Application of ML based denoise algorithms to the EELS data of the 3rd generation Medium Mn Steel

Martin Børstad Eriksen[1], Oleg Usoltsev[2], Seyedeh Leila Panahib[2], Marc Raventós[2], Marcel Carpio[3], Núria Cuadrado Lafoz[3], Núria Bagués[2], David Frómeta Gutiérrez[3], Jie-Feng Chan[1], Gonzalo Merino[1], Joaquín Otón[2]
[1]*Port d'Informació Científica,Carrer de l'Albareda Edifici D, Campus UAB, Bellaterra, Barcelona, 08193, Spain*
[2]ALBA-CELLS Synchrotron Light Facility, Cerdanyola del Vallès, Barcelona,08290, Spain
[3]Eurecat, Center Tecnologic de Catalunya Unit of Metallic and Ceramic Materials, Placa de la Cìencia 2, Manresa,08243, Spain

eriksen@pic.es

The 3rd generation Medium Manganese (MMn) Steel has attracted the attention of the automotive industry due to its unique mechanical properties, which help reduce automobile weight, improve performance and decrease CO2 emissions. However, the phase composition and microstructural properties of these steel varieties have not been thoroughly investigated, thus application of transmission electron microscopy (TEM) and prior focused ion beam (FIB) sample preparation are promising techniques.

In this study electron energy loss spectroscopy (EELS) was applied to an MMn steel samples in order to reveal the local atomic environments of Fe and Mn centered species, remove sample thickness effects and estimate Mn/Fe structural geometries on grain boundaries. The study was conducted using a Spectra 300 microscope for sample rastering. Initially, the data complexity hindered the clear differentiation of various phases.

To enhance clarity, we applied and compared different unsupervised denoising techniques. The noise2void network [1] can be trained to remove noise without needing ground truth data. We compare the result with other neural networks such as pn2v [2] and HDN [3]. Additionally, the results is compared with an auto-encoder network [4], trained to compress each spectra into a lower dimensional space, leading to a denoised signal.

As shown in Figure 1, after applying an advanced denoising technique to the EELS spectra significantly increased the data quality, allowing for a more precise analysis.

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References

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Figures

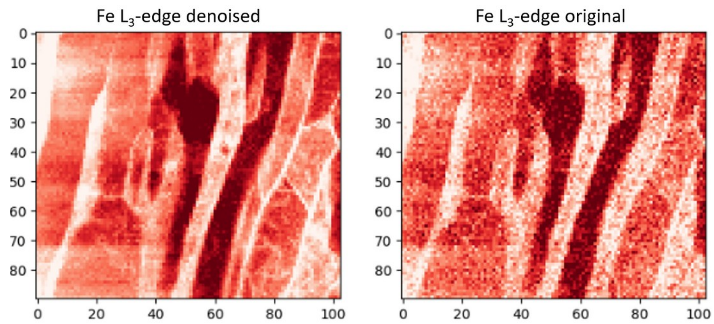

Figure 1: Fig 1. Map of edge jump for Iron L3-edge with and without application of denoising by an auto-encoder.