Application of the Ensemble Kalman Filter for Improved Mineral Resource Recovery (PPT)

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Publication date
2015

Document Version
Final published version

Citation (APA)

Important note
To cite this publication, please use the final published version (if applicable). Please check the document version above.
Application of the Ensemble Kalman Filter for Improved Mineral Resource Recovery

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The Flow of Information

1. Exploration and Data Collection
2. Resource Modelling
3. Mine Design Equipment Selection Reserve Estimation
4. Production Scheduling and Operation
5. 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

Exploration and Data Collection

Resource Modelling and Reserve Estimation

Mine Planning and Prediction

Operation

Processing and Sale

Discontinuous and Intermittent Process Monitoring and Decision Making

INNOVATION

Near-Continuous Process Control and Optimization

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

$Z^*(x)$

Sensor stations (Online ore quality)

Differences between model based forecast and sensor measurement

Feedback of differences in the planning model

- Excavator 1
- Excavator 2
- Excavator n
- Stock and Blending Yard

Product 1
Product 2
Product x
Towards Closed-Loop Management

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 $z(x_i), i=1,…,n$

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 $Z(x)$

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

Sampling

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

Decisions e.g. Mine Planning $A$

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

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

Sequential Updating

Closing the Loop Feed – Back - Loop

Production Monitoring

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

Observations

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

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

Model Uncertainty  
Extraction Sequence  
Sensor Precision
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 $(l - AZ_0(x))$

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

(Reproduced after Geir Evensen 1993)
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](image)

- Blue line: True Block Grade
- Red line: True Block Grade + Dispersion Variance
- Green line: True Block Grade + Dispersion Variance + Sensor Error
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

- Posterior Mean from Rejection Sampling
- Posterior Variance from Rejection Sampling
- Posterior Mean from Real-Time Update Framework
- Posterior Variance from Real-Time Update Framework

Average mean and variance maps of 290 posterior realizations accepted according to rejection sampling method.

Average mean & variance maps of 1000 posterior realizations updated with EKF framework.

The Difference Between
The Accepted Posterior Realizations Mean (from Rejection Sampling) and The Updated Posterior Realizations Mean (from Real-Time Update Framework)

Difference map between the accepted posterior realizations from rejection sampling and updated posterior realizations from real-time update framework.
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 resource

• 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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Source: RWE