Application of the Ensemble Kalman Filter for Improved Mineral Resource Recovery

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The Flow of Information

- Exploration and Data Collection
- Resource Modelling
- Mine Design
  - Equipment Selection
  - Reserve Estimation
- Production Scheduling
  - and Operation
- Processing and Sale

TU Delft
Challenge the future
Uncertainty in Model-based Prediction
New Potential: Sensor Data

Increasing Availability of Sensor Based Online Data:

- Material characterization (geo-chemical, textural and physical properties)
- Equipment performance, upstream and downstream (e.g. efficiency, down-time)
- Equipment location (e.g. GPS, UPS)
Content

How can we make best use of the available data?

- Closing the Loop: A feed-back framework for Real-Time Resource Model Updating
  - A Kalman Filter Approach
- Using Online Data for Improved Production Control
- Illustrative Case Study: Coal
Towards Closed-Loop Management

Discontinuous and Intermittent Process Monitoring and Decision Making

Near-Continuous Process Control and Optimization

INNOVATION

- Exploration and Data Collection
- Resource Modelling and Reserve Estimation
- Mine Planning and Prediction
- Operation
- Processing and Sale

Mine Planning and Prediction

Real-Time Resource/Reserve Model Update

Prediction vs. Measurements

Operation of Mine Plan

Online Sensor-based Measurements
Towards Closed-Loop Management

- Block model based on original information (planning/exploration)
- Mined blocks, updated with process information
- Updated block model based on exploration and process information

- Sensor stations (Online ore quality)
- Differences between model-based forecast and sensor measurement
- Feedback of differences in the planning model

- Stock and Blending Yard
  - Product 1
  - Product 2
  - Product x

$Z^*(x)$
Towards Closed-Loop Management

Drillhole Data

Prior Model (s)

Model Based Prediction

Sensor Observation (Production Data)

Updated Model (s)

Challenge the future
Resource Model

Generation of Prior Models

**Interpolation (Kriging)**
- Best local estimation,
- Minimization of error-variance estimate.

**Simulation Realisation 1&10 (Conditional Simulation)**
- Represent possible scenarios about the deposit,
- Represent structural behavior of data (in-situ variability),
- Modelled by many different realizations,
- Differences between realizations capture uncertainty

Seam Geometry and CV

(Benndorf 2013)
Closed-Loop Concept

Feed - Forward - Loop

True but unknown deposit \( Z(x) \)

Sampling

Exploration Data Set \( z(x_i), i=1,\ldots,n \)

Modelling

Estimated Deposit Model \( Z^*(x) \) + Uncertainty

Model Based Prediction \( f(A,Z^*(x)) \)

Decisions e.g. Mine Planning \( A \)
Closed-Loop Concept

True but unknown deposit $Z(x)$

Sensor Measurements $V_j, j=1,...,m$

Production Monitoring

Closing the Loop Feed – Back - Loop

Sampling

Exploration Data Set $z(x_i), i=1,...,n$

Model Based Prediction $f(A,Z^*(x))$

Difference $f(A,Z^*(x)) - V_j$

Sequential Updating

Estimated Deposit Model $Z^*(x) + Uncertainty$

Decisions e.g. Mine Planning $A$
Linking Model and Observation

- $n$ mining blocks
- each of the blocks contributes to a blend, which is observed at a sensor station at time $t_i$
- $m$ measurements are taken
- $a_{i,j}$ proportion block $i$ contributes to the material blend, observed at time $j$ by measurement $l_i$

Production sequence – Matrix $A$

Mining Blocks

$$
\begin{bmatrix}
a_{1,1} & \cdots & a_{1,m} \\
\vdots & \ddots & \vdots \\
a_{n,1} & \cdots & a_{n,m}
\end{bmatrix}
$$

Observations
Resource Model Updating
Sequential Model Updating - A Kalman Filter Approach

\[ Z^*(x) = Z^*_0(x) + K (v - AZ^*_0(x)) \]

\( Z^*(x) \) … updated short-term block model (a posteriori)
\( Z^*_0(x) \) … prior block model based (without online sensor data)
\( v \) … vector of observations (sensor signal at different points in time \( t \))
\( A \) … design matrix representing the contribution of each block per time interval to the production observed at sensor station
\( K \) … updating factor (Kalman-Gain)
Resource Model Updating

Sequential Model Updating – A “BLUE”

Estimation error:

\[ e(x)_{t+1} = z(x)_{t+1} - z^*(x)_{t+1} \]

Estimation variance to be minimized:

\[ C_{t+1,t+1} = E\left[ e(x)_{t+1} e(x)_{t+1}^T \right] \]

Updating factor:

\[
K = C_{t,t} A^T (A C_{t,t} A^T + C_{v,v})^{-1}
\]
Resource Model Updating

Sequential Model Updating – The Integrative Character

\[ K = C_{t,t}A^T(AC_{t,t}A^T + C_{v,v})^{-1} \]
Resource Model Updating

Sequential Model Updating

Main challenges:
• Large grids
  • Industrial Case: 4,441,608 blocks
• Non-linear relationships between model and observation
• Non-Gaussian data
Resource Model Updating

Sequential Model Updating
A Non-Linear Version – The Ensemble Kalman Filter

Model based prediction $AZ_0(x)$
Observations $l$
Difference $(l - AZ_0(x))$

$Z^*(x) = Z_0(x) + K(l - AZ_0(x))$
Resource Model Updating

Sequential Model Updating
To handle Non-Gaussian Data... N-Score-Ensemble Kalman Filter*

Illustrative Case Study

Updating the Calorific Value in a Large Coal Mine

**Case Study:** Walker Lake Data Set

(Exhaustive “true” data are available)

**Model based prediction:**

- Estimated block model (5200t/block)
- Capacity Excavator 1: 500 t/h
- Capacity Excavator 2: 1.000 t/h
Illustrative Case Study

Updating the Calorific Value in a Large Coal Mine

Sensor Observations:

- Artificial sensor data for a 10 minute average (representing 250 t)
- Relative sensor error is varied between 1%, 5% and 10%
- Sensor data obtained:
  - Model based prediction + dispersion variance + sensor error

![Graph showing CV in MJ/kg]
Illustrative Case Study

Prior Block Model based on Exploration Data

Updated Block Model Integrating Sensor Data

Differences
Illustrative Case Study

Comparison to Reality

Kalman-Filter: 2 Excavators

\[ \text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (Z^*(x_i) - z(x_i))^2 \]
Illustrative Case Study

Rejection Sampling

1000 (Realizations) Prior Models

Implementation of Rejection Sampling

290 accepted Posterior Model

Comparison

1000 updated Posterior Model

Implementation of Real-Time Update Framework
Illustrative Case Study

Rejection Sampling
Illustrative Case Study - Results

- Significant improvement in prediction
- Increased confidence in dispatch decisions
  - Less miss-classified blocks (ore/waste)
  - Less shipped train loads out of spec
- Increased customer satisfaction and revenue
- Magnitude of improvement depends on level of exploration, variability and sensor error
Current Work

- EU - RFCS funded project RTRO-Coal
Conclusions

• Modern ICT provides online data, which can be the basis for (near-) continuous process monitoring at different stages of the mining value chain

• Utilizing these data for (near-) real-time decision making offers huge potential for more sustainable extraction of mineral resources

• Closed Loop Concepts offer:
  • Integration of prediction and process models with data gathering
  • Interdisciplinary and transparent project communication (breaking the silos)
  • More complex use of data for increased resource efficiency
Thank You for Your Attention

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