Efficiency are well known:

- A Drop of 1% excess $AlF_3$ ⇔ + 2°C overheat,
- +10°C overheat⇔ - 1% CE,

If 30% of the pots are outside the optimum range, a gain of a precious fraction of a % CE is probably achievable by reducing the variability

We can legitimately question whether we are using to the fullest possible extent the information available and if appropriate data processing developments would allow to initiate CI projects enabling to reduce this variability.

## A pre-requisite: know the accuracy of the readings

A pre-requisite is to know (and verify permanently) the accuracy of the readings provided by the sampling and measurement chain: it can be defined as the standard deviation of approx 10 successive readings of a given variable on a same pot, carried out on 10 pots within a period of time representative of the sampling schedule.

One should always keep in mind that any correction table must be defined as a function of the accuracy of the measurements: it is illusory to correct a difference of 0,5 unit if the measurement spread is +/-2 units.

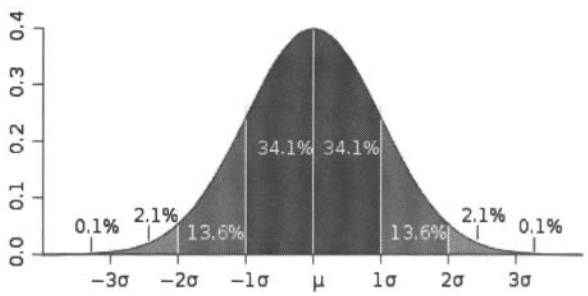


Figure 6: Gaussian probability distribution (source Wikipedia)

## A Variability Matric to analyse the changes of the KPI between two successive readings

We present the application to the $AlF_3$ excess but the same methodology is equally applicable to all KPVs.

The starting point is the ranges defined by the current variability of the KPV

| a | b | c | d | e |
|---|---|---|---|---|
| < 8,5 | 8,5 to 10 | 10 to 1 3 | 13 to 14,5 | >14,5 |

Table 1: Example of a Table of $AlF_3$ ranges of variability

We have a distribution

| a | b | c | d | e |
|---|---|---|---|---|
| $n_a$ | $n_b$ | $n_c$ | $n_d$ | $n_e$ |

Table 2: Table of distribution in the $AlF_3$ ranges

The purpose of the adjustment table is to bring any pot outside category "c" back as quickly as possible

If we define the probability of change of one pot from category "x" to "y" as $P_{xy}$, the result in an ideal world should be that :

$P_{ac} = 1$
$P_{bc} = 1$
$P_{cc} = 1$
$P_{dc} = 1$
$P_{ec} = 1$

This should be achieved in one or two readings: It is obviously not the case when we look at real potline data meaning there must be room for improvement.

We have developped a specific variability analysis tool in the form of a matrix, we should say a series of matrices enabling to follow up daily the probabilities defined above.

| | | | | |
|---|---|---|---|---|
| $P_{aa}$ | $P_{ab}$ | $P_{ac}$ | $P_{ad}$ | $P_{ae}$ |
| $P_{ba}$ | $P_{bb}$ | $P_{bc}$ | $P_{bd}$ | $P_{bc}$ |
| $P_{ca}$ | $P_{cb}$ | $P_{cc}$ | $P_{cd}$ | $P_{ce}$ |
| $P_{da}$ | $P_{db}$ | $P_{dc}$ | $P_{dd}$ | $P_{dc}$ |
| $P_{ea}$ | $P_{eb}$ | $P_{ec}$ | $P_{ed}$ | $P_{ee}$ |

Table 3: Variability Matrix

This analysis can be carried over one, two or more readings.

The following is a made-up example for illustration purpose.

We assume potline with 240 pots, with a distribution as follows on day" j" expressed in number of pots.

| | |
|---|---|
| a < - 2 sd | 6 |
| - 2sd<b< -1 sd | 32 |
| - 1sd<c< +1 sd | 164 |
| +1sd<d< +2 sd | 32 |
| +2sd<e | 6 |

Table 4: Numerical example of a table of distribution of pots in the AlF3 range sof variability on day "j"

On day "j+1" the distribution is not significantly different, yielding not significantly different figures for average and standard deviatioin.

| | |
|---|---|
| a < - 2 sd | 6 |
| - 2sd<b< -1 sd | 37 |
| - 1sd<c< +1 sd | 159 |
| +1sd<d< +2 sd | 32 |
| +2sd<e | 6 |

Table 5 : numerical example of a table of distribution of pots in the AlF3 ranges of variability on day "j+1"

We will introduce here a new way of looking at KPVs changes : the Variability Matrix. Made public today for the first time, this innovative approach focuses on the evolution of the pots as a group with heterogeneous behaviours (and not only on the state of the pots at a given moment, or on their average behaviour).

If we take a finer look through a matrix representing the changes from one category to the other, we can capture additional information...

| | nb pots | | a | b | c | d | e |
|---|---|---|---|---|---|---|---|
| | | | | | | | |
| a < - 2 sd | 6 | | 3 | 1 | 2 | | |
| - 2sd<b< -1 sd | 32 | | 1 | 12 | 16 | 2 | 1 |
| - 1sd<c< +1 sd | 164 | | 2 | 17 | 119 | 23 | 3 |
| +1sd<d< +2 sd | 32 | | | 3 | 21 | 6 | 2 |
| +2sd<e | 6 | | | 2 | 3 | 1 | |

Table 6: Numerical example representing the individual changes from day "j" to day "j+1"

...which we can convert into frequencies of category changes.

| P xy | | | a | b | c | d | e |
|---|---|---|---|---|---|---|---|
| | | | | | | | |
| a < - 2 sd | 6 | | 50% | 17% | 33% | 0% | 0% |
| - 2sd<b< -1 sd | 32 | | 3% | 38% | 50% | 6% | 3% |
| - 1sd<c< +1 sd | 164 | | 1% | 10% | 73% | 14% | 2% |
| +1sd<d< +2 sd | 32 | | 0% | 9% | 66% | 19% | 6% |
| +2sd<e | 6 | | 0% | 33% | 50% | 17% | 0% |

Table 7: Numerical example of the Variability Matrix from day "j" to day "j+1"

Then we can see a few evidences, e.g.

- Approx. 25-30% of the pots within the target range on day "j" have exited the range on day "j+1"
- Certain pots "cross" the target range $P_{bd}$ or $P_{eb}$
- Certain pots do not react to the $P_{eb}$ adjustment and "stick" in their zone :e.g. $P_{aa}$

A more visual "3D" representation can be developed enabling a faster analysis and easier sharing of the conclusions. As this analysis is supported by a control and display software it is easy to show the results in a form which can widely shared.

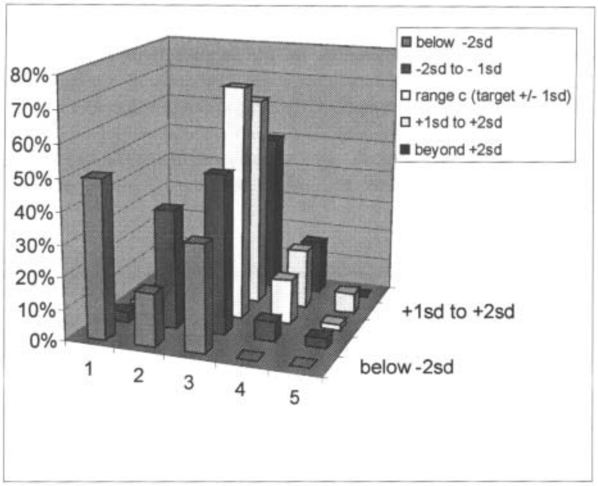


Fig 6: a visual projection of the Variability Matrix

The same analysis can be made routinely according to the frequency of analyses.

It will enable to structure Continuous Improvement programs aiming at optimizing the capability of the KPV control process:

- increasing the frequency of pots staying in the target range
- reducing the frequency of "over and under corrections"

It is also a tool to assess the global evolution of the potline by identifying the direction of the majority of changes.

## Conclusion

The Variability Matrix allows to analyze systematically the variability of a series of KPVs of each individual pot against a control grid, making it possible to identify avenues for improvement by optimizing the control processes and procedures with:

- the "immediate" effects on Current Efficiency specific, energy consumption, pot emissions... by bringing the whole population of pots closer to a tighter optimum range of the adjustment;
- the "longer term" effects such as amperage increases, better metal purity, improved potlife...

## References:


- Understanding Variation: the key to managing chaos by Donald J. Wheeler
- Managing smelters in turbulent times (TMS 2010 Short course) by Jean-Paul Aussel, Pierre Baillot, Claude Savariau.