Classification of Iron deposit zones using self organizing maps

S. ANGORANI[1]*, M. SHARIAT PANAHI[2], M. SHADMAN KHAKESTAR AND S. EBRAHIMI

[1]School of Mining Engineering, University of Tehran (*correspondence: angorani@ut.ac.ir)
[2]School of Mechanical Engineering, University of Tehran

Classification Method

Self Organizing Maps (SOMs) are a class of Artificial Neural Networks (ANNs) that can learn to identify patterns and correlations among their input data and apply the identified patterns to future input data. Unlike common (Multi-Layer Perceptron) networks that would need certified input-output data pairs to establish a relationship between input vectors and their corresponding outputs in a 'supervised' manner, SOMs only rely on the input data and their inherent similarities to introduce 'clusters' of data where contents of each cluster share certain characteristic attributes. Through an Unsupervised learning process, SOMs assign an individual processing unit (or Artificial Neuron) to each group of input vectors with similar attributes in such a way that only a single neuron would respond to a future input vector and consequently similar input vectors are classified into the same class [1].

In this study, we propose an SOM-based strategy for the classification of Iron deposit zone's data. As a case study, we investigate the iron anomaly 12A located in the tectono-stratigraphic zone of the Bafgh block, 23 km N-NE of Choghart iron mine in central Iran. The genesis of the ore deposit appears to be metasomatic and volcano-sedimentary. The calc-sandstone (Rizu series), volcanic units (Dezu series), intrusive (diorite-granite) and metamorphic rocks are the units and formations include the ore deposit [2]. Chemical analyses were carried out on the Fe, S, P, P_2O_5, TiO_2, FeO and Fe/FeO contents of samples from 10 exploration logs.

Discussion of Results

We introduce 10 different feature vectors using element sets of 3, 4, 5, 6, and 7 elements where a combination of all 7 features in a set would represent the best output. Using the proposed strategy, the logs are classified into three groups. The first group includes the host rocks with low iron values. The second and third groups include iron ores of poor and rich magnetite ore, respectively. The classification results are shown to be in good agreement with existing geological evidences.

[1] Demuth & Beale (2002) *Neural Network Toolbox Users guide*, Version 4.0, Chapter **8.** [2] Shadman Khakestar (2010) *Geology study & ore estimation of anomaly 12A*, MSc thesis, A.K. University of Technology, pp.26–41.

Neutron reflectivity sample cells for geochemically relevant environments

JOHN F. ANKNER[1]*, JAMES F. BROWNING[1], CANDICE E. HALBERT[1], BRAD S. LOKITZ[1,2], JUSTIN R. CARMICHAEL[3] S. MICHAEL KILBEY II[2], GERNOT ROTHER[4] AND DAVID J. WESOLOWSKI[4]

[1]Neutron Scattering Sciences Division, Oak Ridge National Laboratory, Oak Ridge, TN 37831 (*correspondence: anknerjf@ornl.gov)
[2]Center for Nanophase Materials Science, Oak Ridge National Laboratory, Oak Ridge, TN 37831
[3]Neutron Facilities Development Division, Oak Ridge National Laboratory, Oak Ridge, TN 37831
[4]Chemical Sciences Division, Oak Ridge National Laboratory, Oak Ridge, TN 37831

One of the great strengths of neutrons as probes of matter is their ability to penetrate complex sample environments. Neutrons are absorbed very little by such common structural materials as aluminum and quartz. In addition, for reflectivity measurements, one can use perfect crystalline substrates such as silicon, quartz, or alumina as the incident medium to probe solid/fluid interfaces. We will describe sample environments currently available and under development at the Spallation Neutron Source, including ambient and temperature-controlled liquid/solid, pressure, and controlled humidity cells.