Anode Spike Detection Using Advanced Analytics and Data Analysis

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Abstract

Anode spikes crises have a deleterious effect on current efficiency to the point of jeopardizing smelter operation. All the time spent with a spike under an anode is a period where current is lost, and the longer the spike remains present, the more serious are the mid-term consequences for the reduction process. It is therefore most important to detect these spiky anodes as early as possible and remove them from the pots. A new tool based on anode current measurements, combined with machine learning, has been developed and tested. It is an effective way of detecting many of these spikes, usually a few days before they become obvious. This article describes the development of the tool and the first results obtained on industrial cells.

Keywords: Aluminum electrolysis, anode spikes, machine learning.

1. Introduction

The effects of anode spikes in aluminum electrolysis are well-known. Examples are the disruption of operations, the thermal and chemical imbalance of pots and the loss of current efficiency; and there are many more. Especially after a spike crisis, some of these consequences can degrade operations for weeks or even months after the faulty anodes have been changed. Studying the reduction in alumina feeding in pots before spikes are spotted clearly shows the loss of current efficiency involved by such incidents, as seen in Figure 1.

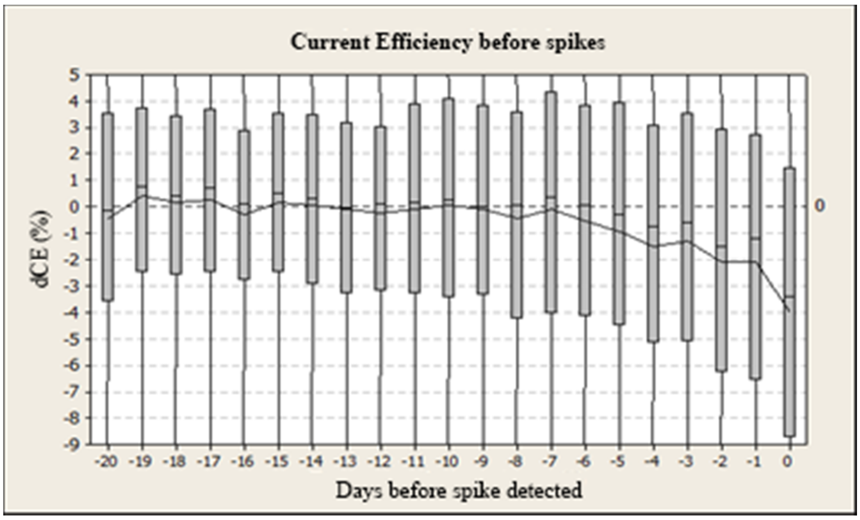

Figure 1. Current efficiency over the period before a spike is detected.

This indicates how important it is to react as fast as possible, since the loss of production (and the extent of the consequences, especially on thermal and chemical balance) is proportional to the time spent with a spike on the pot. Effects are even bigger when the spike is fully developed, just before the faulty anodes are changed, with more than 3 % reduction in current efficiency. A study has been carried out to see how data analysis, through machine learning models, can help process teams to spot such spikes as early as possible.

General Approach & Measurements

This seemed to be a good opportunity to make use of anode current measurements [1]. Not only can they be expected to contain information enabling spike detection, they are also available in sufficient detail to make it possible to locate the faulty anode(s), instead of just flagging the pot itself.

In some of Rio Tinto's R&D pots anode current measurements are made at a rate of 1 Hz, much more frequently than with the usual electrolysis pot instrumentation, so these were the data that were analyzed in order to provide the required tool.

2. Statistical Modeling

2.1. Hidden Markov Models

The approach that was chosen for this study was to build a classifier intended to distinguish "healthy" anodes – those without spikes – from anodes having a spike. Anode currents are measured continuously, but for the analysis they are considered as discrete time series. It is difficult to predict when a spike will be detectable, even if anodes seem more likely to develop spikes at certain periods in their operating life, as can be seen in Figure 2. Most of the spikes are spotted either around the first third of the anode's lifetime or else right at the end, when it is in any case due for changing. This pattern may be technology-dependent, since the spikes in the pots that were studied were mainly on the edges of the anodes, probably starting to develop right after anode changing.

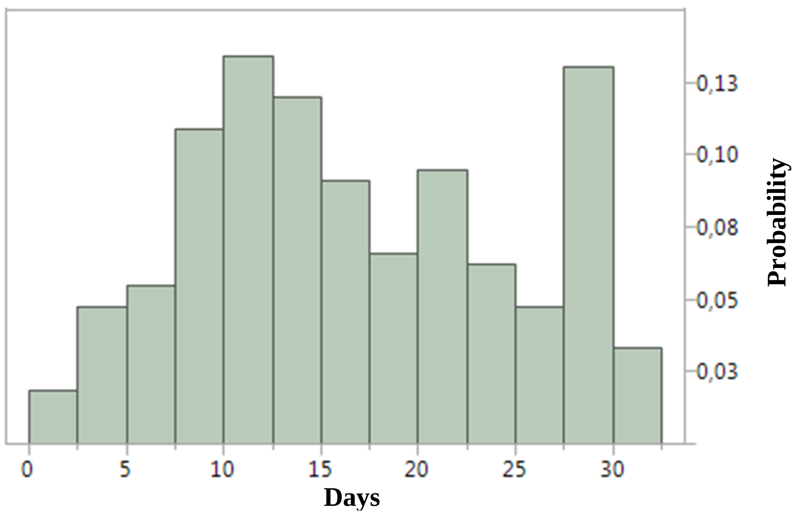

Figure 2. Distribution of the number of days before a spike is spotted.

These properties of the data being analyzed led us to consider using Hidden Markov Models (HMM's) [2]. HMM's are statistical models that allow analyzing sequences of observations, and are designed to identify state changes - transitions in these observations - enabling pattern recognition. They were firstly used in speech recognition, where words are successions of sounds of different properties and variable durations.

A similar approach can be applied to the analysis of the anode current, where the amperage signal over an anode life (or features taken from this signal) is the sequence, and the HMM converges to detect patterns in this signal and the transition from a normal anode to a spiky one - although the model can actually detect finer state transitions than this.

in properly flagging spikes, since flagging is mandatory in most of the machine learning algorithms.

4. Conclusion

This proof of concept shows how machine learning can help analyze data and statistically detect incidents provided the relevant data are available and given the flagging of incidents in operational logs. In applications such as this, given the low number of samples, a good knowledge of process and data is required to target measures and build relevant features. This process can be time consuming, especially when using data that were not originally intended to be used in this way. Nevertheless, gathering data as soon as possible, building up bigger and more accurate databases and getting used to such tools seems to hold out promise for use in similar cases.

5. References

1. Jeffrey Keniry and Eugene Shaidulin, Anode signal analysis – The next generation in reduction cell control, *Light Metals* 2008, 287-292.
2. Walter Zucchini and Iain L. MacDonald, *Hidden Markov Models for time series: an introduction using R*, Chapman and Hall/CRC (2009), ISBN 9781420010893.