

Understanding and Improving Chemical Capability in the Casthouse

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Abstract

An aluminium casthouse casts aluminium in charges (or drops). These charges are made to particular customers' ordered chemistry specification. The ability for a casthouse to accurately and consistently produce charges inside the customers' specification is crucial for productivity. In addition, it is important that a casthouse can accurately and consistently measure the real composition of each charge.

In this paper the sources of uncertainty in the chemistry are classified and discussed. The use of a model to study sensitivities on the predicted process capability (Cpk) from changes in charging accuracy, conditions during analysis, sampling and adjustment is demonstrated. The model can be used as a tool to identify improvement potentials.

Introduction

In an aluminium product casthouse liquid metal is cast from a furnace into solid products. These units that are cast are commonly referred to as charges (or drops). The composition of a charge is specifically manipulated to be inside certain composition ranges for a number of elements; that is the alloy specification ordered by the customer. The composition of a charge should always be measured before casting and also during casting to certify that the composition is as desired [1].

The measurement and control of the chemical composition is an important part of casthouse operations. This is because a casthouses' customer is buying only a certain composition, charges of the same alloy should be made with a consistent quality and with a minimum variation, and alloying should be performed in a consistent and precise manner to give a certain level of productivity (related to the extra time and cost related to adjustments in the compositions). A simple model has been developed by Hydro Aluminium to study the sensitivities on the predicted process capability (Cpk) for the analysis of particular elements. This model can be used to make improvements in the process.

Uncertainty in Chemical Analysis

The composition is typically measured by an optical (atomic) emission spectrometer with sample excitation by electric spark discharges (S-OES). The S-OES procedure yields results with measuring uncertainties. The uncertainty in the measured chemical composition is made up of contributions from the measurement equipment itself (calibration, time drift, and working order), sample taking (sample mould, quality of the sample, positions or times the samples are taken at) and melt inhomogeneities.

To minimise the uncertainties related to the OES equipment it is vital to maintain good routines for the spectrometer that must be described in internal "best practice" procedures developed by input from sources like EN486 [1] and ASTM E1251-11 [2]. These include regular running of certified control samples and

monitoring of the control samples analyses, drift correction, regular cleaning of the spectrometer and regular maintenance by the equipment supplier. In addition, in Hydro Aluminium a yearly inter-laboratory test (round-robin) is performed between 21 casthouses to ensure the consistency of analysis from different sources.

To minimise uncertainties related to consistency of sample taking the sampling equipment and sampling procedure must be described in an internal "best practice" procedure developed by input from sources like ASTM E716-10 [3]. Internal standard operating procedures for melt treatment (such as stirring) must also be followed to minimise any inhomogeneities in the melt before taking samples.

"Measurement noise" or -precision

If a charge is imagined to be analyzed many times over then the random variation in the measured composition for a main element such as Si will often consume a large portion of the specification window due to random uncontrollable measurement variation or "measurement noise". For an acceptable measurement process, including sampling variation and melt inhomogeneities, the "6 sigma variation width" from this "measurement noise" should be less than 35% of the tolerance interval (35% of distance between the upper and lower limits for an element) [4]. If the uncertainty in a charge analysis lies inside the specification limits then this is a good indication that the true average content also lies inside the specification limits.

Process capability and -performance

Process indicators (or indices such as the Cpk and Ppk) are often used to monitor the chemical analysis procedures, to check if the process is in control and there are no deviations or drift in the process.

The potential process capability (Cpk), for the charge analyses of a single element within the one alloy, is estimated by comparing the typical short-term variation of charge analyses with the specification limits. If there is no additional long-term variation, (no time trends and shifts) then the process is in control. In this case the short- and long-term variations are equal. The term potential process capability can therefore be abbreviated to process capability to indicate what the process is capable of based on typical short-term variation. The actual (long-term) process performance, the Ppk, including noise from the measurement process, can be calculated from the average and standard deviation from a limited set of charge analyses. The long-term variation of charge analyses can then be followed up by moving Ppk values (using moving average and standard deviations for a certain subset size).

Model to study of variation on charge analysis

As discussed above analyses of disc samples taken during processing of a charge are influenced by many variables linked to

accuracy of charging, drift of the spectrometer (OES), sampling, melt homogeneity and adjustment of melt composition.

It is interesting to study the influence of variable/s in order make improvements to reduce the variation of charge analyses around the aiming point. These effects are often difficult to study directly in production since the resulting effects are often relatively small and require many costly observations. Since operators strive to keep the analysis variation as small as possible, both within and between charges (within the same alloy), then this uncontrollable “residual” analysis variation can be approximated by a combination of values from a set of normal distributed variables. A list of input values must be specified by the user that gives the centre value (or level) and “random noise” to a set of variables. The user can also activate final type correction and also specify if single (or average) disc sample analyses from the furnace are compared to the control limits to trigger an adjustment. The model is developed by use of MS-Excel and is simple to use.

This model can be used to study the effects on process capability from:

- A change in the control limits used to decide if an alloying element adjustment is needed.
- A change in the aiming point.
- Activating final type correction.
- The use of single disc sample analyses or average analysis to decide adjustment of the melt content.
- Changing the degree of dissolution of an element when the first sample is taken.
- Changing “burn-off” of an element from charging or alloying to casting.
- Systematic difference between furnace- and casting sample analyses, for instance due to different condition of sampling moulds.
- Change in the accuracy of adjustment to the melt content (for instance due to different aiming points).
- Change of sampling error in furnace and homogeneity of melt during casting.
- Change of calibration and time drift of OES.
- Improved accuracy of charging that gives less variation in the analysis level from charge to charge before adjustment.
- Variation only due to the measuring system (that is analysis, sampling and melt homogeneity).

The model is a Monte Carlo type and can be regarded as a simple “expert system” or a tool to capture the accumulated knowledge. The main objective of this model is to simulate the average analysis level and the analysis variation between charge analyses and predict the resulting process capability (Cpk). The model assumes that all analysis variation is independent and normally distributed. This is assumed to give good estimates of the average analysis level and analysis variation. The model simulates disc sample analyses from 1000 charges and gives the total average and standard deviations. These two statistics from the 1000 possible outcomes of OES charge analyses are compared with the specification limits to estimate process capability Cpl, Cp and Cpu. This is repeated each time the Excel worksheet is recalculated.

Figure 1 shows a simple flow sheet of the calculation steps for the model. The first input shown on the top of the figure is used to simulate the true average content of the element within a charge (the charging accuracy). This is dependent on knowledge within

the casthouse of the charge input material source (cold metal source, alloying elements). The background for this input can be illustrated by introducing three levels of uncertainty for an addition from a given source during charge planning. The first level is the uncertainty of the added weight from this source. The second level is the uncertainty of the content of the element within this source and finally there is the uncertainty of the yield of the element.

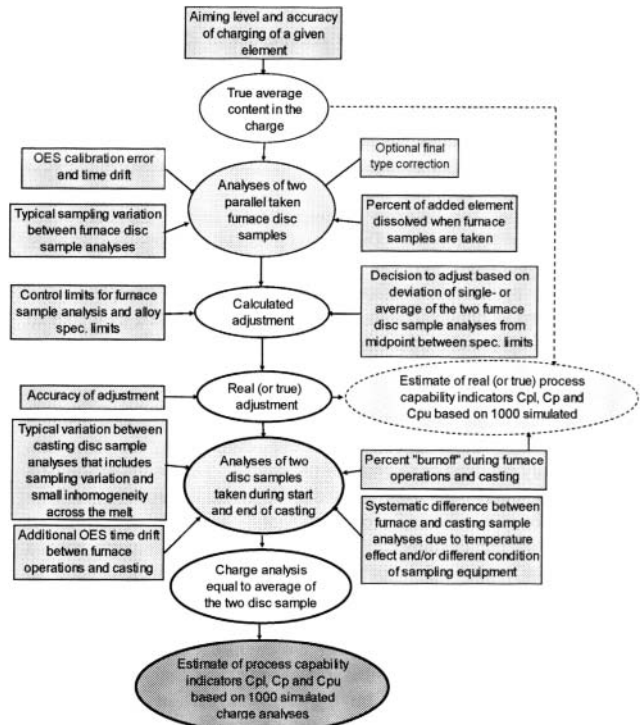


Figure 1: Calculations steps of the model. The input values given by the user are shown as squares and resulting simulation values within a charge are given by ellipses.

The final uncertainty of the calculated value during charge planning is dependent on these three input uncertainties across all sources that are to be used. A (separate) similar model is developed to estimate this uncertainty of the calculated value. A long term objective is to use this model to improve charge planning by checking the uncertainty of the calculated values against the specification limits for a given cost effective proposal of additions available for charge planning. This is of special interest for increasing the use of scrap sources. The rest of the input values are used to simulate a charge analysis equal to the average of the two simulated disc sample analysis taken during casting.

From the 1000 simulated charge analyses the following indicators of process capability are calculated:

$$C_{pu} = \frac{USL - \text{Average}}{3 \text{ St.dev.}} \quad C_p = \frac{USL - LSL}{6 \text{ St.dev.}} \quad C_{pl} = \frac{\text{Average} - LSL}{3 \text{ St.dev.}} \quad (1)$$

where St.dev is equal to the standard deviation and LSL and USL are the Lower and Upper specification limits. The Cpk is defined as the smallest of Cpl and Cpu. If there is more than four standard

deviations from the average to nearest specification limit, or the Cpk is bigger than 1.33, then the process is categorised as capable.

With this model there is also an opportunity to estimate the “true” process capability that is not reduced by the disturbance from measurement noise of the disc sample analyses.

Table 1 gives an example of an input values given by the user:

Table 1: Example of input values for silicon analysis from casthouse X. Second column indicates type of input value: L = measure of level that determines the “centre value” of simulated values, S = measure of variation (sigma) that determines the variation between simulated values.

Specifications / IMS limits for		
0,454	USL	Upper
0,395	LSL	Lower
Value		Description
Simulation of variation of true content between charges		
0,425	L	Aiming point
0,03	S	Max difference between true content and target over many charges - 2 St.deviation
Simulation of OES analysis		
0	L	Systematic calibration error of the OES (Bias)
0	L	Average concentration at 3 mm cutting depth minus "true" average concentration of disc sample
0,01	S	Max time drift away from calibration level (5% chance of bigger drift) - 2 St.deviation
0	S	Max time drift between sampling from furnace and during casting - 2 St.deviation
Simulation of final type correction		
0		0: No type correction 1: Type correction (Rotational)
0,4217	L	Nominal content in type standard sample
0	L	"True" minus nominal content in type standard sample
0,0108	S	Variation width of parallel spark analyses on type standard (95% stays inside this interval) - 4 St.deviation
4		Number of sparks on type standard
Simulation of analyses from two parallel taken furnace disc samples		
0,018	S	Variation width of parallel disc sample analyses from furnace (95% stays inside this interval) - 4 St.deviation
100	L	Percent of real content that is dissolved when furnace samples are taken
Simulation of adjustment based on difference between spec. midpoint and average of the two furnace disc sample analyses		
0,45	UCL	Upper control limit for a single disc sample analysis or average of two disc sample analyses
0,41	LCL	Lower control limit for a single disc sample analysis or average of two disc sample analyses
0		0: Single disc sample analysis is compared with control limits to decide adjustment 1: Average is used
50	S	Max relative difference between real adjustment and calculated adjustment - 2 St.deviation
Simulation of analyses from two disc samples taken during casting (One during start and one during end of casting)		
0,026	S	Variation width of the two disc sample analyses taken during start and end of casting - 4 St.deviation
0	L	Systematic difference between casting- and furnace sample analyses due to difference in condition between sampling moulds
100	L	100 minus "burnoff" or loss from sampling from furnace to sampling during casting

Study of Si capability for alloy (6XXX) from Casthouse X.

In the following section a number of case studies are shown. The figures show examples of the output from the model for different input sets using Si with specification limits of 0.40 and 0.45 wt%.

The first case, the baseline case, is based on realistic input values representing the current situation in Casthouse X, the input of charging accuracy was used to tune the output level of the Cp and Cpk values to the real life situation. In general, after performing this procedure to define the baseline a user can then perform new simulations based on proposed “what if” input values.

Since the expected Cp and Cpk will vary a little between simulations then, for instance, five simulations can be performed with the same input set to illustrate the “uncertainty” of these output values from the model indicators.

The main results are shown in Figures 3-7. In these figures the terms “low-red” and “high-red” deviations refer to furnace sample analyses outside the specification limits and “low-yellow” and

“high-yellow” deviations refer to furnace sample analyses outside the control limits but inside the specification limits. All deviations require an alloying or dilution adjustment within the model.

Case 1: Baseline case

In this case the upper control limit is set just below the upper specification limit (0,004wt% below). This means that charges with measured Si contents towards the upper specification limit are not adjusted down. Since diluting a charge is much more time consuming than adding alloying additions to it, this case is realistic. Figure 2 shows an example of output from the first 40 charges based on the input values for the baseline case, this type of data is used to make Figures 3-7 (with the respective input values), but is not shown for each case.

Figure 3 shows five outputs of process capability indicators and the relative amounts of deviations in percent for the baseline case. Each output is obtained by recalculation of the MS-Excel file containing the model. It is expected that the “true centre value” of the output values lies with more than 90% confidence within the interval from the smallest to the biggest value of the five outputs.

The expected output is a process capability determined by the low frequency of “high-yellow” deviations that gives a value of Cpu

lower than Cpl, the Cpk is 0.8 in this base case.

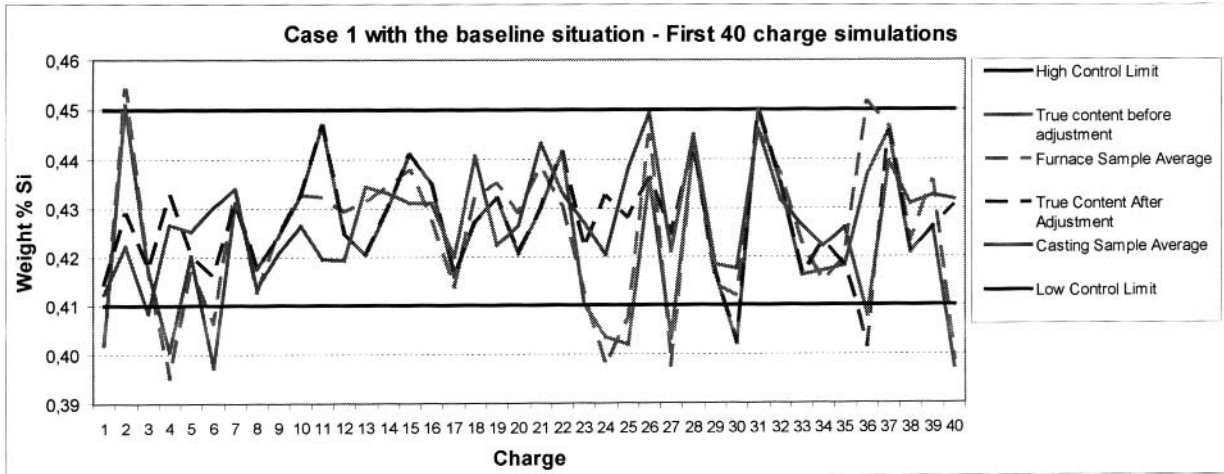


Figure 2: First 40 simulations of contents and charge analyses of Si for the baseline case from 1000 simulated charges.

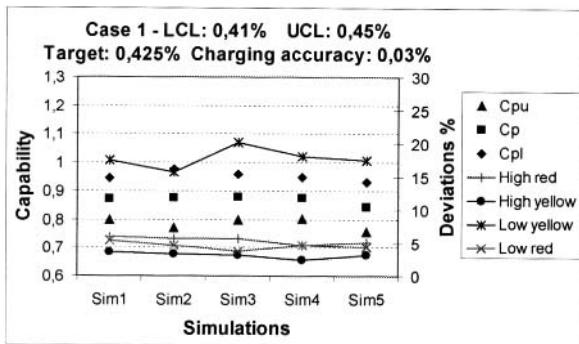


Figure 3: Level of Cpk is only about 0.80 due to few adjustments by diluting the melt.

Case 2: Baseline case plus a high control limit

In this case the high control limit is lowered compared to Case 1; from 0.45 to 0.44 wt% Si. This means that if an analysis is above the upper control limit but below the upper specification limit the charge must be diluted to lower the Si content. Figure 4 is similar to the previous figure for Case 1 however due to the change there are more “high-yellow” deviations and a higher process capability (Cpk=1.0).

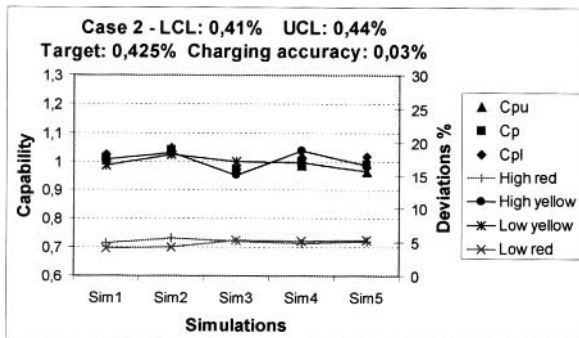


Figure 4: Compared to case 1 the charge analyses are now more

centred on the midpoint between the specification limits since Cpl, Cp and Cpu are about the same and the estimated level of Cpk has increased to 1.0.

Case 3: Case 2 with tighter control limits

Figure 5 is similar to the previous figure for Case 2 where the input set is changed by reducing the width between the control limits. This is expected to lead to more “high-yellow” and “low-yellow” deviations and a higher process capability (now the Cpk =1.1).

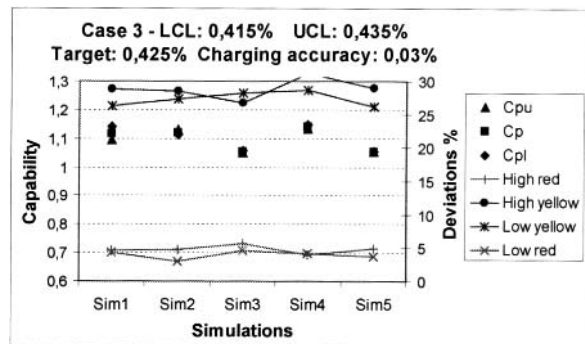


Figure 5: Compared to case 2 the estimated Cpk has increased to 1.1 but the frequency of yellow deviations (and corresponding adjustments) has also increased from about 17 to 27%.

Case 4: Case 3 and improved “accuracy of charging”

The following Figure 6 is similar to the previous figure for Case 3 where the input set is changed by increasing the “accuracy of charging” by reducing the 2-sigma value from 0.03 to 0.01%. There is then about a 5% chance that a true average content of Si will deviate more than 2-sigma from the aiming point. This is expected to lead to less frequency of deviations and a higher process capability. Here it is important to note that the charging accuracy has been improved considerably but the outcome is only a small improvement in the Cp-values. This demonstrates a case where the time drift, sampling variation and melt inhomogeneities are limiting factors.

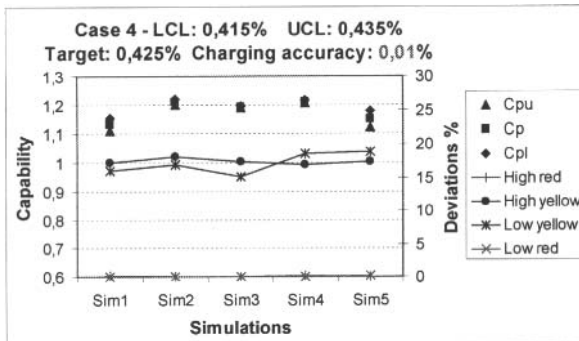


Figure 6: Estimated Cpk lies now between 1.1 and 1.2. Compared to case 3 the frequency of “yellow deviations” has decreased to 17%. The frequency of “red deviations” is almost removed due to improved “accuracy of charging”.

Case 5: Case 4 and half of OES time drift

Figure 7 is similar to the previous figure for Case 4 where the input set is changed by reducing the OES time drift by reducing the 2-sigma value from 0.01 to 0.005%. There is then about a 5% chance that the analysis level of Si will drift more than 2-sigma from the base calibration. This is expected to lead to a lower frequency of deviations and a higher process capability. In addition to time drift between charges, this study includes possible time drift from time of sampling from the furnace until time of the last sampling from casting.

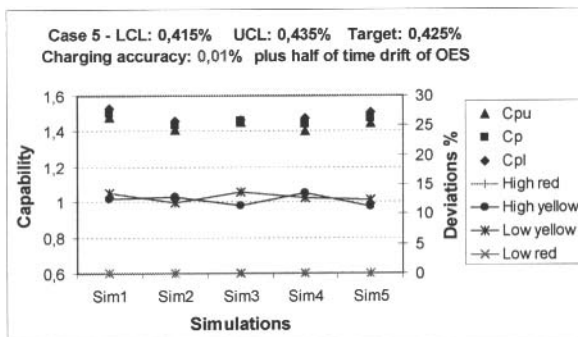


Figure 7: Compared to case 4 the estimated process capability has increased to more than 1.33 and the frequency of “yellow deviations” has decreased to about 12%. This is a very good situation compared with the baseline situation. Note the change of scale of the left y-axis.

Conclusions

- This study is limited to include effects from changing only the accuracy of charging, control limits and the time drift of the OES analysis level.
- The power of this type of model is that it gives the user an opportunity to study the simultaneous interaction of 22 input values on the expected process capability.
- In this study even if the accuracy of charging is improved so that the variation of the true content after charging is reduced to one third of the baseline situation then it will be difficult to obtain a process capability greater than 1.2.
- A reduction in the OES time drift should contribute to a process capability larger than 1.2.

- It is therefore important to have good procedures for drift correction, equipment and sampling to ensure good performance from the measurement system.
- The frequency of alloying adjustments depends on both the accuracy of charging and the measurement noise. An increasing frequency of adjustment leads to longer furnace cycle times and potentially lower productivity. This is one of the driving forces in production to improve alloying. This model gives an opportunity to study which variables should be addressed first in order to obtain this improvement.

References

[1] EN 486: Aluminium and aluminium alloys – extrusion ingot – specifications (2009).
 [2] ASTM E1251-11: Standard test method for analysis of aluminum and aluminum alloys by spark atomic emission spectrometry.
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