ANALYSIS OF MINING SAMPLES USING INFRARED SPECTROSCOPY AND MACHINE LEARNING

MATLAB CONFERENCE
PERTH, MAY 2017
Who is Bureau Veritas?

Bureau Veritas Minerals Services

Infrared Spectroscopy

Machine Learning and Matlab

Summary
WHO IS BUREAU VERITAS

Established in 1828, Bureau Veritas is a global leader in Testing, Inspection & Certification services in the areas of Quality, Health & Safety, Environment and Social Responsibility across eight global businesses.
8 GLOBAL BUSINESSES
2015 REVENUE: €4.6 BILLION

Global network comprising of 66,500 employees in 1400 offices and laboratories across 140 countries.

Marine & Offshore: 8%
Commodities: 17%
Consumer Products: 14%
Government Services & International Trade: 6%
Industry: 23%
In-Service Inspection & Verification: 13%
Construction: 11%
Certification: 8%
MINING DEVELOPMENT

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INFRARED SPECTROSCOPY
INFRARED SPECTROSCOPY

Sample is presented to a light source. – No special preparation
The response from the sample is measured by a detector.

- Near Infrared, Short Wave Infrared
- FTIR – Fourier Transform Infrared Spectroscopy – Mid to Thermal Infrared

Spectra is representative of the molecular bonding in the sample
Absorption of incident light at specific characteristic wavelengths
Bond vibration, bending and stretching

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SPECTRA OF IRON ORE SAMPLES

Examples by dominant mineral

- Quartz
- Kaolinite
- Hematite

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EXAMPLE SPECTRA

1200 – 2500 Datapoints per sample
SPECTRAL INTERPRETATION

- Spectral Library
- Analyse Features for DEPTH LOCATION SHAPE
- Major Minerals Only
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MACHINE LEARNING AND MATLAB
1. **Mineralogy and Proxies**
   - Mineralogy drives block model design
   - Metallurgical testing is expensive
   - Proxies are unreliable

2. **Infrared Red Spectra**
   - Simple and low cost
   - Laboratory Workflow
   - Spectral fingerprint
How do we use this data for routine analysis?

Two step process:
Mineralogy
- Hematite, Goethite, Gibbsite, Kaolinite, Talc, Mica, Quartz

Physical properties
- LOI, SG, Bulk Density

Ore processing properties
- Comminution energy, recovery, acid consumption

Chemistry
- Fe, Al, Si for laterites and Cu, Ni, Pb, Zn for base metal ores
RESULTS

Matrix/dominant minerals – Fe ore

Hematite

Goethite

FTIR (wt.%) vs XRD (wt.%)

FTIR prediction
1:1 line
Line of best fit
Matrix/dominant minerals – Fe ore

**RESULTS**

**Kaolinite**

**Quartz**

FTIR (wt. %) vs. XRD (wt. %) graphs for Kaolinite and Quartz.
RESULTS

Substitution Analyte – Fe ore

![Graphs showing Al in Hematite (>30%) and Al in Goethite (>20%)](image)
RESULTS

Element – Ni laterite

![Graph showing correlation between Ni by FTIR model and Laboratory Data (Ni by XRF)]
RESULTS

Element speciation – Fe$^{2+}$

y = 1.0079x - 0.14

$R^2 = 0.9886$
Physical property - Density

Pulp Density by Gas Pycnometer

FTIR model vs. Pycnometer

- Data
- Fit
- Confidence bounds
Ore Processing Properties

The diagram shows a scatter plot with the Bond Work Index (BWI) on the y-axis and Laboratory Data (kWh/t) on the x-axis. The data points are plotted and connected by a line, indicating a positive correlation between BWI and Laboratory Data. The title 'RESULTS' is visible at the top of the page.
SUMMARY
► Low cost analysis (Spectral <$10 per sample vs XRD >$100 per sample)
► Obtain complete mine picture from a routine laboratory workflow
► Predict future processing conditions – high value data !!
► Create a digital mine record.

J Carter, K Auyong and L Dixon

Fourier Transform Infrared (FTIR) spectroscopy and other NIR tools have been used in the bauxite industry for many years. Infrared spectroscopy exploits the differences in chemical composition and lattice structure to produce a characteristic response. Spectral devices, such as those from ASD Inc. and the Hylogger™, provide qualitative mineralogical data targeted towards hydrated minerals detected in the near and short wave infrared region. The FTIR spectrum extends into the mid and thermal infrared range and can therefore respond to the presence of silicates and oxides, in addition to hydrates and carbonates.

The key to successful utilisation of infrared spectra, however, is the interpretation methodology. In this study, FTIR spectra were calibrated against quantitative x-ray diffraction data for the determination of the mineralogy of iron ore. A full pattern machine learning technique was utilised for the calibration, and the assessment of the regressions determined from an independent validation set. The abundance of key minerals - hematite, goethite, kaolinite and quartz - were determined and the results correlated against X-ray fluorescence assays and loss on ignition data. The results of the study indicate that spectral techniques using a full pattern machine learning approach and artificial neural networks can be used successfully to obtain objective and quantitative mineralogical data to support field observations and analytical results for iron ore resource modelling. A comparison of this technique to the cost, quality and timeliness of other quantitative mineralogy tools is also made.
Move Forward with Confidence