Canada Research Chair (Tier I) in
Sustainable Mineral Resource Development and Optimization under Uncertainty

COSMO – Stochastic Mine Planning Laboratory
Dept. of Mining and Materials Engineering

LUNCHTIME SEMINAR

"Automated modeling: Gleaning information from mine data"

Rajive Ganguli, Phd, PE
University of Alaska Fairbanks

Automated modeling:
Gleaning information from mine data

Rajive Ganguli, Phd, PE
University of Alaska Fairbanks

- “**In New Military, Data Overload Can Be Deadly**” New York Times, Jan 17, 2011

I thought there was no such thing as too much data …

- Data in itself is not “information”
  - Requires digesting

Data overload not the only issue in the mining industry

- Too many inter-related varieties:
  - Engineering: Different equipment, processes
  - Non-engineering: costs, labor, time
- Sensor data quality issues
  - Difficult physics governs sensor principles or operating conditions
- Engineering relationships not understood → tough to use data
  - “How is rock size related to the mill power consumption?”
- Sufficient advanced data analysis skills not available at mine sites

Auto-Analysis

- Analysis is logical and math driven → easily programmed
- Can happen in the background
- Minimal human interaction

Current Problem

- Model power consumption at Fort Knox SAG Mill
- Factors ‘impacting’ power consumption: 15
- Data Source: The Process Information System
  – 1 minute intervals

Past Work: Manual Modeling*

- Artificial Intelligence (neural networks)
  - Used Commercial Software: Neuroshell2
- Pre-processing: Clean up data
  - 20,120 minutes of clean data
- Modeling process:
  - Develop model on 80% of data
  - Predict the unused 20%
  - Eliminate inputs systematically to test input relevance

*Ganguli, R., Dutta, S. and Bandopadhyay, S., 2006, "Determining Relevant Inputs for SAG Mill Power Draw Modeling," in Advances in Comminution, Ed. Kawatra, SME Publication.

Past Work: Results

- 6 inputs found useful
  - rpm, recycle, feed rate, density, bearing pressure, noise

- Coefficient of Determination (COD): 0.87

Auto-Modeling Scope

- Limited in scope (graduate student project)…
  - Pre-processing not included
  - Only one type of neural network programmed
  - MS Excel tool
- … but still achieves the “meat” of the process
  - Eliminating “related” inputs
  - NN modeling
  - Identification of “essential” inputs

Auto-NN Modeling Details

- Core NN features “free”
  - #neurons, activation function
- NN performance evaluation metric
  - COD, RMSE, AIC (Akaike Info Criteria)
  - Tough balancing act: maximizing one metric can minimize another
- Identifying “useful” inputs: Combinatorial approach

Auto-Modeling: Results

- When forced to use the same six inputs
  - COD = 0.84
- When “free”, eliminated noise and density
  - COD = 0.82
- Direct comparison between past work and current work not entirely legitimate
  - Auto-modeling dataset smaller
  - Type of neural network different

Auto-modeling: Final Thoughts

- Shows promise
- Pre-processing is very essential
- Real world datasets (large!) will intensify computational need
  - Models on carefully selected subsets may work
  - Strategic human touch essential

Questions?

Acknowledgments

Siddhartha Agarwal, MS (Mining Engineering, 2010), did some of the work reported here.

Thanks to Fort Knox for allowing use of their data