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Data analytics for advanced process monitoring and control in primary aluminum smelting

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Outline

- Context
- Data analytics
- Advanced monitoring and control
- Some applications
- Challenges
- Latent Variable Methods vs Machine Learning

Manufacturing process

Environmental conditions

Electricity

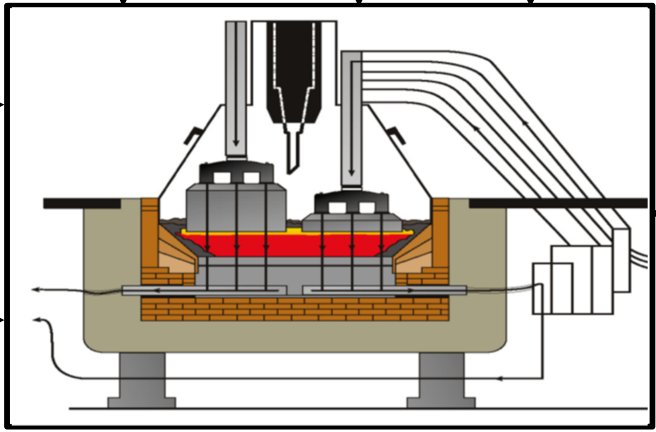
Others

Raw materials

- Coke
- Pitch
- Butts

→ Baked anodes →

Alumina →

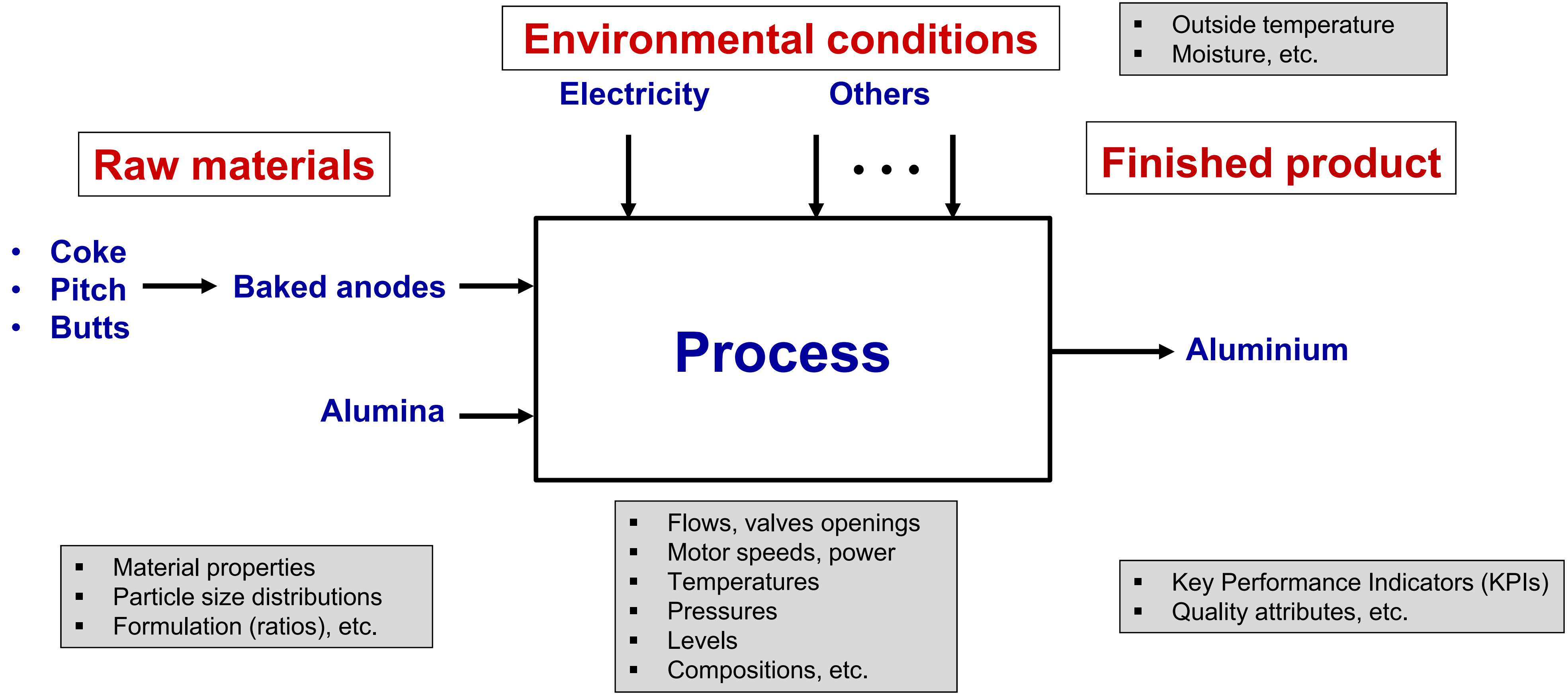


→ Aluminium

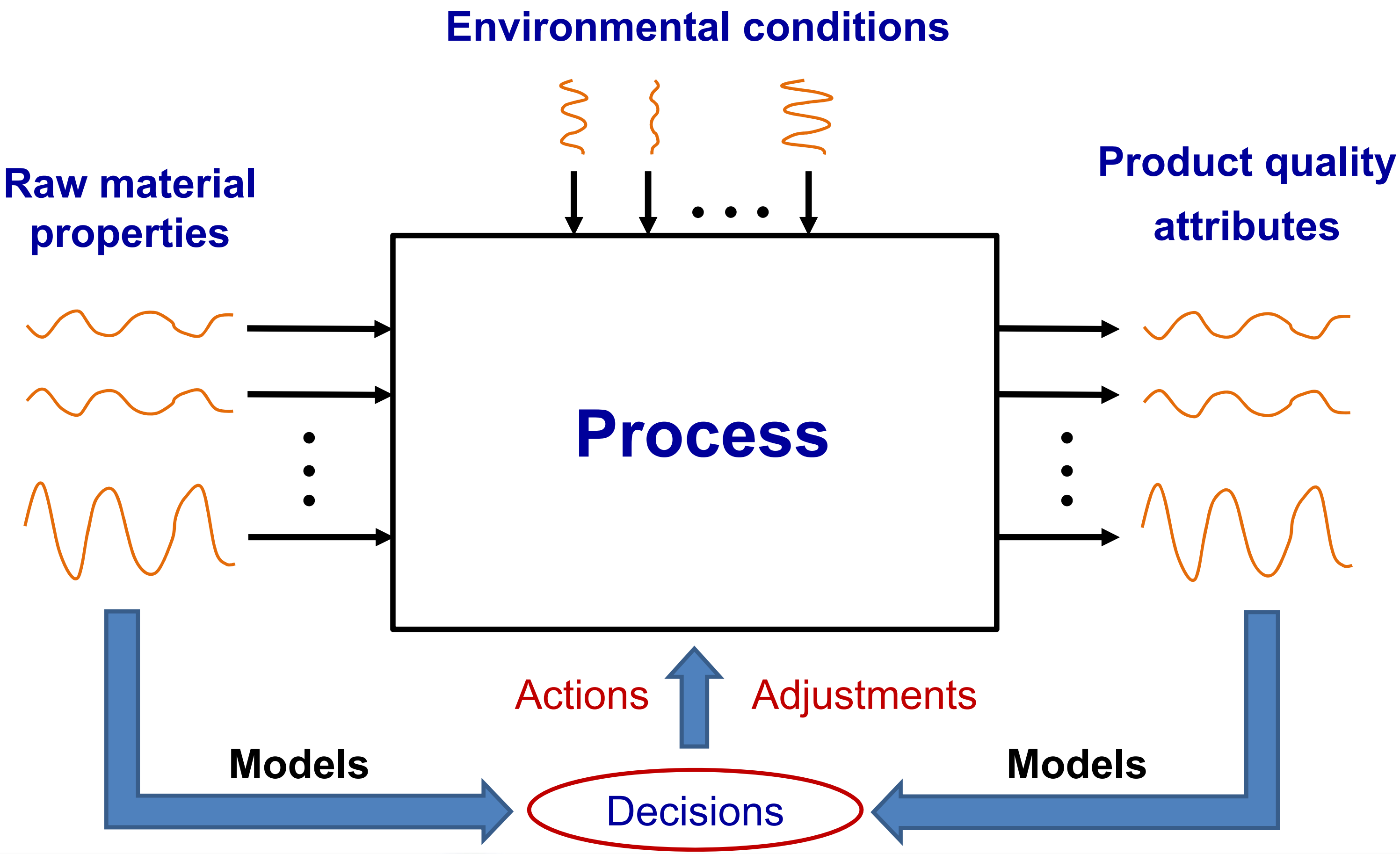
Finished product

Process

Process Data



Data analytics



Applications of data-driven models

- Process analysis / troubleshooting
- Develop sensors, process analytical technologies (PAT)
- Process monitoring, abnormal situation detection, diagnosis
- Quality control of raw materials and finished products
- Process control and optimization

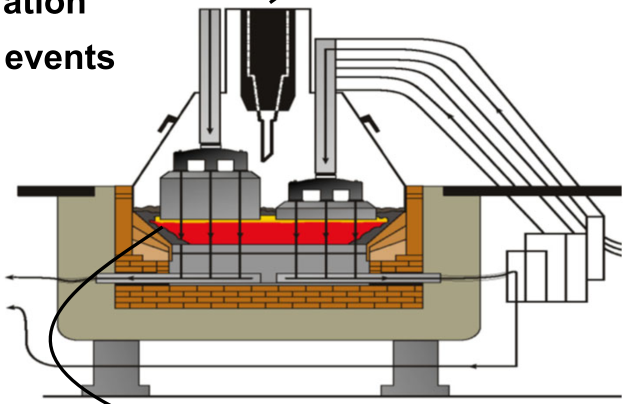
Latent Variable Methods

- Also known as Multivariate Statistical Methods
- Principal Component Analysis (PCA), Projection to Latent Structures (PLS)
- Efficient methods to cope with the highly collinear structure of process data
- Deal with missing data
- Interpretable using process knowledge

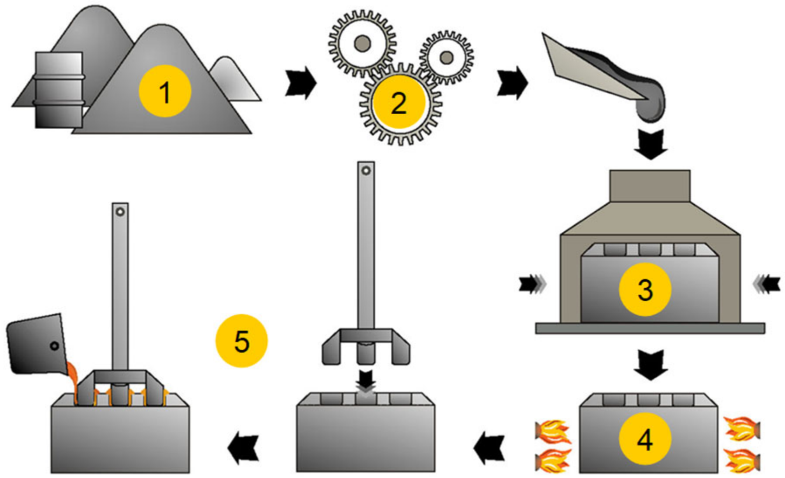
Advanced monitoring in primary Al production

<u>Ultimate goals</u>:

- **Monitor cell operation**
- **Detect abnormal events**
- **Find root causes**
- **Take action**



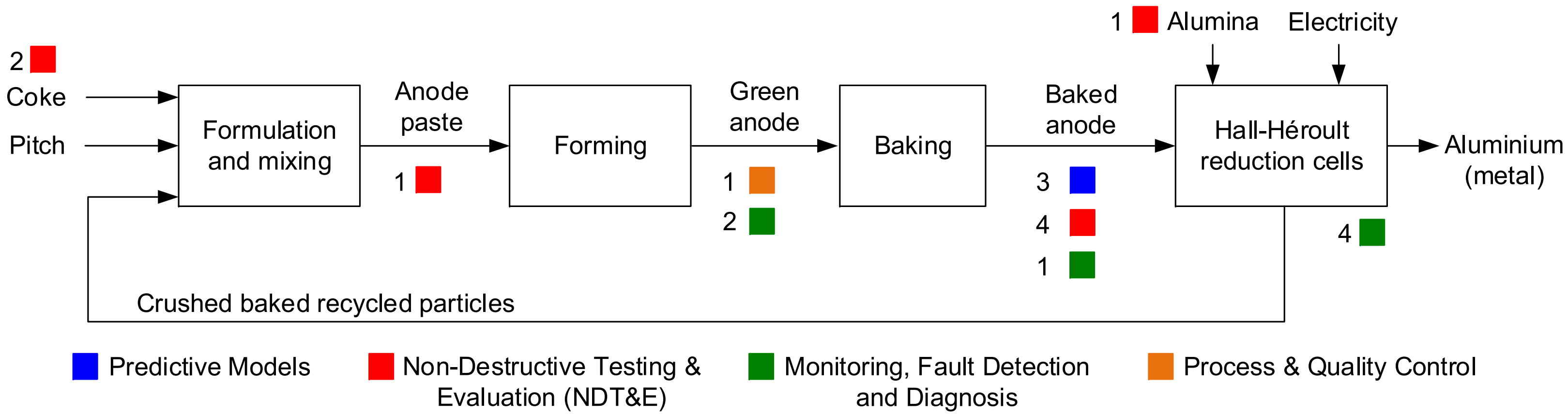
Alumina properties



Anode Plant

Tracability: Anode Tracking Systems

Research program on data analytics



- **Lack of measurements on key materials**
  - **Coke properties**
  - **Paste**
  - **Green anodes**
  - **Baked anodes**

Alcoa

CRSNG NSERC

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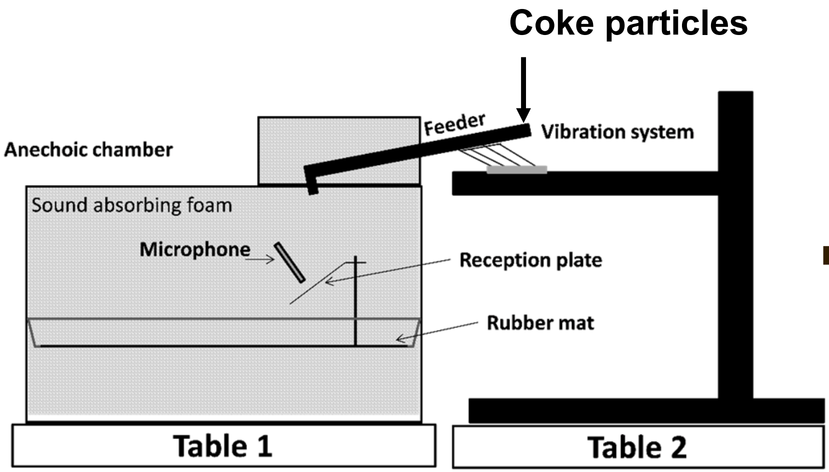
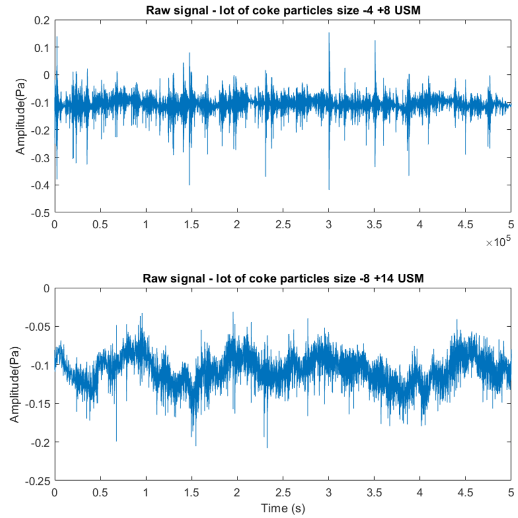
Some applications

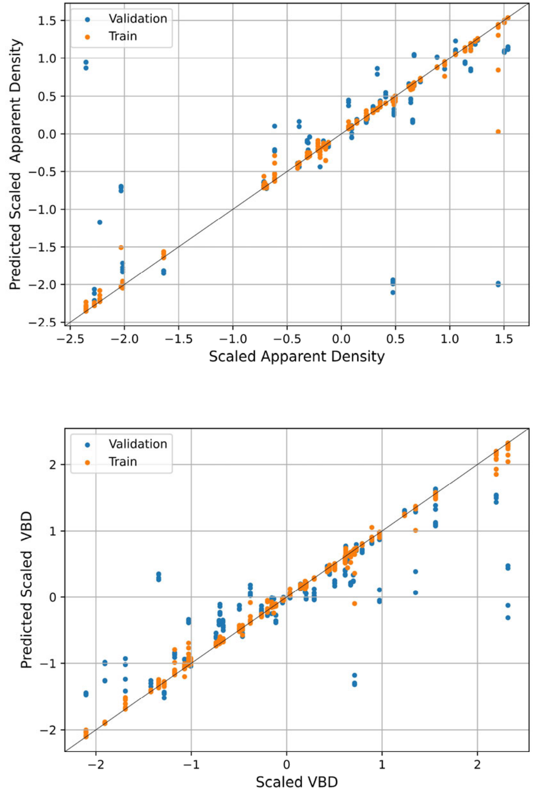
- **Measurements on materials**
  - **Coke : impact acoustics**
  - **Paste imaging**
  - **Baked anodes : Modal Analysis (MA) and Acousto-Ultrasonics (AU)**

- **Baked anodes in operation**
  - **Detection of anodic incidents using individual anode currents**

Impact acoustics for coke particles







Cokes:

- Different suppliers
- Different sizes
- Unmixed and blends

➡ Impact sound ➡ Features ➡ Models ➡ Predictions

E. Ishak. (2020), M.Sc. Thesis, U. Laval and unpublished work

Optimal pitch demand of dry aggregates

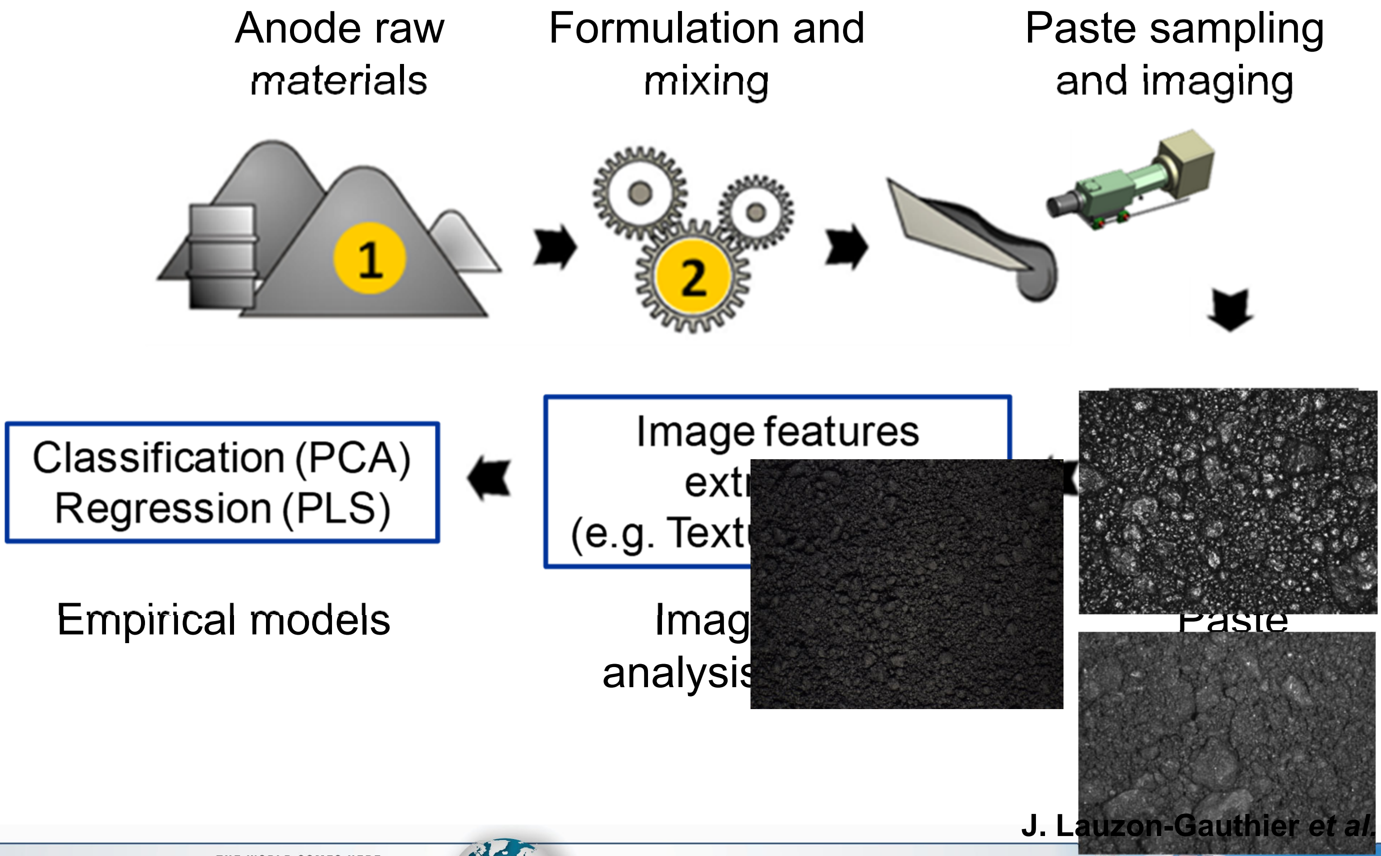
- Increasing variability of coke properties

- Impact on pitch demand of dry aggregate mix

- Optimal pitch demand (OPD) determined experimentally at the plant
  - Infrequent
  - Disruptive
  - Costly

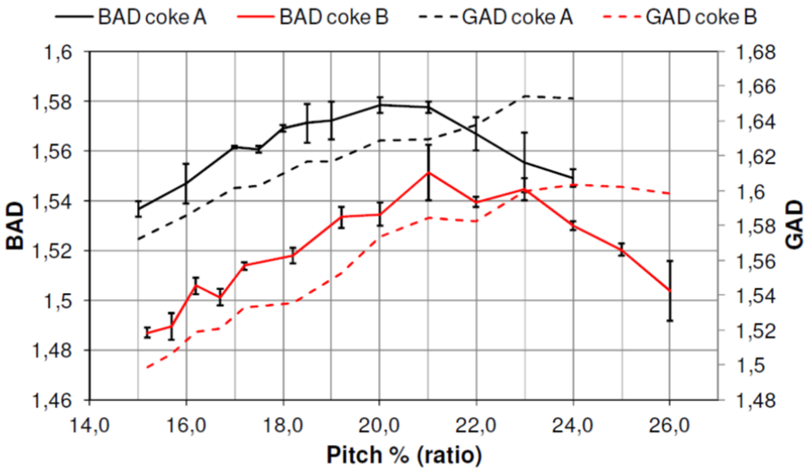
- Measure from images of the anode paste?

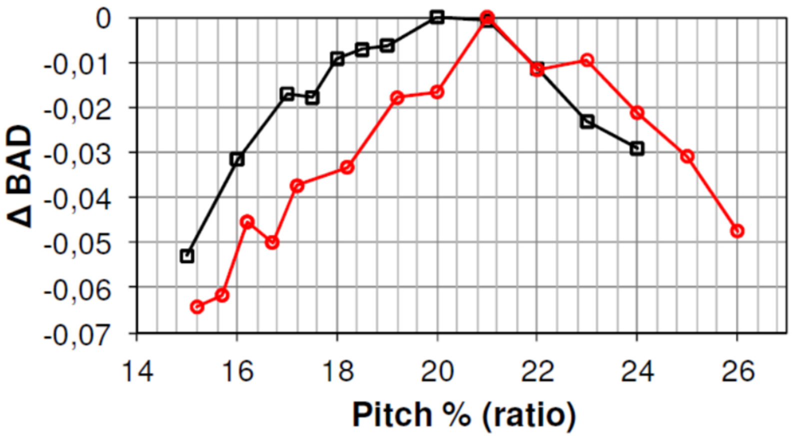
Anode paste imaging – pitch demand



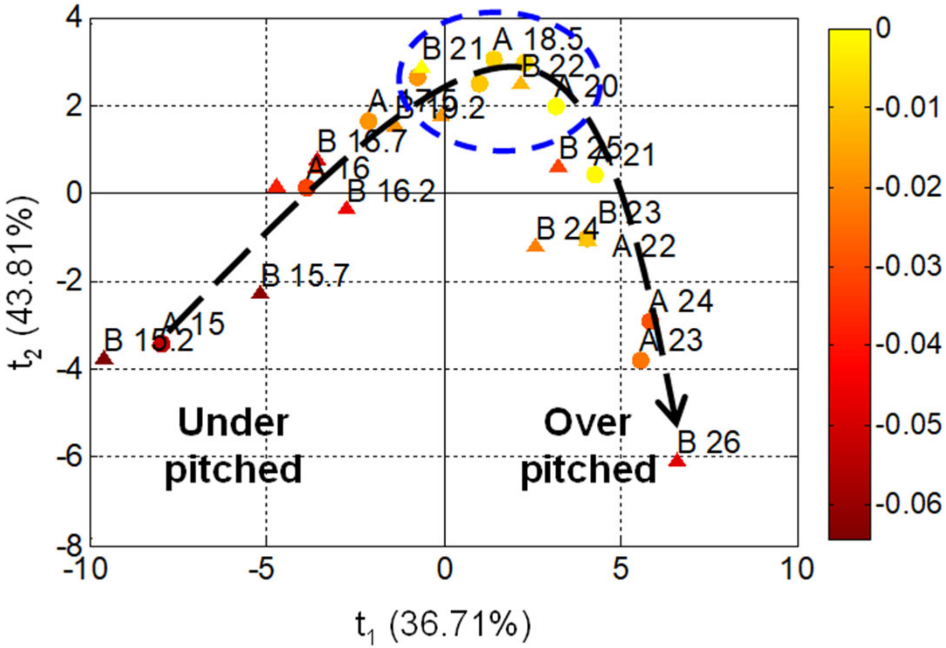
J. Lauzon-Gauthier *et al.* (2020), JOM, 72(1), 287-295

Anode paste imaging – pitch demand





Optimal pitch ratio



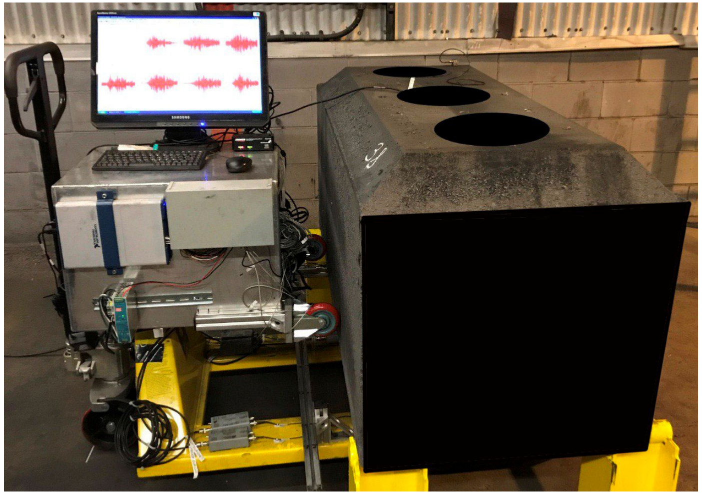
Clustering of images features

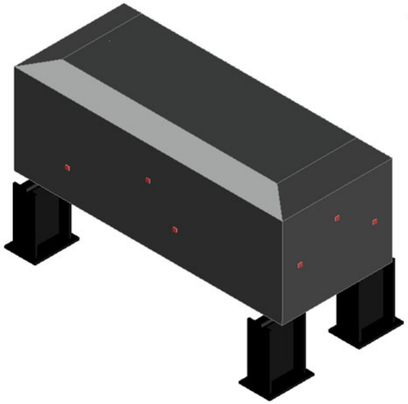
J. Lauzon-Gauthier *et al.* (2020), JOM, 72(1), 287-295

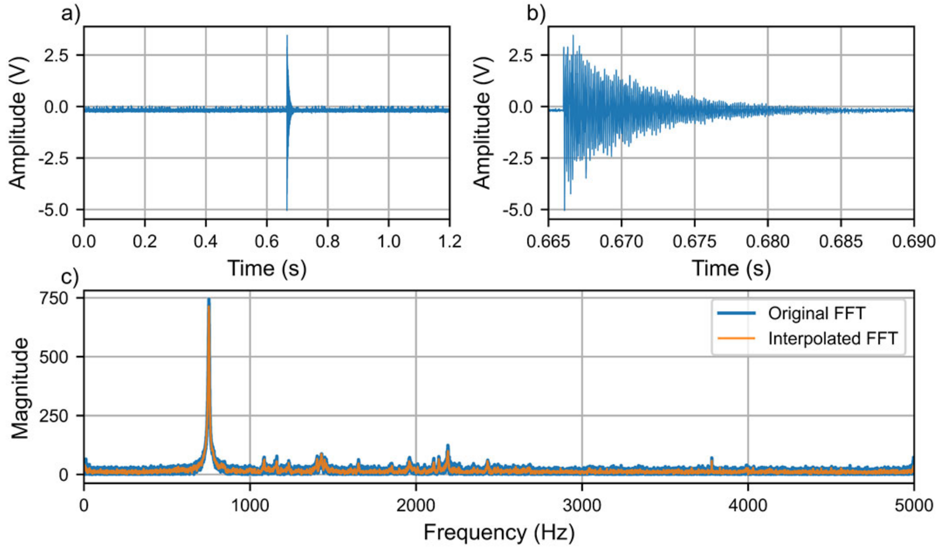
Non-destructive inspection of pre-baked anodes

- Quality control scheme currently used in the field
  - Core sampling of <1% of anode production
  - Characterization in the lab (delay of ~2 weeks)
  - Cores representativeness (0.13% of anode block volume)
- Probability of detecting defects?
  - Cracks, abnormally porous regions, compositional heterogeneities
- Defect anodes strongly affect reduction cell performance
- Rapid and non-destructive inspection of the anodes

Modal Analysis





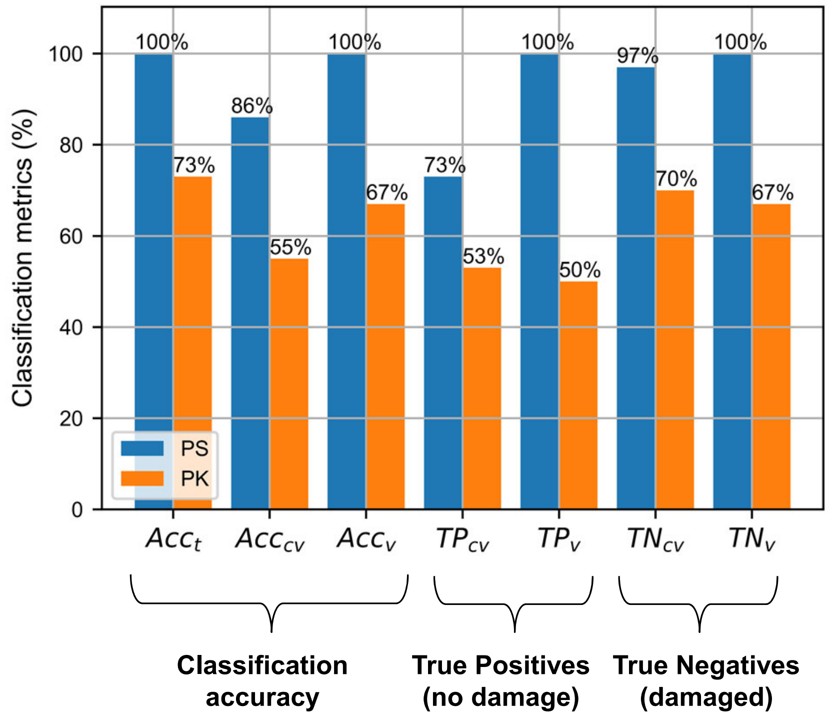


- **Accelerometers**
- **Laser vibrometers (contactless)**

D. Rodrigues *et al.* (2022), JOM, 72(2), 697-705

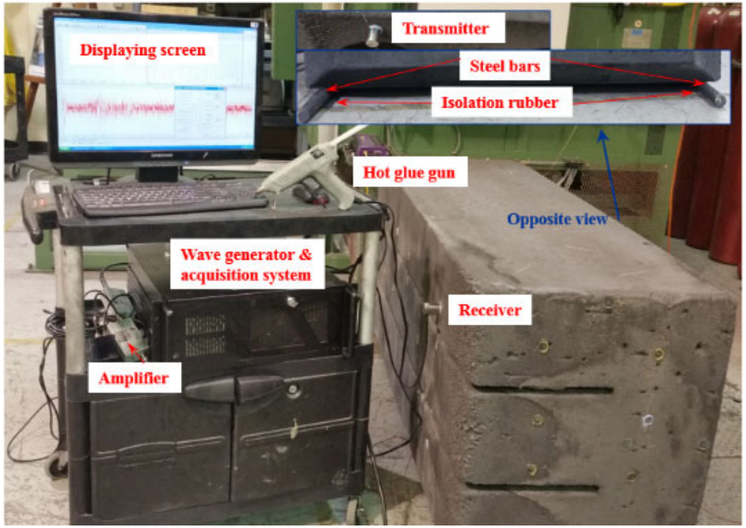
Modal Analysis

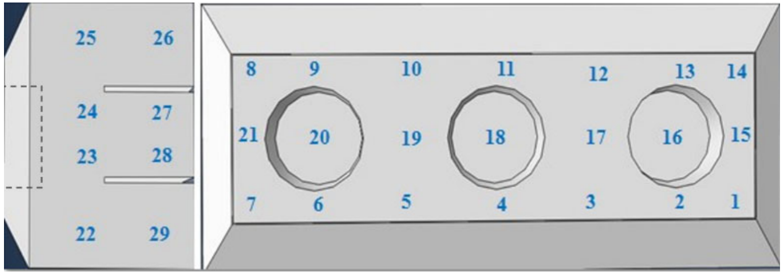
- **82 pre-baked anodes sampled from an Alcoa plant**
  - **No external defect: 36**
  - **Damaged: 46**
- **External damage (cracks, loose or broken pieces, etc.)**
- **Classification based on FFT periodograms of anode response**



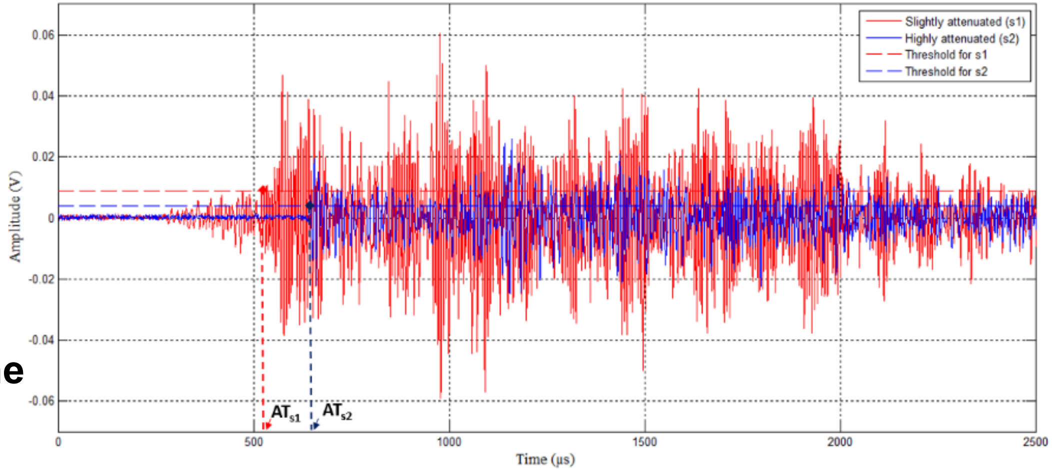
D. Rodrigues *et al.* (2022), JOM, 72(2), 697-705

Acousto-Ultrasonic Inspection





AT = arrival time

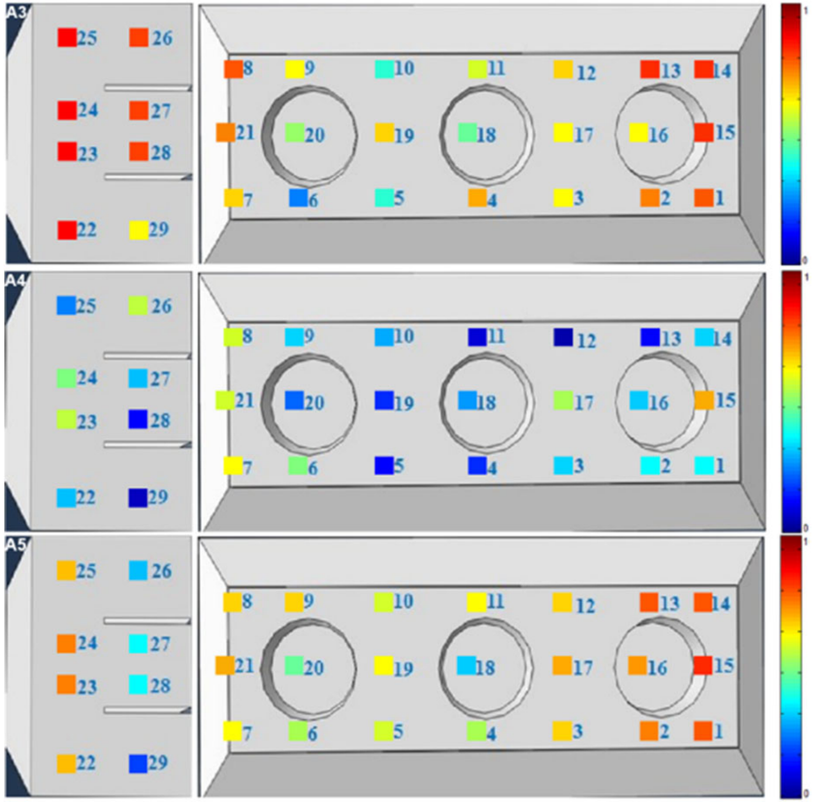


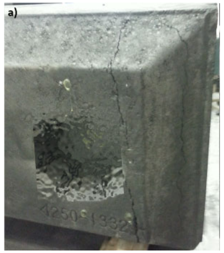
M. Ben Boubaker *et al.* (2018), Ultrasonics, 89, 126-136

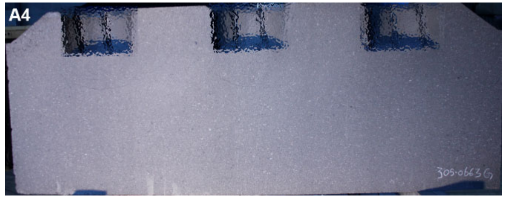
Acousto-Ultrasonic Inspection

Maps of AU signal attenuation by damage

- **Blue**: low
- **Red**: high







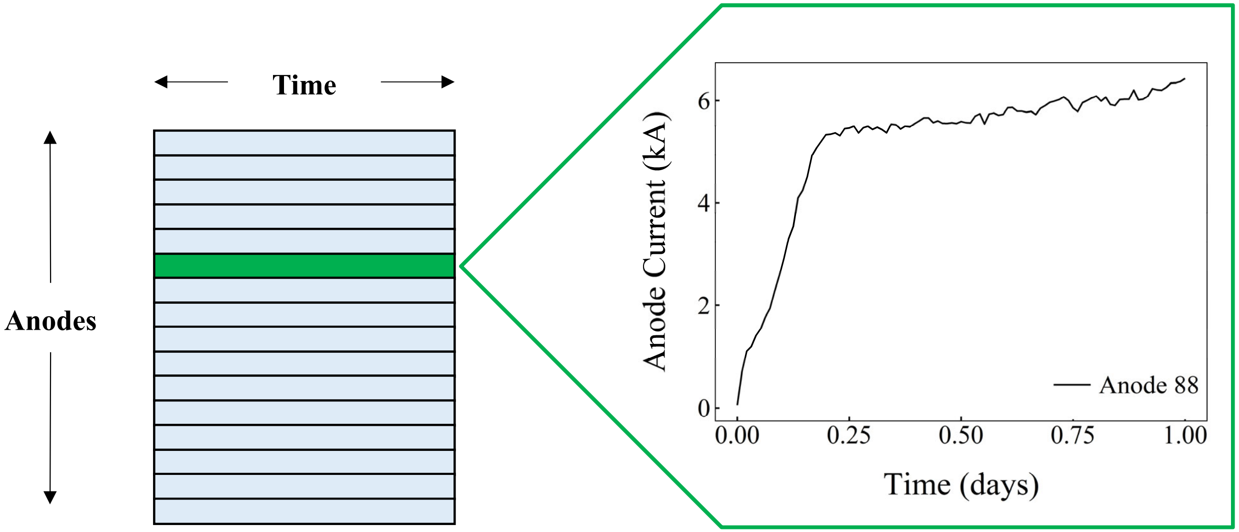
M. Ben Boubaker *et al.* (2018), Ultrasonics, 89, 126-136

Detection of anodic incidents

- **Individual anode electrical currents**
  - **Increasingly used in plants**
  - **Mainly studied for anode effect detection**
- **Early detection of anodic incidents?**
  - **Spikes and other types of deformations**
  - **Anodes set too low**

D. LaJambe *et al.* (2020), Light Metals 2020, 535-542
D. LaJambe *et al.* (2021), Minerals Engineering, 172, 10744

Detection of anodic incidents



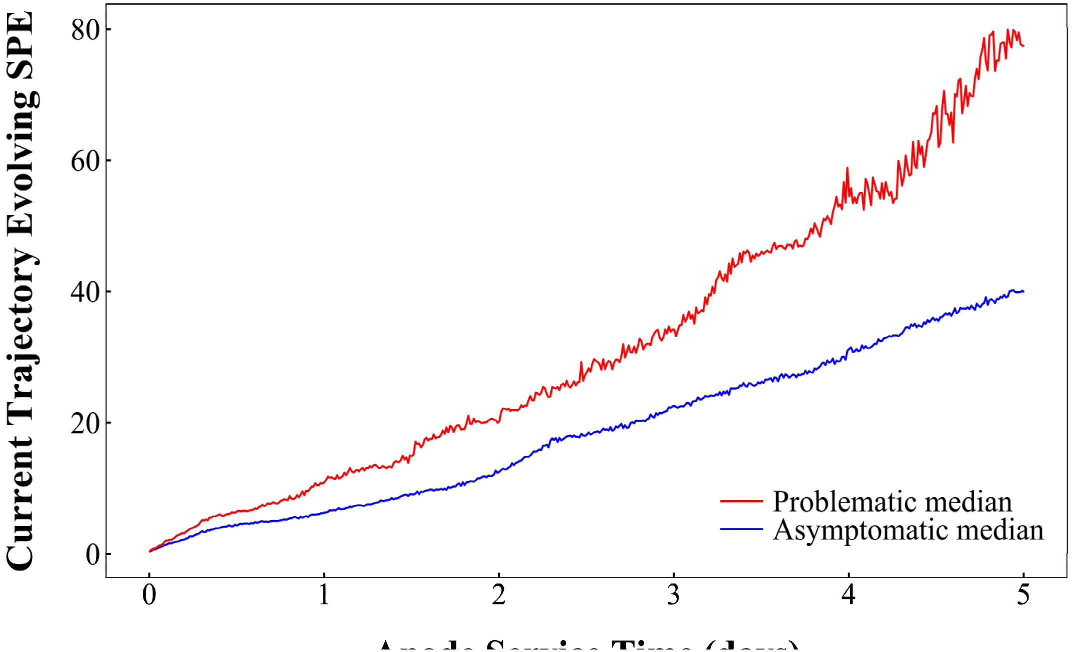
Anodes (~ 2500) set in:

- **Different cells**
- **Different positions**

➡ **Current trajectories** ➡ **Feature extraction (Batch PCA model)** ➡ **Classification (asymptomatic vs problematic)**

D. LaJambe *et al.* (2020), Light Metals 2020, 535-542
D. LaJambe *et al.* (2021), Minerals Engineering, 172, 10744

Detection of anodic incidents



Classification performance metrics at a recall level of 0.25

Cell	False Positive Rate	Precision	Detection Antecedence
B103	0.13	0.44	10.9
B104	0.07	0.39	5.9
B106	0.13	0.30	7.2
B108	0.17	0.29	7.6
B109	0.16	0.22	14.9
B120	0.06	0.38	0.5

False alarm

Fraction of true alarms raised by system

Days ahead of detection by operators

D. LaJambe *et al.* (2020), Light Metals 2020, 535-542
D. LaJambe *et al.* (2021), Minerals Engineering, 172, 10744

Challenges

- Data extraction and organization
  - Different sampling rates
  - Continuous and discontinuous process units (synchonization issues)
  - Few measurements on anode raw material properties
- How to set quality targets for pre-baked anodes?
  - Performance in the cell?
- Staff limitations at plant sites for technology transfer
- Need business case for testing technologies but need to implement them to demonstrate benefits (Catch-22 problem)

Latent Variable Methods vs Machine Learning

- **Avantages**
  - Model uniqueness
  - Interpretability using process knowledge
  - Require reasonable amounts of data
- **Drawbacks**
  - Structure less flexible
  - Basic methods are linear

- **Avantages**
  - Very flexible structures
  - Wide range of algorithms
  - Nonlinear methods
- **Drawbacks**
  - Black boxes (no interpretation possible)
  - Require massive amounts of data for training and validation
  - Overfitting (e.g. millions of parameters to estimate)

Acknowledgements

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  - Jayson, Julien, Moez, Kamran, Amélie, Wilinthon, Adéline, David, Elias, Daniel, Petre
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