Inspection of Prebaked Carbon Anodes Using Multi-Spectral Acousto-Ultrasonic Signals, Wavelet Analysis and Multivariate Statistical Methods

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Abstract

Reduction cell operation in primary aluminum production is greatly influenced by the baked anodes properties. Producing consistent anode quality is more challenging nowadays due to the increasing variability of raw materials. Taking timely corrective actions to attenuate the impact of raw material fluctuations on anode quality is also difficult based on the core sampling and characterization scheme currently used by most anode manufacturers because it is applied on a very small proportion of the anode production (about 1%), and long-time delays are required for lab characterization. The objective of this work is to develop rapid and non-destructive methods for inspection of baked anodes. In past work, it was shown that acousto-ultrasonic signals collected from anode parts at different frequencies were sensitive to anode defects (pores and cracks) and this was validated qualitatively using X-ray computed tomography. This work attempts to improve the method by using multi-spectral excitation signals and by establishing quantitative relationships between the acousto-ultrasonic signals and defects extracted from tomography images using Wavelet Transforms and Partial Least Squares (PLS) regression. This results in shorter acquisition time and a more specific and robust model for anode inspection. The method performance is illustrated using samples collected from industrial scale anodes.

Keywords: Non-destructive testing; acousto-ultrasonic signals; CT-Scan images; PCA; PLS.

1. Introduction

The performance of acousto-ultrasonic techniques in detection of various defects in carbon anodes has been demonstrated in previous work using sequential acoustic excitation at different frequencies of anode slices followed by the analysis of the acoustic responses of the samples using Principal Component Analysis (PCA). The results were validated qualitatively using X-ray images collected from the slices [1]. However, this method needs to be improved and adapted for real time control in order to pave the way for industrial application. In particular, it is necessary to reduce the cycle time of the approach using sequential excitation and to further validate the method through a quantitative use of the X-ray CT scan images of the samples.

To reduce the cycle time, it is proposed to excite the materials using a single multi-frequency acoustic signal. However, this would lead to a more complex acoustic response of the anode samples requiring the use of some frequency decomposition techniques to extract from the response signals features at different frequencies. One approach consists of using the Fast-

Fourier transform (FFT) [2-5]. In this method, acousto-ultrasonic signals are decomposed in different frequency bands that can be used to identify various failure modes. However, time domain information cannot be extracted using FFT (i.e., variations in signal frequency content through time) and this may limit the performance in defect detection and identification. An alternative approach that is becoming increasingly popular in industrial applications consists of using the Wavelet Transforms (WTs) where both frequencies and time information can be obtained from acousto-ultrasonic signals [6-9]. In addition, WTs were shown to be a powerful tool in all areas dealing with transient signals [10-12]. Qi et al. [13, 14] showed the effectiveness of the Discrete Wavelet Transform (DWT) to process the acousto-ultrasonic signals from composite materials. A similar approach could be used for the analysis of baked carbon anode materials.

To validate the performance of the acousto-ultrasonic approach more precisely, it is also proposed to quantify defects from X-ray CT-scan images of the carbon anode samples and to establish a relationship between the features extracted from the acoustic response of the samples and the types of defects and their severity. To quantify defects in tomographic images image texture analysis techniques can be used since the defects introduce local variations in grey level intensity in the images according to some relatively well defined patterns (i.e., round spots for pores and streak lines for cracks). Again here, one could extract textural features from tomographic images using the two-dimensional Fast Fourier transform (2D-FFT) [15]. In this method, the frequency decomposition of the images could be used determine the severity of defects. However, variations in frequency content within the images (i.e., spatial information) cannot be extracted using this approach. On the other hand, the 2D Discrete Wavelet Transforms (2D-DWTs) are effective for extracting both frequency and spatial information could be obtained [16]. Moreover, wavelet texture analysis has been shown to be a powerful tool in several areas dealing with noise and low variation in images.

In order to build relationships between the acoustic response signals of the samples and their CT-scan images, multivariate statistical methods such as Principal Component Analysis (PCA) and Partial Least Squares (PLS) regression can be used [17], allowing a good classification of patterns in the case of several input data [18, 19]. These methods project a set of features from a higher to a lower dimensional space, simplifying the analysis of big data sets. Some authors [20, 21] have combined wavelet analysis and PCA, called Wavelet PCA, to improve the results of feature extraction. In order to correlate both acousto-ultrasonic and tomography images dataset blocks, Projection to Latent Structures (PLS) is implemented [22, 23].

This work aims at investigating the use of acousto-ultrasonic technique for volumetric inspection of baked carbon anodes. It focuses on mapping morphological constituents in this carbon material in order to evaluate spatial distribution of pores and cracks using acousto-ultrasonic wave attenuation. In this approach, an industrial baked anode was sliced along its length and some slices were used as real samples. The latter was scanned by X-Ray tomography and the resulting images were analyzed by wavelet to reveal the internal structure. Further, several acousto-ultrasonic features were extracted from the signals propagated through the corresponding parts using wavelet analysis. To simplify the analysis, both PCA and PLS were used to provide classification and regression models. The clustering patterns show the good potential of the proposed approach to detect and distinguish the pores from cracks.

7. References

1. M. Ben Boubaker et al., The Potential of Acousto-Ultrasonic Techniques for Inspection of Baked Carbon Anodes, *Metals*, Vol. 6, No. 7, 151, (2016), 1-13.
2. M. Suzuki, H. Nakanishi, and M. Iwamoto, Relationship between acoustic emission characteristics and structural factors of composite materials. Composites '86: Recent Advances in Japan and the United States, Proceedings of Japan–US CCM-III, Tokyo, 1986, 631–638.
3. N. Qing-Qing and J. Eiichi, Acoustic emission and fracture of carbon fiber reinforced thermosoftening plastic (CFRTP) materials under monotonous tensile loading, *Engineering Fracture Mechanics*, Vol. 45, No. 5, (1993), 611–625.
4. N. Qing-Qing and J. Eiichi, Fracture behavior and acoustic emission of SFC, *Journal of the Society of Materials Science*, Vol. 42, (1993), 561–567.
5. E. Jinen, Acoustic emission technique in the single-filament-composite test. *In: First International Conference on Composite Engineering (ICCE/1)*, August 28-31, Louisiana, New Orleans, USA, (1994), 883–884.
6. E.P. Serrano and M.A. Fabio, Application of the wavelet transform to acoustic emission signal processing, *IEEE Transactions on Signal Processing*, Vol. 44, No. 5, (1996), 1270–1275.
7. H. Suzuki et al., Wavelet transform of acoustic emission signals, *Journal of Acoustic Emission*, Vol. 14, No. 2, (1996), 69–84.
8. N. Qing-Qing and Y. Misada, Analysis of AE signals by wavelet transform, *Journal of the Society of Materials Science*, Vol. 47, (1998), 305–311.
9. L. Cohen, *Time–frequency analysis*, Prentice-Hall, Englewood Cliffs, NJ (1995).
10. R. Kronland-Martinet, J. Morlet, and A. Grossmann, Analysis of sound patterns through wavelet transforms, *International Journal of Pattern Recognition and Artificial Intelligence*, Vol. 1, No. 2, (1987), 273-302.
11. J.D. Aussel and J.P. Monchalin, Structure noise reduction and deconvolution of ultrasonic data using wavelet decomposition (ultrasonic flaw detection), *Proceedings of Ultrasonics Symposium*, Montreal, Canada, IEEE 1989, 1139-1144.
12. R.S. Loe et al., Status report on wavelets in signal detection and identification: comparative processing and technology evaluation, *Proceedings of IEEE Sixth SP Workshop on Statistical Signal and Array Processing*, Susono, Japan, 1992, 46-49.
13. G. Qi et al., Discrete wavelet decomposition of acoustic emission signals from carbon-fiber reinforced composites, *Composites Science and Technology*, Vol. 57, No. 4, (1997), 389–403.
14. G. Qi, Wavelet-based AE characterization of composite materials, *NDT & E International*, Vol. 33, No. 3, (2000), 133–145.
15. N. Sandirasegaram and R. English, Comparative analysis of feature extraction (2D FFT and wavelet) and classification (L_p metric distances, MLP NN, and HNeT) algorithms for SAR imagery, *Proceedings of SPIE 5808, Algorithms for Synthetic Aperture Radar Imagery XII*, Orlando, Florida (USA), March 28 2005, 314-325.
16. S.G. Mallat, A theory for multiresolution signal decomposition: the wavelet representation, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 11, No. 7, (1989), 674-693.
17. L. Eriksson et al, *Multi and megavariate data analysis: Part I: basic principles and applications*, 2nd ed., Umetrics Academy, Umea, Sweden, (2006).
18. M. Cherfaoui et al., The study of acoustic emission from composites by means of multivariate data analysis, *In: 6th International Conference on Composite Materials, and 2nd European Conference on Composite Materials*, London, England, (1987), 424-432.
19. M. Cherfaoui, A. Lemascon, and J. Roget, Detection and evaluation of defects in acoustic emission monitoring of bending tests". *In Eighth International Acoustic Emission Symposium*, Vol. 3, Tokyo, Japan, (1986), 586-593.

20. M. R. Gupta and N. P. Jacobson, Wavelet principal component analysis and its application to hyperspectral images, *In: IEEE International Conference on Image Processing*, Atlanta, GA, USA, October 8-11 2006, 1585-1588.
21. K. Tong, Wavelet transform and principal component analysis based feature extraction, Department of Mathematics, University of Washington, Seattle, WA, USA, June 3 2010. (http://www.math.washington.edu/~morrow/336_10/papers/kent.pdf last access August 24, 2016).
22. A. Höskuldsson, PLS regression methods, *Journal of Chemometrics*, Vol. 2, No. 3, (1988) 211-228.
23. S. Wold, M. Sjöström, and L. Eriksson, PLS-regression: a basic tool of chemometrics, *Chemometrics and Intelligent Laboratory Systems*, Vol. 58, No. 2, (2001), 109-130.
24. X. Boespflug et al., Axial tomodensitometry – relation between the Ct intensity and the density of the sample, *Canadian Journal of Earth Sciences*, Vol. 31, No. 2, (1994), 426-434.
25. D. Picard et al., Characterization of a full-scale prebaked carbon anode using x-ray computerized tomography, *Light Metals* 2011, 973-978.
26. K. Ono, J.S. Jeng, and J.M. Yang, Fracture mechanism studies of a carbon fiber-PEEK composite by acoustic emission, *In: Acoustic Emission: Current Practice and Future Directions*, ASTM International, Philadelphia, PA, (1991), 395-403.
27. K. Yamaguchi et al., Acoustic emission waveform characteristics from FRP during tensile test, *In: Progress in Acoustic Emission III, Proceedings of the 8th International Acoustic Emission Symposium (IAES 8)*, JSNDI, Tokyo, Japan, (1986), 594-601.
28. S. Borah, E.L. Hines, and M. Bhuyan, Wavelet transform based image texture analysis for size estimation applied to the sorting of tea granules, *Journal of Food Engineering*, Vol. 79, No. 2, (2007), 629-639.
29. M.H. Bharati, J.J. Liu, and J.F. MacGregor, Image texture analysis: methods and comparisons, *Chemometrics and Intelligent Laboratory Systems*, Vol. 72, No. 1, (2004), 57-71.
30. P. Geladi, H. Grahn, *Multivariate image analysis*, John Wiley & Sons, (1996).
31. S. Wold, K. Esbensen, and P. Geladi, Principal component analysis, *Chemometrics and Intelligent Laboratory Systems*, Vol. 2, No. 1-3, (1987), 37-52.
32. S. Wold, Cross-validatory estimation of the number of components in factor and principal component models, *Technometrics*, Vol. 20, No. 4, (1978), 397-405.