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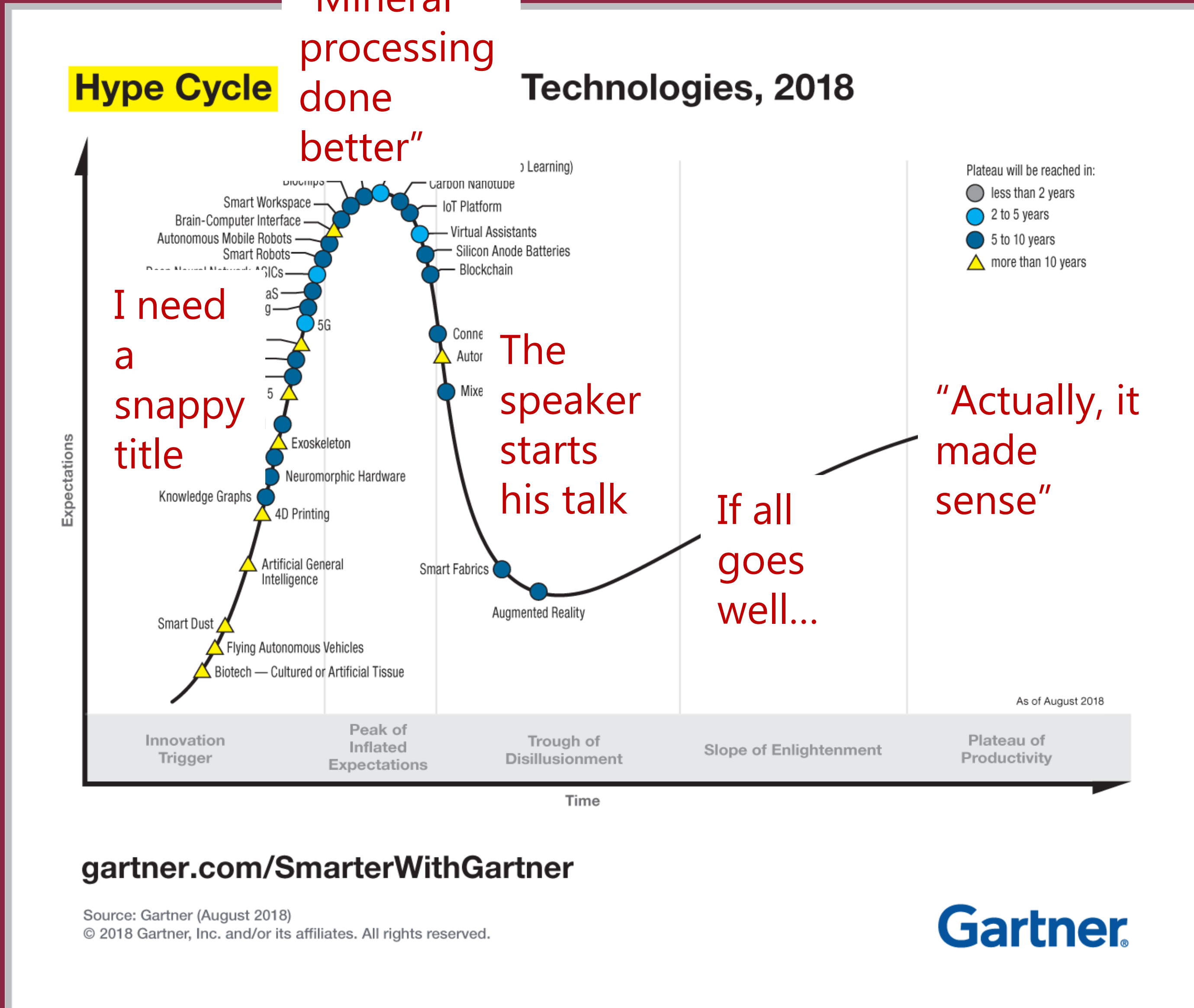
forward together · saam vorentoe · masiye phambili

Mines, data mines and urban mines – mineral processing done better

Department of Process Engineering, Stellenbosch University, South Africa

Industrial Open Day 7 June 2019

Tech Hype Cycles



"Mineral processing done better"

I need a snappy title

The speaker starts his talk

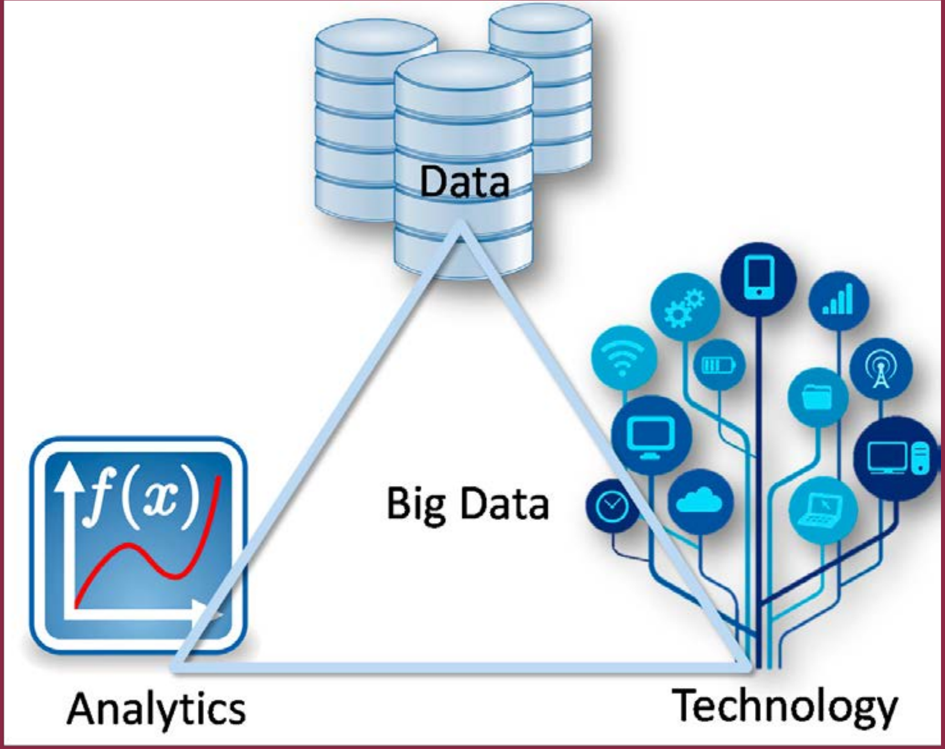
If all goes well…

"Actually, it made sense"

Contents

Big Data/Industry 4.0

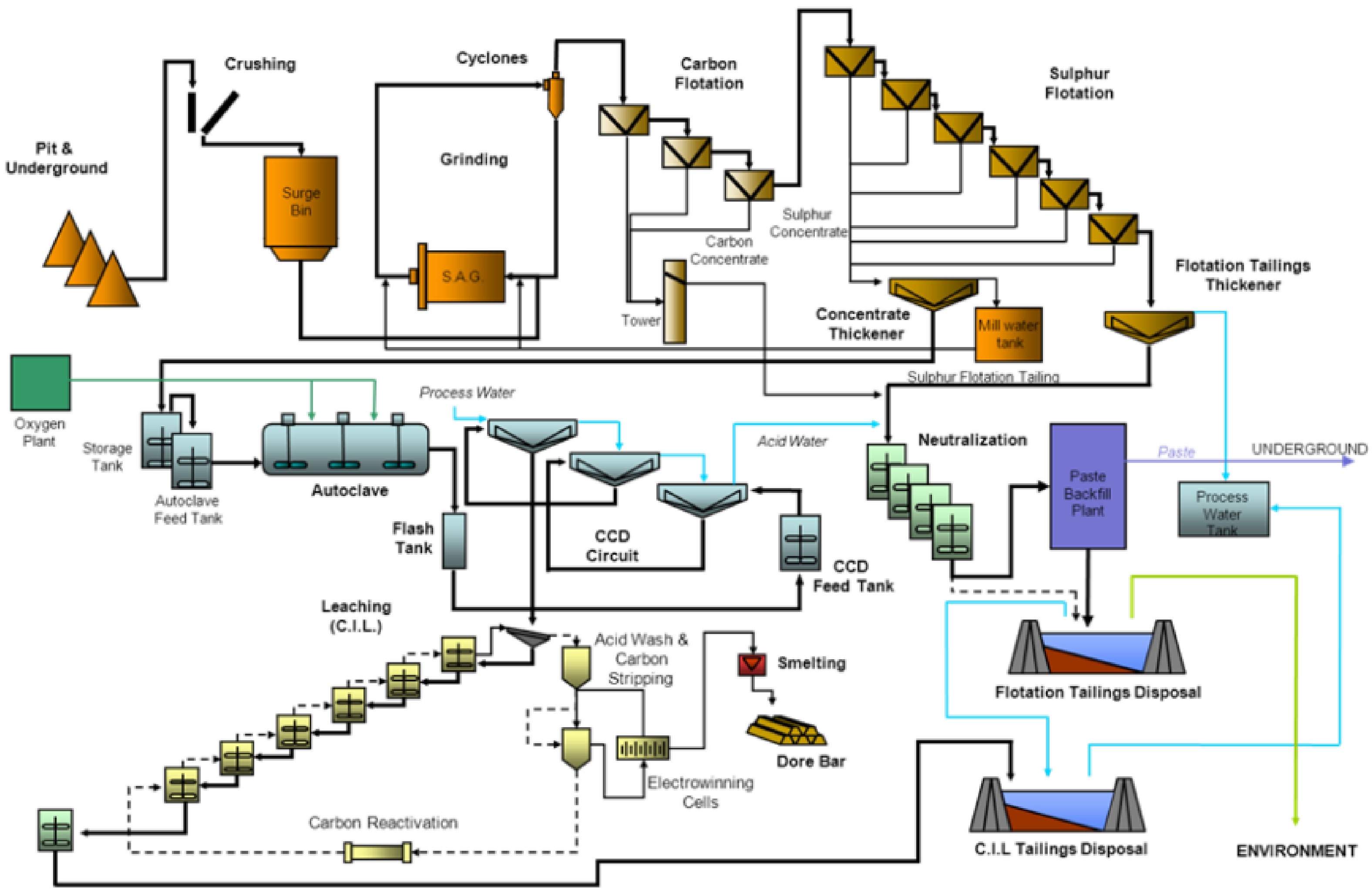
- Big Data provides the opportunity to enhance industrial performance
  - Operationally, economically, SHE
- Machine learning provides mathematical/statistical models that turn data into actionable information



Source: Reis and Gins, Processing 2017, 5, 35

Mineral processing challenges and opportunities

Continuous, connected, controlled, circulating, complex, changing



Mineral processing data

- **Online data**
  - Physical property sensors (~seconds)
    - E.g. mass flow rate, density, temperature, pressure
  - Image data (~minutes)
    - E.g. rocks on conveyor belts, flotation froth
- **Offline data**
  - Laboratory data (~hours)
    - E.g. metal content, particle size distribution
  - Image data (~days)
    - E.g. microscopic grain shape and colour
  - Text data (~days)
    - E.g. maintenance logs, metallurgist reports

Machine learning definitions

$$\boldsymbol{Y} = f(\boldsymbol{X}, \boldsymbol{\theta})$$

$\boldsymbol{Y} = output\ variables$	$Y \sim continuous; Y \sim categorical$
$\boldsymbol{X} = input\ variables$	$X \sim continuous\ X \sim categorical$
$\boldsymbol{\theta} = parameters$	$\theta_m = model\ parameters;$
	$\theta_h = hyperparameters$
$f(\quad) = functional\ form$	$Parametric, e.g. linear\ regression$
	$Non-parametric, e.g. neural\ nets$

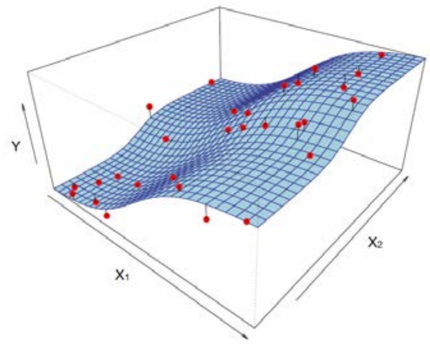
Training: Learn θ_m (e.g. minimize $\sum_i \left(Y_i - \hat{Y}_i\right)^2$)

Validation: Learn θ_h

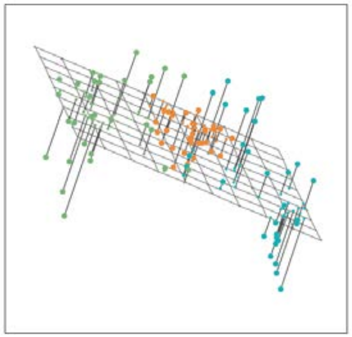
Machine learning definitions

$$Y = f(X, \theta)$$

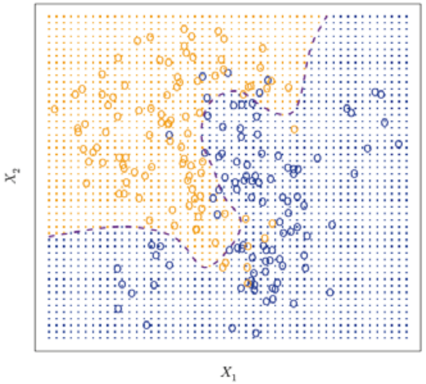
Supervised learning	Unsupervised learning



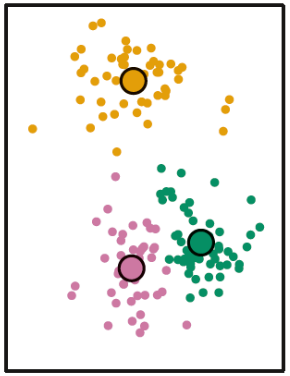
Regression
$Y \sim continuous$



Noise removal, feature extraction
$\widehat{X} = f(X, \theta)$
$T = f(X, \theta)$

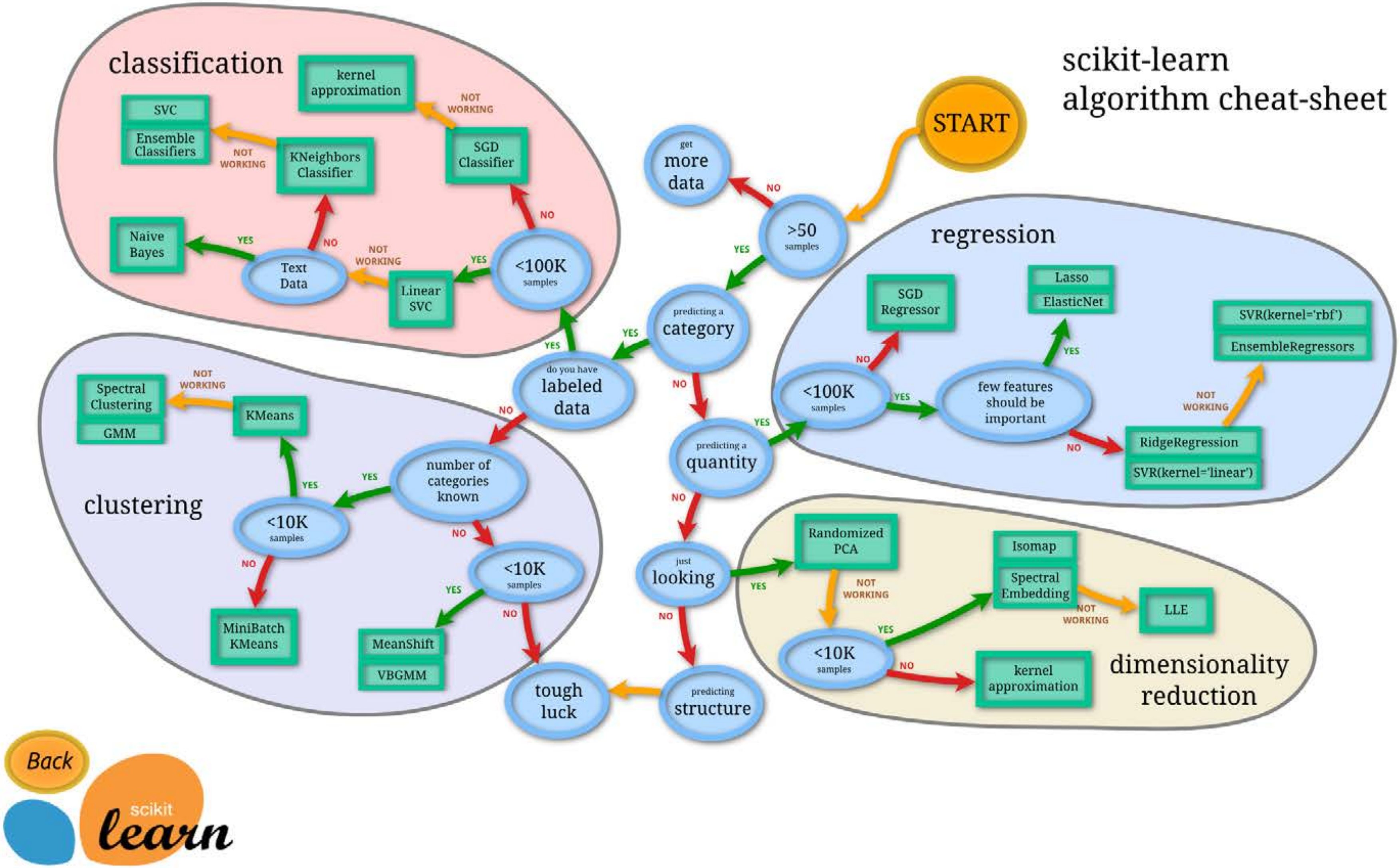


Classification
$Y \sim categorical$



Clustering
$C = f(X, \theta)$

Machine learning definitions



Hype

BIG DATA! INDUSTRY 4.0! ARTIFICIAL INTELLIGENCE! (?)

$Y = f(X, \theta)$ More data + Better computers + Better methods

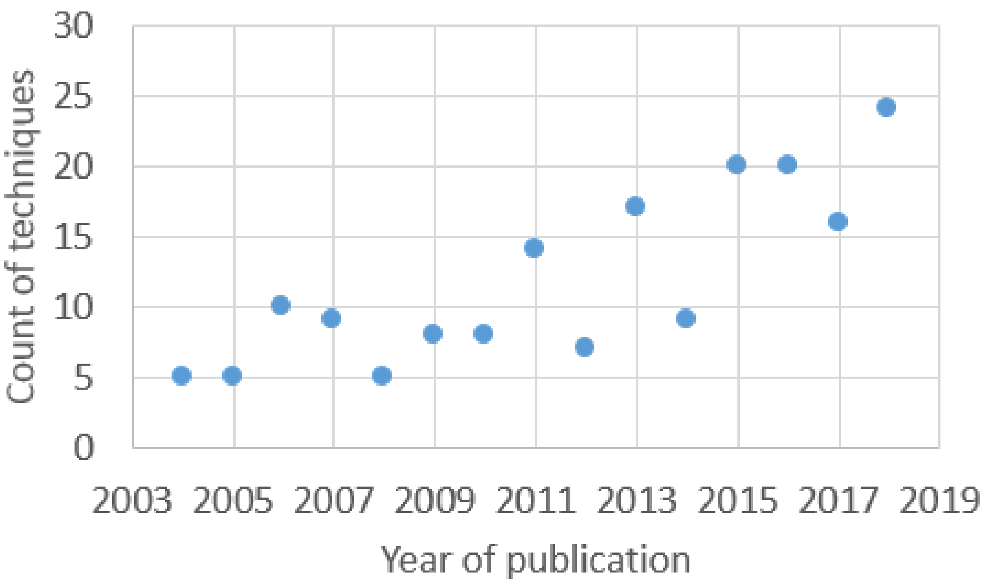
Hype

- Increasing popularity in many applied sciences
  - Special issues in journals of medicine, finance, environmental science, etc.

- Review undertaken: 13 journals and conference proceedings (2004 – 2018):
  - AIChE; Chemometrics and Intelligent Laboratory Systems; Computers and Chemical Engineering; Control Engineering Practice; Engineering Applications of Artificial Intelligence; Journal of Process Control; IFAC MMM; Industrial and Chemical Engineering Research; International Journal of Mineral Processing; International Journal of Mining, Reclamation and Environment; JSAIMM; Minerals and Metallurgical Processing; Minerals Engineering

- Tool for researchers: Searchable summaries
  - Category and application
  - Method, inputs, outputs, hyperparameters
  - Success and implementation

Hype



177 technique applications

Implementation	Count
Experimental data	105
Simulated data	8
Industrial data	40
Industrial implementation	24

Success	Count
Yes	141
Limited	35
No	1

Category	Count
Fault detection and/or diagnosis	30
Data-based modelling	40
Machine vision	107

Data-based modelling

Fast, easy measurements

eg flow rate
pressure
temperature
spectra

→

Supervised learning

Data-based modelling techniques

PCA, PCR, PLS
kNN, k-means clustering
CART, RF
SVM, SVR, ANN, ELM
QTA

→

Slow, difficult measurements

eg composition
size distribution
mill load
equipment failure

Trends

Soft sensors
Industrial implementation: relatively mature

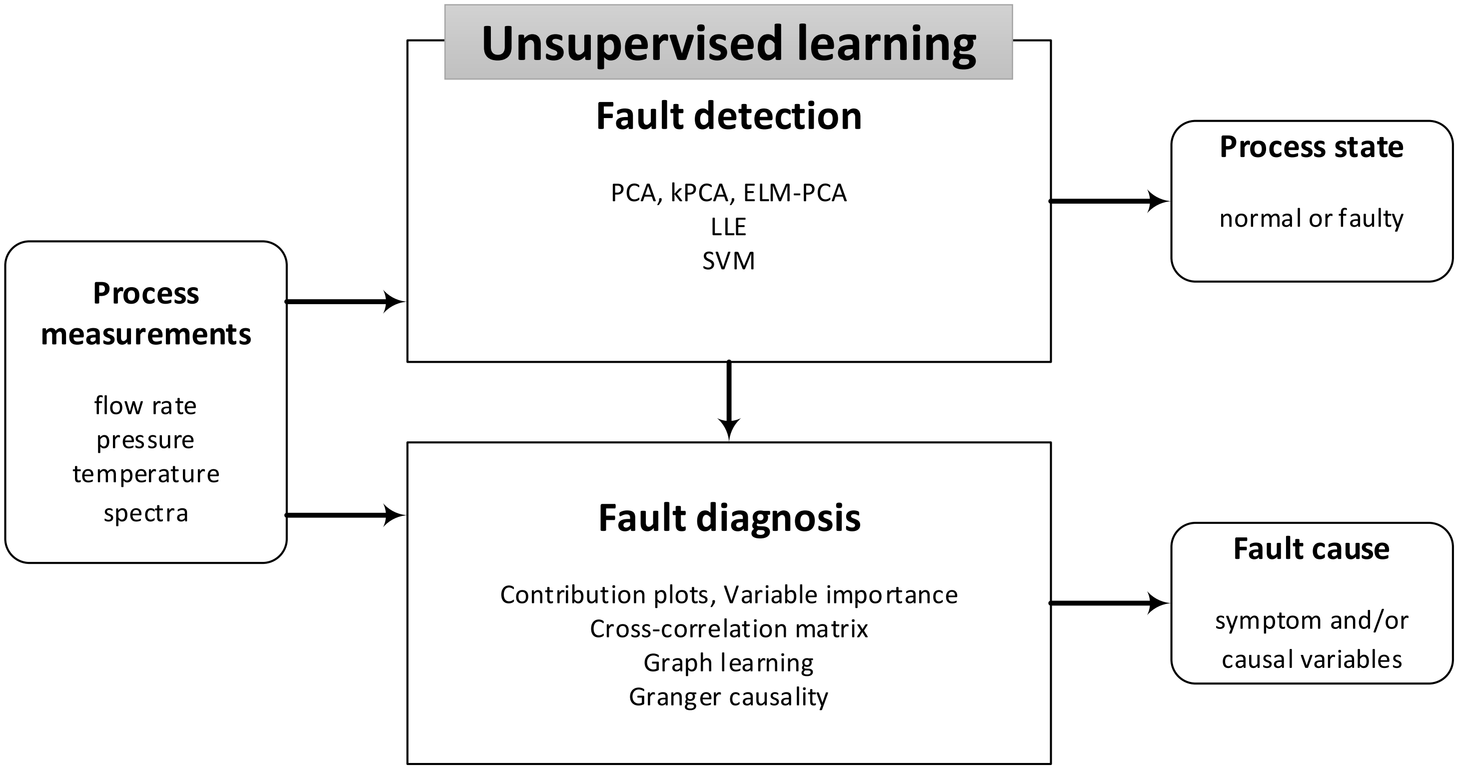
Challenges

Non-stationary
Nonlinear
Multiple modes
Missing values
Faulty and noisy values
Sampling times
Time lags
Correlation

Opportunities

Deep neural networks
Adaptive retraining
Qualitative trend analysis
Dynamic behaviour

Fault detection and diagnosis

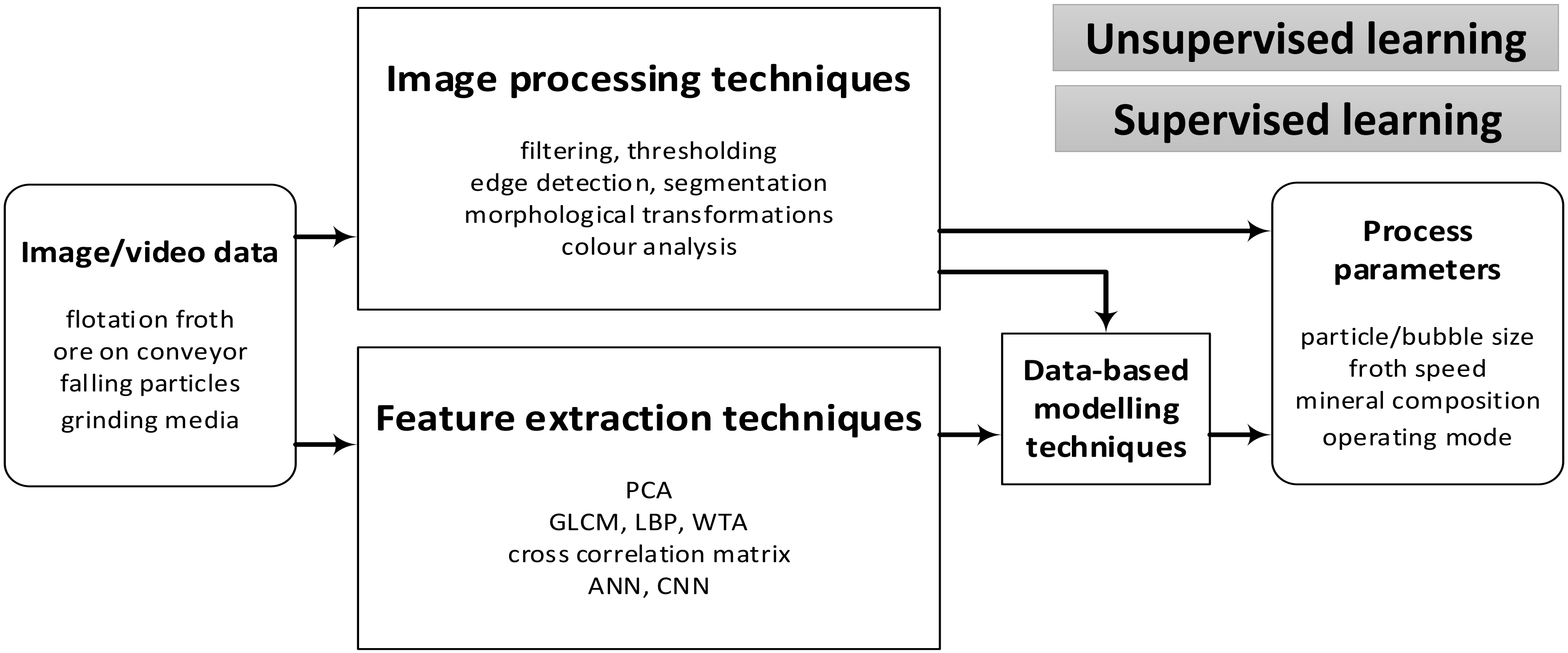


Trends
Industrial data (not implementation)
PCA and modifications

Challenges
Data scarcity
Benefit assessment
Implementation

Opportunities
Root cause analysis
Diverse data
Prognosis

Machine vision



Trends
Simple industrial implementation
relatively mature
Texture features

Challenges
Surface-only
Limited state information
Labelled images

Opportunities
Crowd-sourced labelling
Deep nets
Diverse data

Golden rules

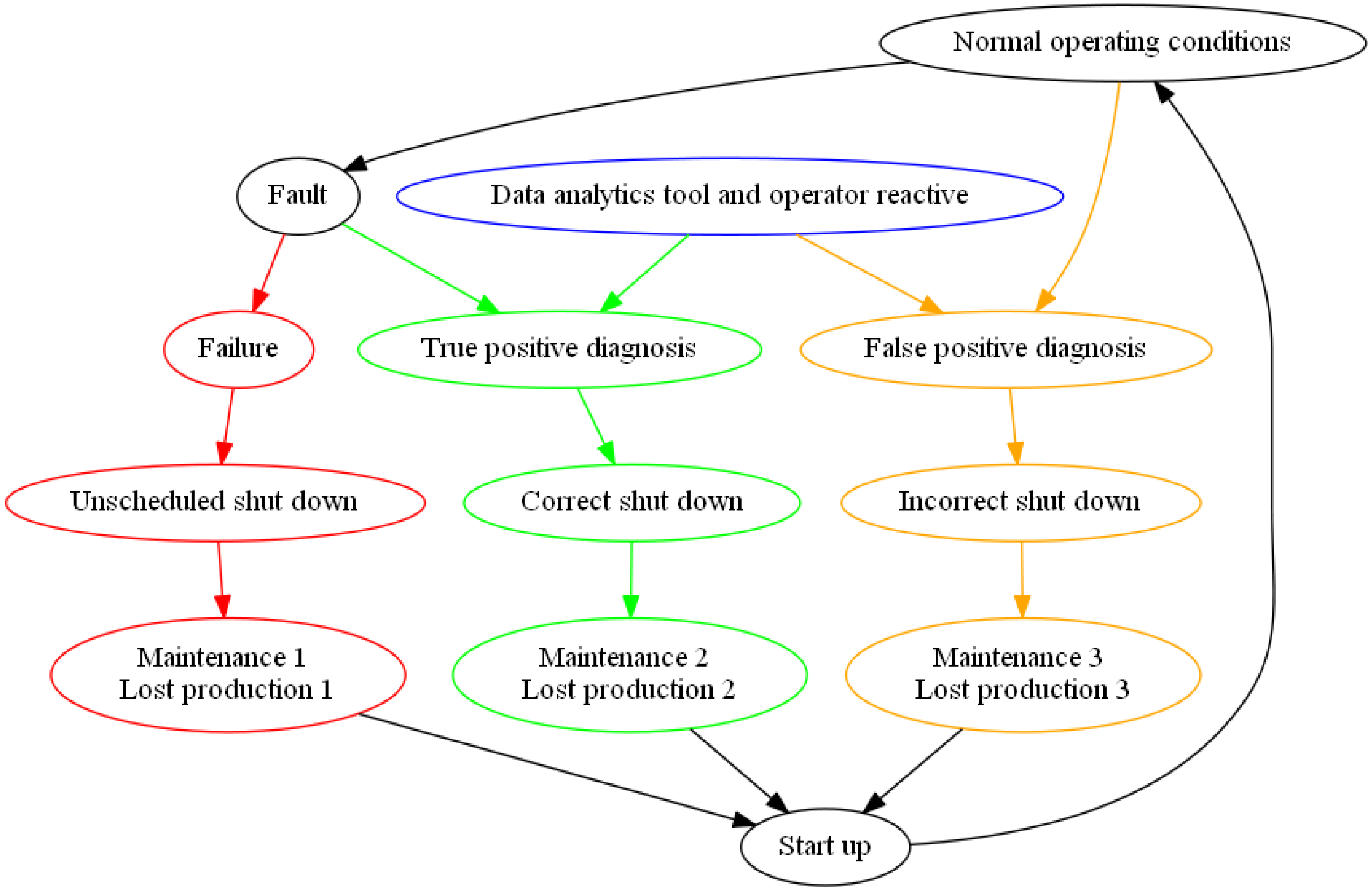
- **Hyperparameter sensitivity and guidelines**
  - Show sensitivity to hyperparameter selection
  - Guidelines relating hyperparameters to industrial context

- **Data diversity and explicit model validity**
  - Training data should include entire expectation of process data variation
  - Model predictions should include metric to indicate level of certainty / extrapolation

- **Comparison to simple and/or fundamental models**
  - Numerical motivation should be given for complex models
    - Compare to simpler techniques
  - Incorporate fundamental knowledge

Future directions

- **Build the business case**
  - Data-based modelling / machine vision: Similar to economic motivation for control
  - Fault detection and diagnosis: More complicated



Future directions

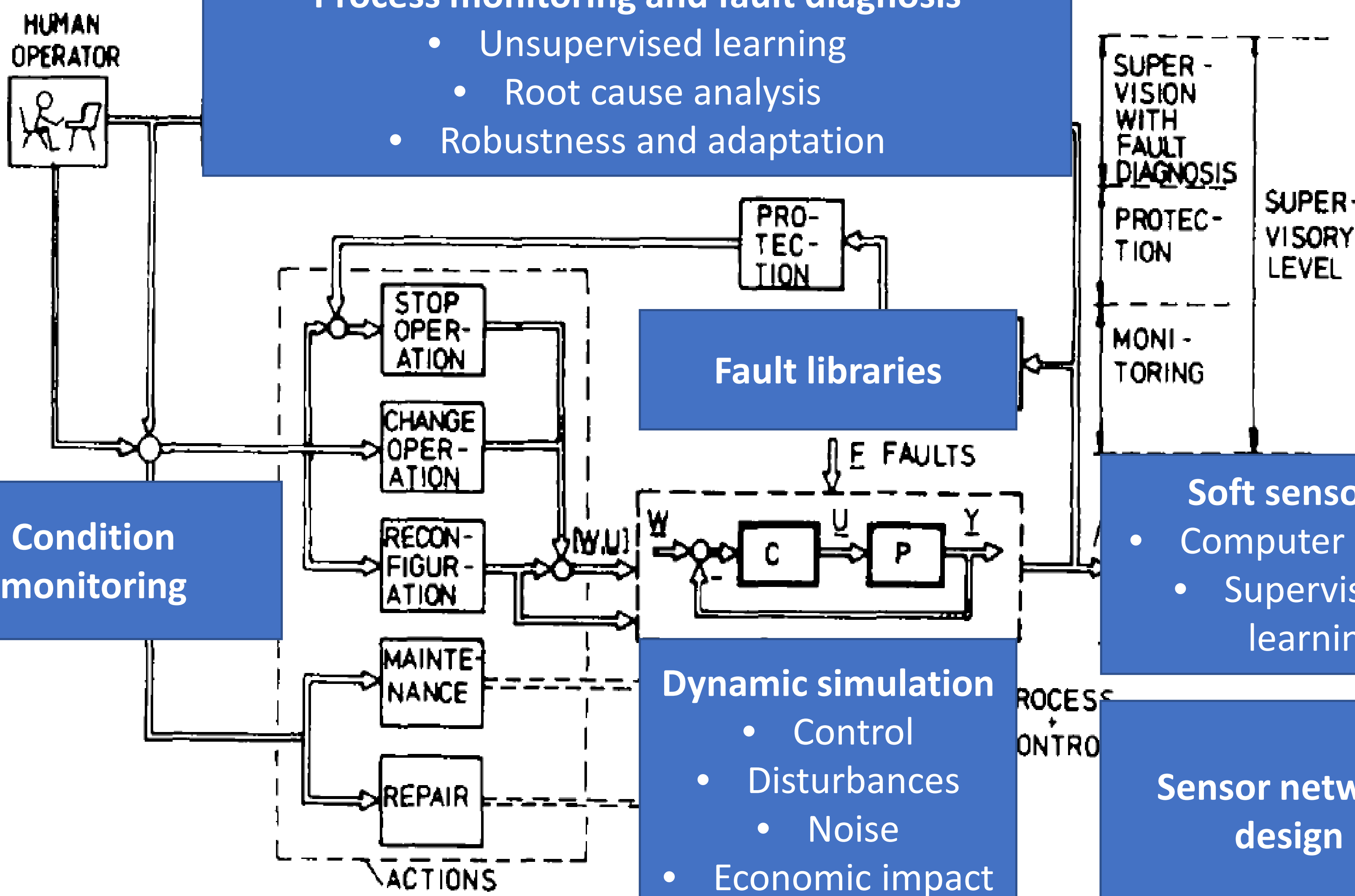
- **De-risk the method**
  - Thorough robustness analysis
  - Availability of benchmark <u>industrial</u> datasets
    - "UCI ML repository" archive.ics.uci.edu/ml for mineral processing
    - Control loop data repository: sacac.org.za/Resources
  - Availability of benchmark <u>simulation</u> datasets
    - "Tennessee Eastman process" for mineral processing
    - Simulation repository: github.com/ProcessMonitoringStellenboschUniversity

Future directions

- **Train the humans**
  - Engineers of today and tomorrow need to be data science literate
  - Not necessary to be an expert in machine learning
    - Basic understanding of goals and types
    - Ability to communicate requirements for new solutions
    - Ability to critically assess the results (check golden rules)
  - At undergraduate and professional levels
  - Challenge: Lack of domain-specific resources (e.g. examples, textbooks)
    - Good place to start: www.statlearning.com

Domain knowledge + Machine learning =
Better solutions

Machine Learning at Process Engineering



Process monitoring and fault diagnosis

- Unsupervised learning
- Root cause analysis
- Robustness and adaptation

Fault libraries

Condition monitoring

Soft sensors

- Computer vision
- Supervised learning

Dynamic simulation

- Control
- Disturbances
- Noise
- Economic impact

Sensor network design

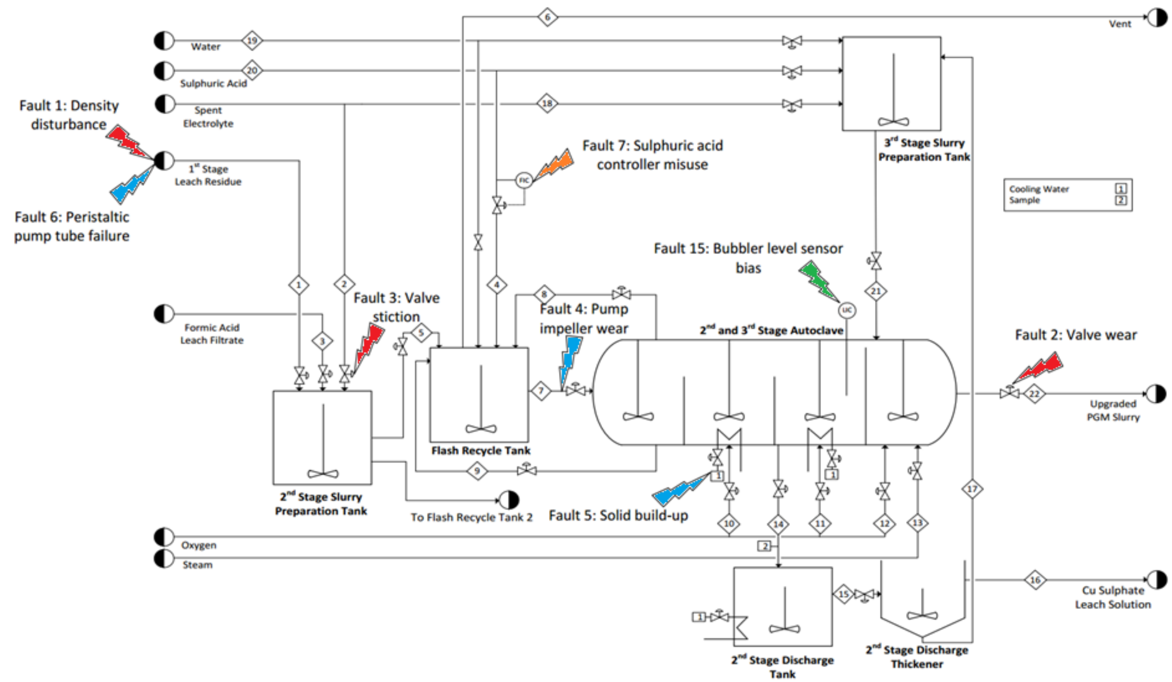
Dynamic simulation and fault libraries

Dynamic simulation

- Falling film evaporator
- Base metal refinery
- Grinding circuit
- Pulp digester

Fault libraries

- Base metal refinery
- Grinding circuit



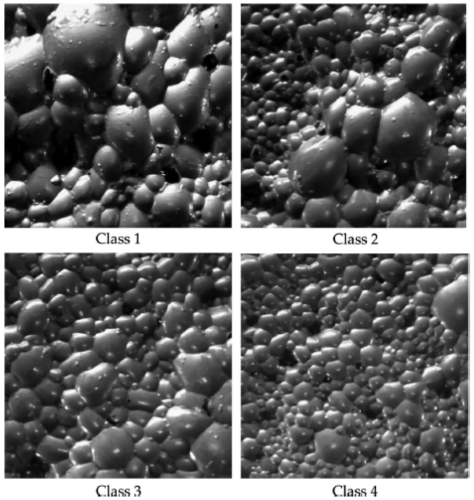
Sensors

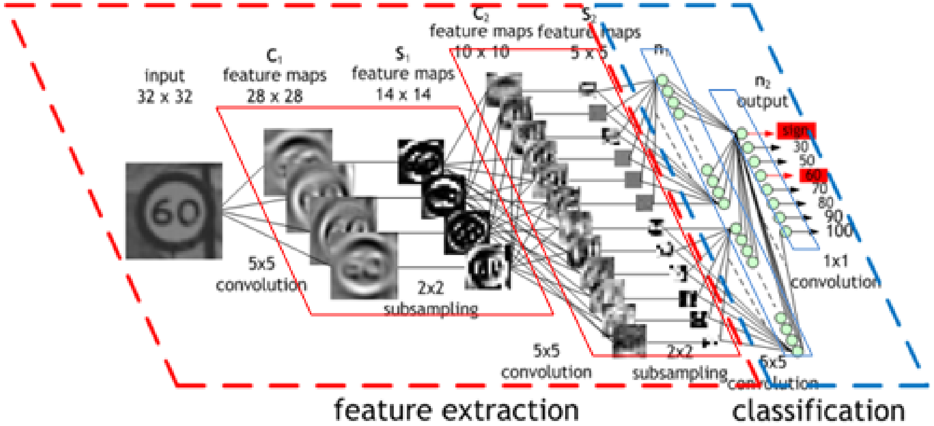
Sensor network design

- Spiral concentrator plant

Soft sensors

- Computer vision – Flotation
- Computer vision – Ore/pellet size
- Computer vision – Spiral slurries

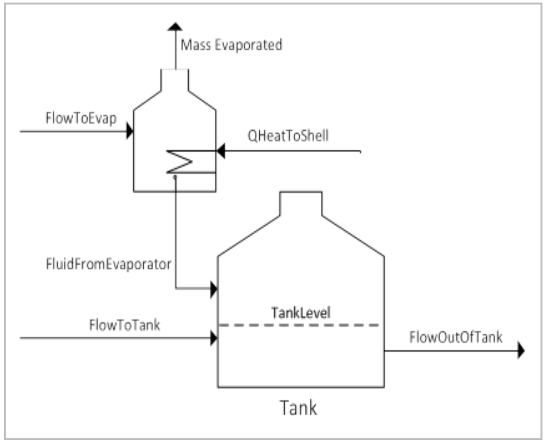


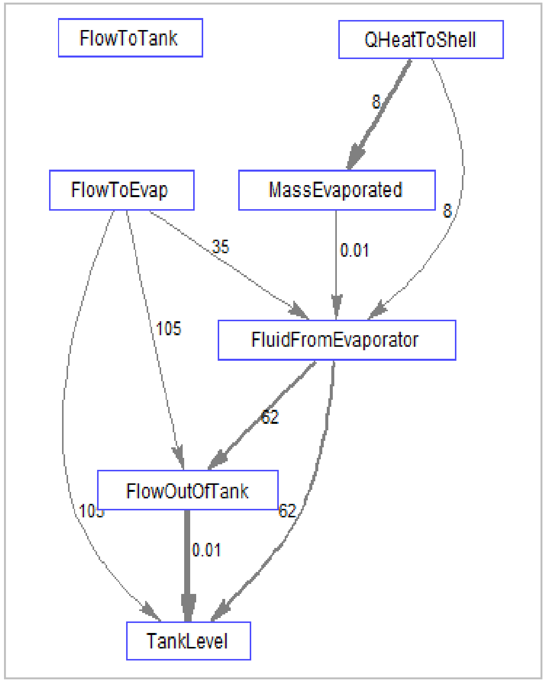


Fault detection and diagnosis

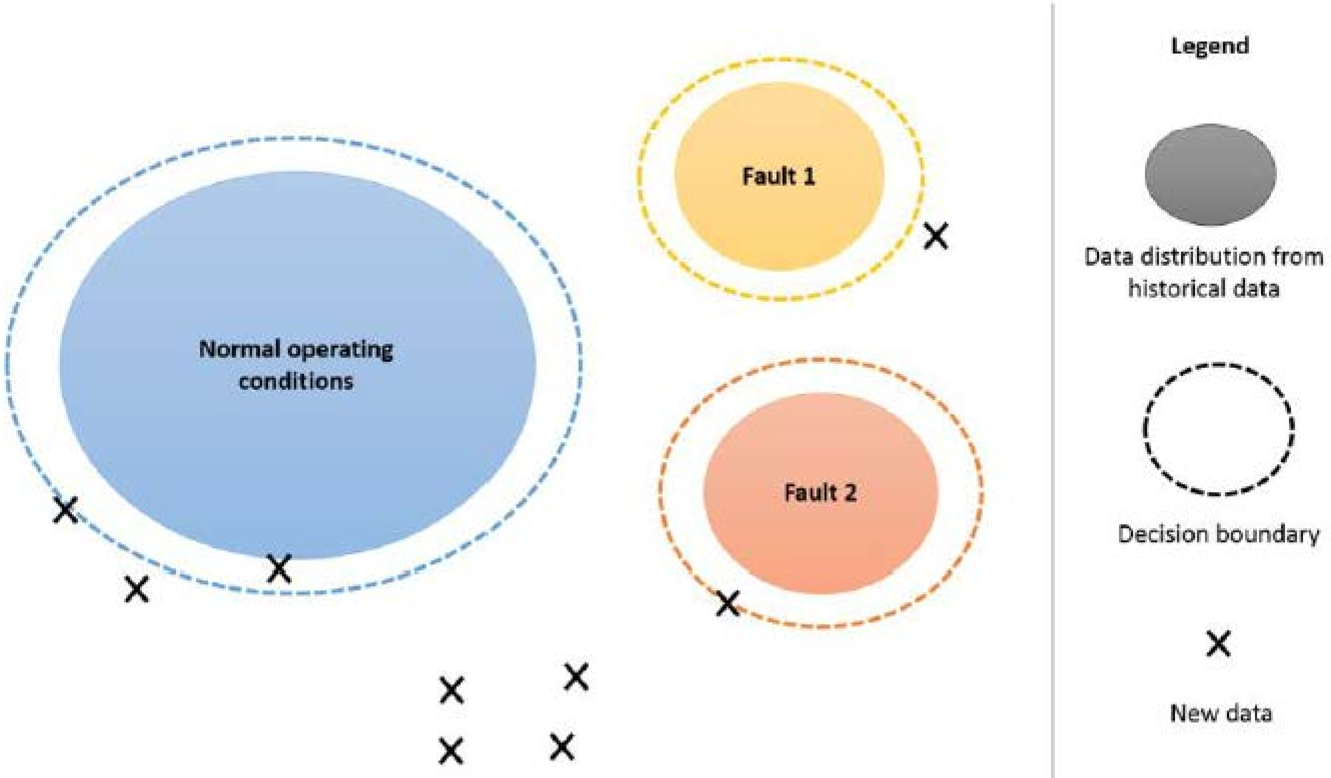
Process monitoring and fault diagnosis

- Data reconciliation and gross error detection
- Root cause analysis with causality maps
- Batch process monitoring (PCA and PLS)
- Nonlinear unsupervised learning (ANN, KPCA, SVM, etc.)
- Economic performance functions
- Dynamic Bayesian networks
- Gaussian mixture models

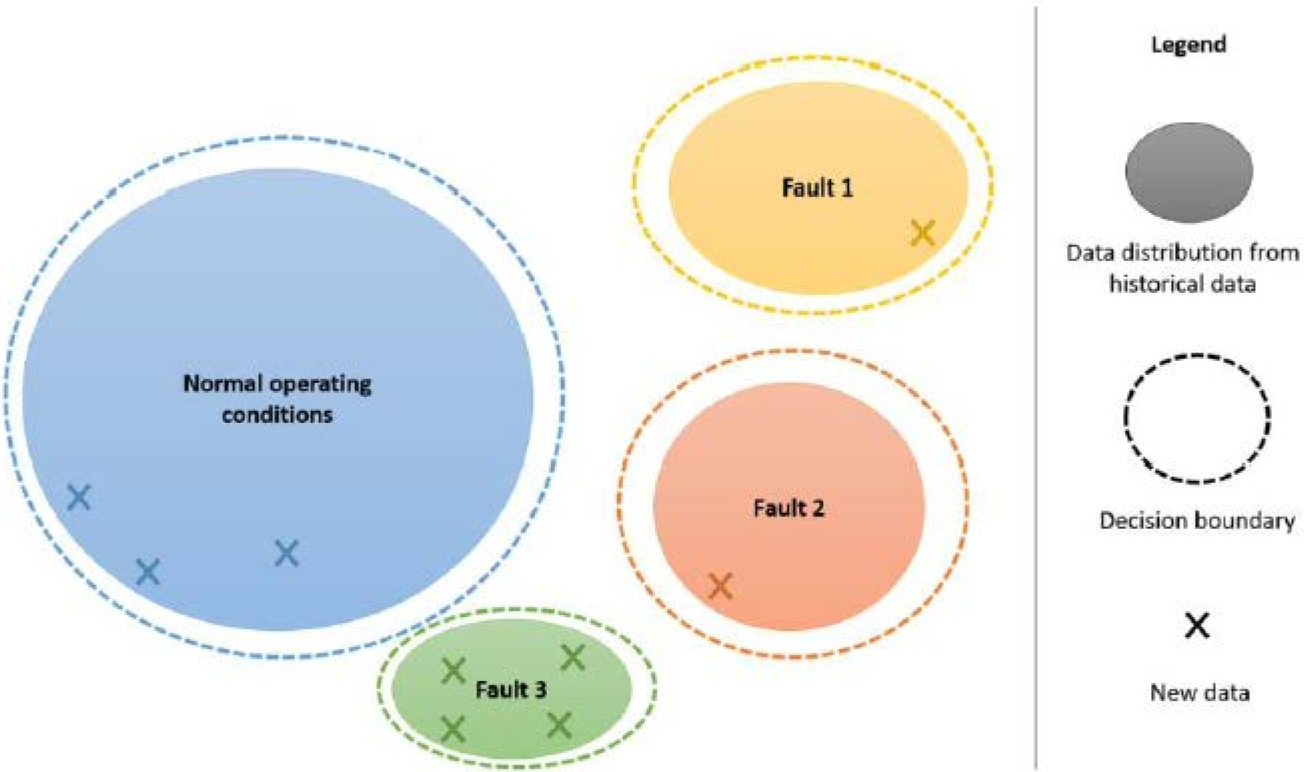




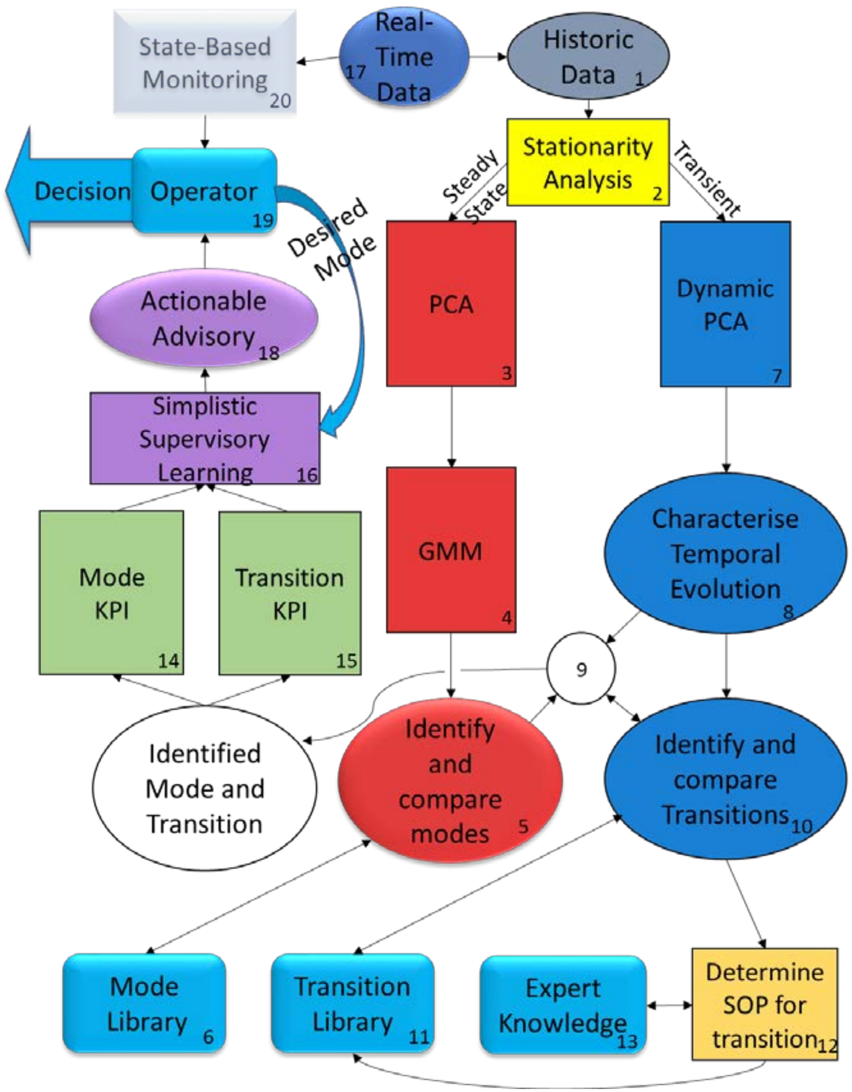
Adaptive process monitoring



Adaptive process monitoring



Condition monitoring



Urban Mines: Recycling valuable metals from e-waste

1. Sustainability and recycling of batteries
2. Rare earth elements
3. Waste printed circuit boards

Sustainability

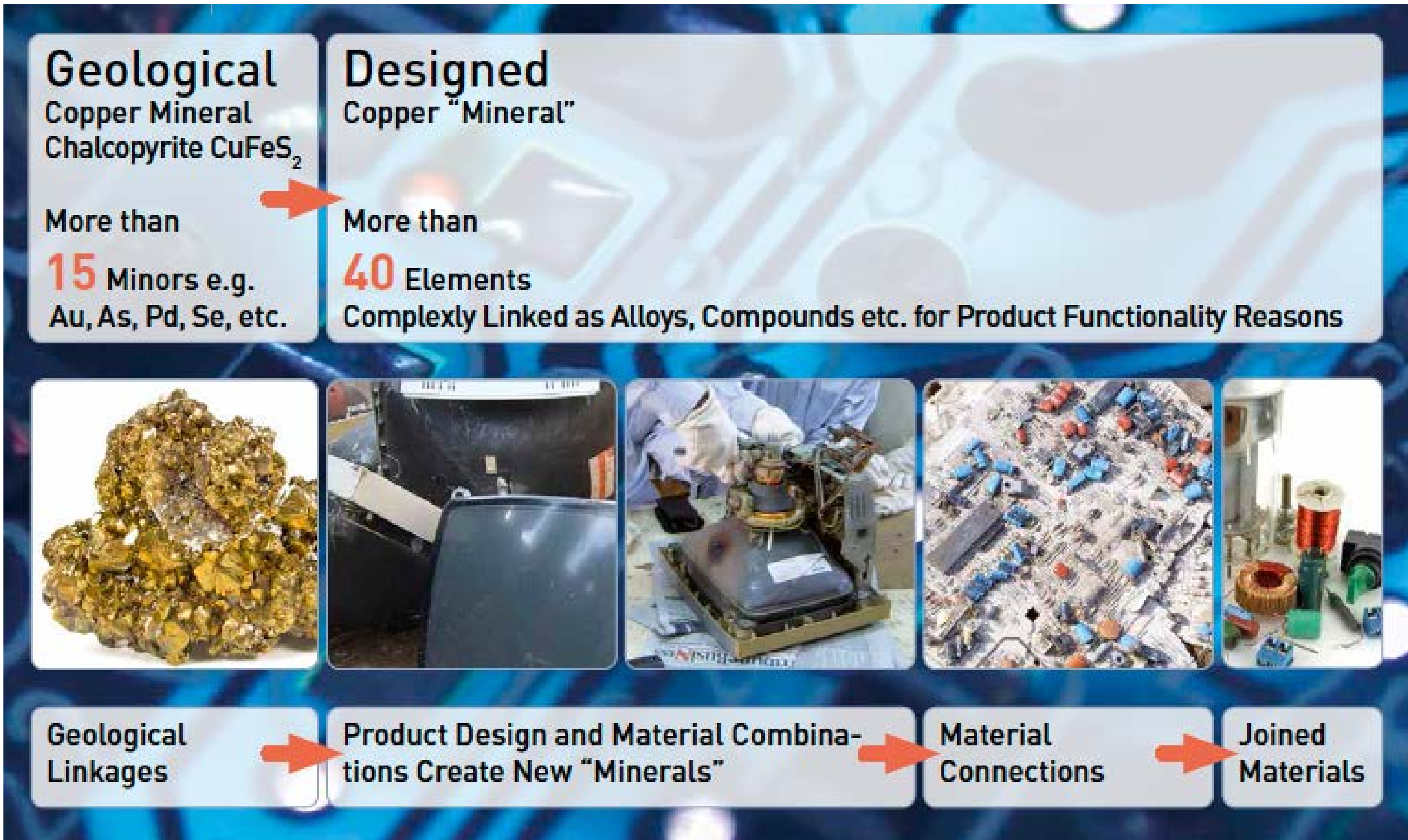
"Humanity has the ability to make development sustainable to ensure that it meets the needs of the present without compromising the ability of future generations to meet their own needs."

Brundtland, G.H., Report of the World Commission on Environment and Development: Our Common Future, 1987

Recycling

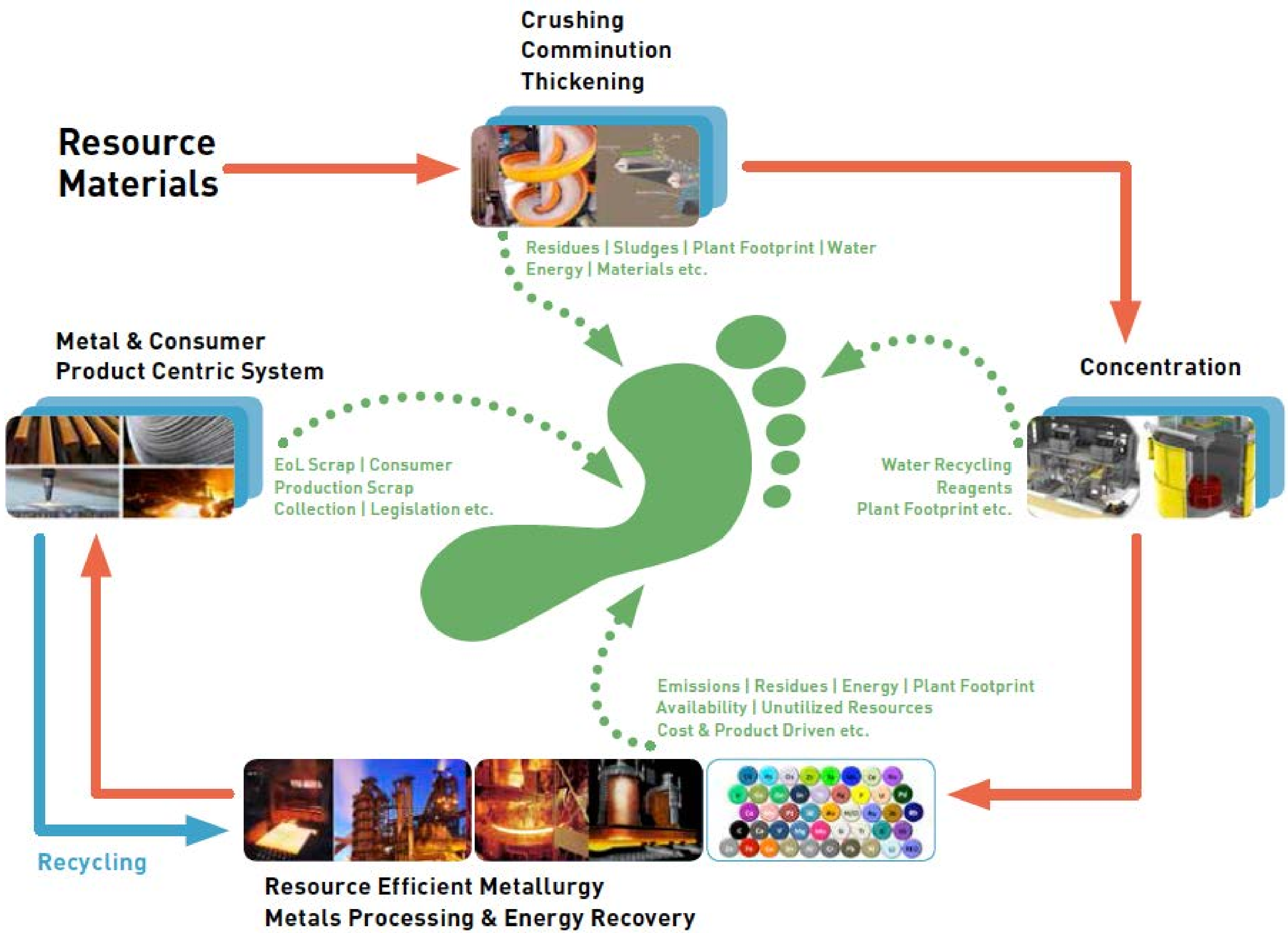
- Reduces future scarcity of high demand elements
- Creates economic value
- Reduces greenhouse gas emissions and limits other environmental harm
- Aids the transition to a green economy
- Provides a source of metals for sustainability-enhancing technology

Designed materials make recycling hard



UNEP (2013) Metal Recycling: Opportunities, Limits, Infrastructure, A Report of the Working Group on the Global Metal Flows to the Inter- national Resource Panel. Reuter, M. A.; Hudson, C.; van Schaik, A.; Heiskanen, K.; Meskers, C.; Hagelüken, C.

Recycling: there are limits



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South African context

- SA landfills ~ 90% of waste
- DEA – National Norms and Standards (landfill)
- DST RDI Waste Roadmap – 2022 Scenario reduce industrial waste by 20% from 2011 baseline
- 11% of WEEE recycled (2011 baseline)
- Value of WEEE waste (collector → recycler) R/t 1000
- 2022 scenario – recycle 50% of WEEE (32 023 t/y)
- Lithium ion battery consumption ~ 10 000 t/y 2020 (2750 t/y $LiCoO_2$)
- Preliminary economic study shows that a 2.5% levy on purchase cost results in capital payback time of 5 years

Source: DST A National Waste Innovation Programme for South Africa: Phase 2 Waste RDI Roadmap

SU context – research into the urban mine

SU metals recycling projects

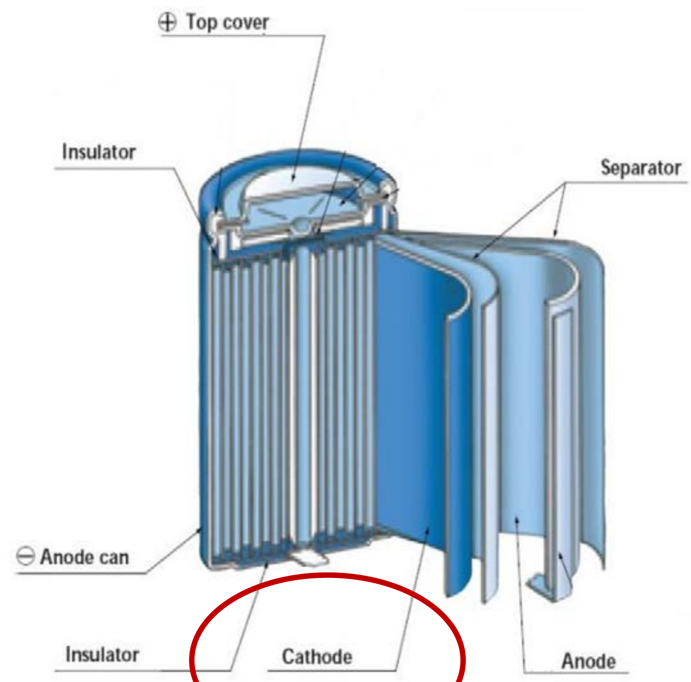
- Effect of mechanical pre-treatment on leaching of base metals from printed circuit board waste
- Gold leaching from printed circuit board waste using ammonium thiosulphate
- Evaluating the applicability of the GlyLeach process for metal leaching from printed circuit board waste
- Base and precious metal recovery from glycine leach solutions using solvent extraction / ion exchange / carbon adsorption
- Investigating options for thermal treatment of PCB waste and its effect on downstream metal recovery processes
- Investigating the use of PCB leach residue as reductant in pyrometallurgical operations
- Evaluating the efficiency of metal recycling processes by means of life cycle assessment and exergy analyses
- Evaluating economics of metal recycling from PCB waste in a South African context
- Recycling rare earth elements from fluorescent lamps
- Development of an environmentally friendly lithium ion battery recycling process

Sustainability and recycling of batteries

- Batteries convert chemical to electrical energy
- Global battery market ~ $65 billion (70% rechargeable)
- Expected to grow to $100 billion by 2025 (WEF Global Battery Alliance)
- Lithium ion battery market grew by 15% (CAGR) between 2005 and 2015
- Significant use of "critical metals" in rechargeable batteries means recycling is of great importance - Co is an example
- Recycling of rechargeable batteries still in its infancy
    - 6.7% collection rate of rechargeables in EU (2008)
    - Growth of HEV market and EU directives on recycling require urgent development of recycling technologies

Batteries

	Primary	Secondary						
	Zinc/Alkaline	Ni/Cd	Ni/MH Button	Ni/MH Cylindrical	Ni/MH Prismatic	Ni/MH Toyota Prius II	Li-ion	Li-polymer
Fe	5–30%	40–45%	31–47%	22–25%	6–9%	36%	24.5%	1%
Ni		18–22%	29–39%	36–42%	38–40%	23%		2%
Zn	15–30%							
Mn	10–25%							
Cd		16–18%						
Co			2–3%	3–4%	2–3%	4%	27.5% [$LiCoO_2$]	35% [$LiCoO_2$]
Li								
REE			6–8%	8–10%	7–8%	7%		
Cu							14.5%	16%
Al								15%
K			1–2%	1–2%	3–4%			
Metals, unspecified						2%		
Graphite/Carbon			2–3%	<1%	<1%		16%	15%
Plastics/Polymer			1–2%	3–4%	16–19%	18%	14%	3%
H_2O			8–10%	15–17%	16–18%			



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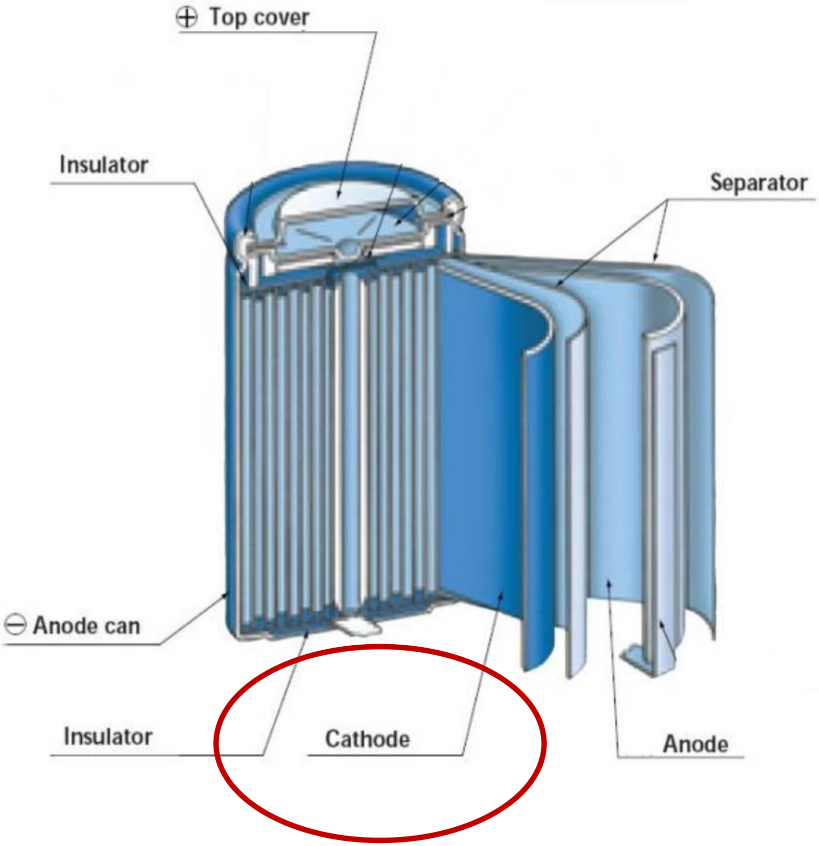
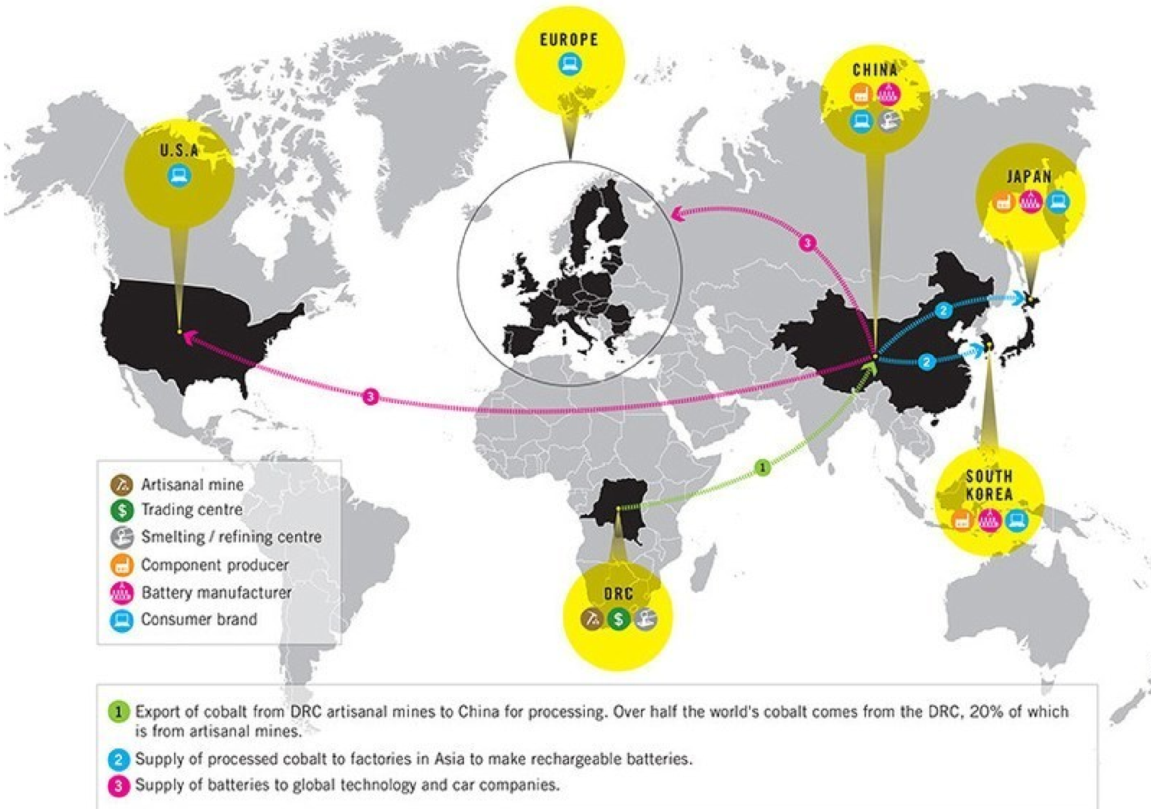
Lithium ion batteries

- Lithium ion batteries widely used in EEE devices e.g. cell-phones, laptops, HEVs



Global context

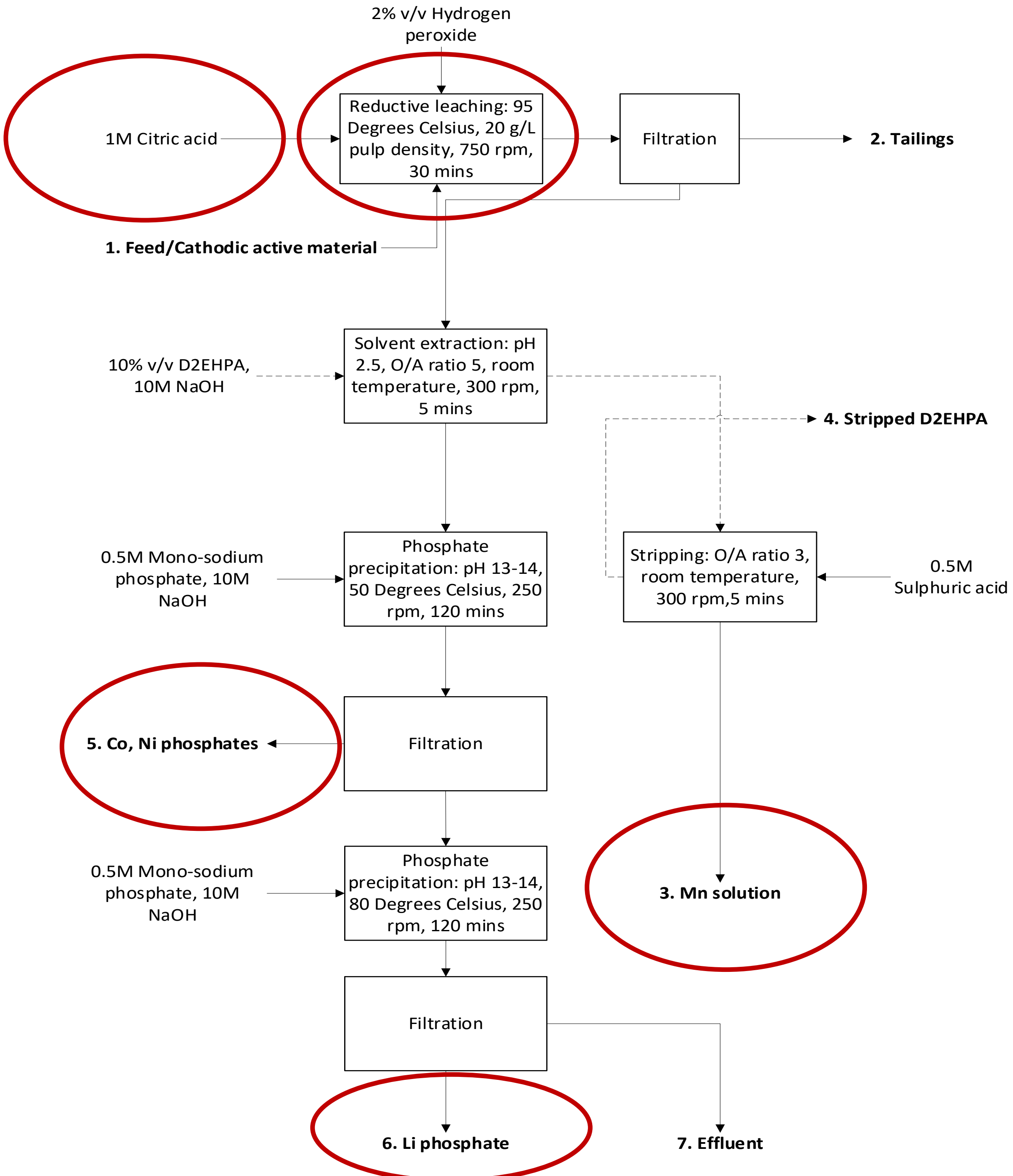
- Drivers for recycling
  - Metal values
  - Scarcity and geopolitical concerns – Co (DRC) , Li (Argentina, Bolivia, Chile)
  - Lower resource use than for primary sources
  - European Battery Directive – 45% collection rate by 2016



Source https://www.weforum.org/agenda/2017/09/global-battery-alliance-child-labour-congo

Environmentally-benign hydrometallurgical flowsheets to recover value metals separately

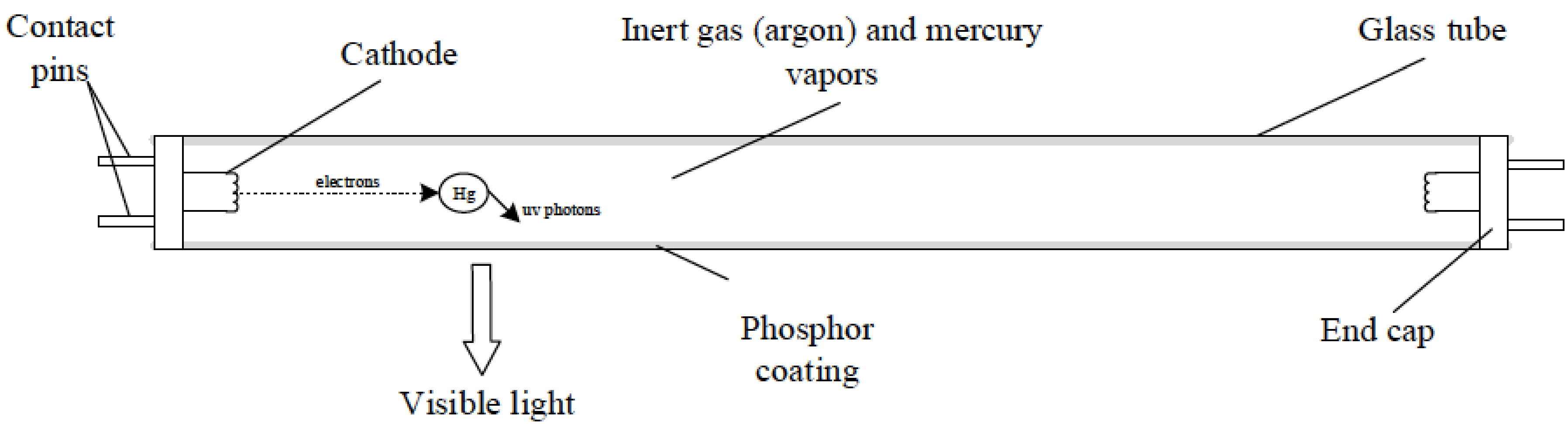
- Organic acids are effective leaching reagents for metal recovery from LIB cathodic material yielding over 95% metal recoveries
- 95% Co, 96% Li and 99% Ni
- Metals recovery from LIB citrate leach solutions is possible through solvent extraction
    - Our current area of research


2% v/v Hydrogen peroxide
1M Citric acid
Reductive leaching: 95 Degrees Celsius, 20 g/L pulp density, 750 rpm, 30 mins
Filtration
2. Tailings
1. Feed/Cathodic active material
10% v/v D2EHPA, 10M NaOH
Solvent extraction: pH 2.5, O/A ratio 5, room temperature, 300 rpm, 5 mins
4. Stripped D2EHPA
0.5M Mono-sodium phosphate, 10M NaOH
Phosphate precipitation: pH 13-14, 50 Degrees Celsius, 250 rpm, 120 mins
Stripping: O/A ratio 3, room temperature, 300 rpm,5 mins
0.5M Sulphuric acid
5. Co, Ni phosphates
Filtration
3. Mn solution
0.5M Mono-sodium phosphate, 10M NaOH
Phosphate precipitation: pH 13-14, 80 Degrees Celsius, 250 rpm, 120 mins
Filtration
6. Li phosphate
7. Effluent

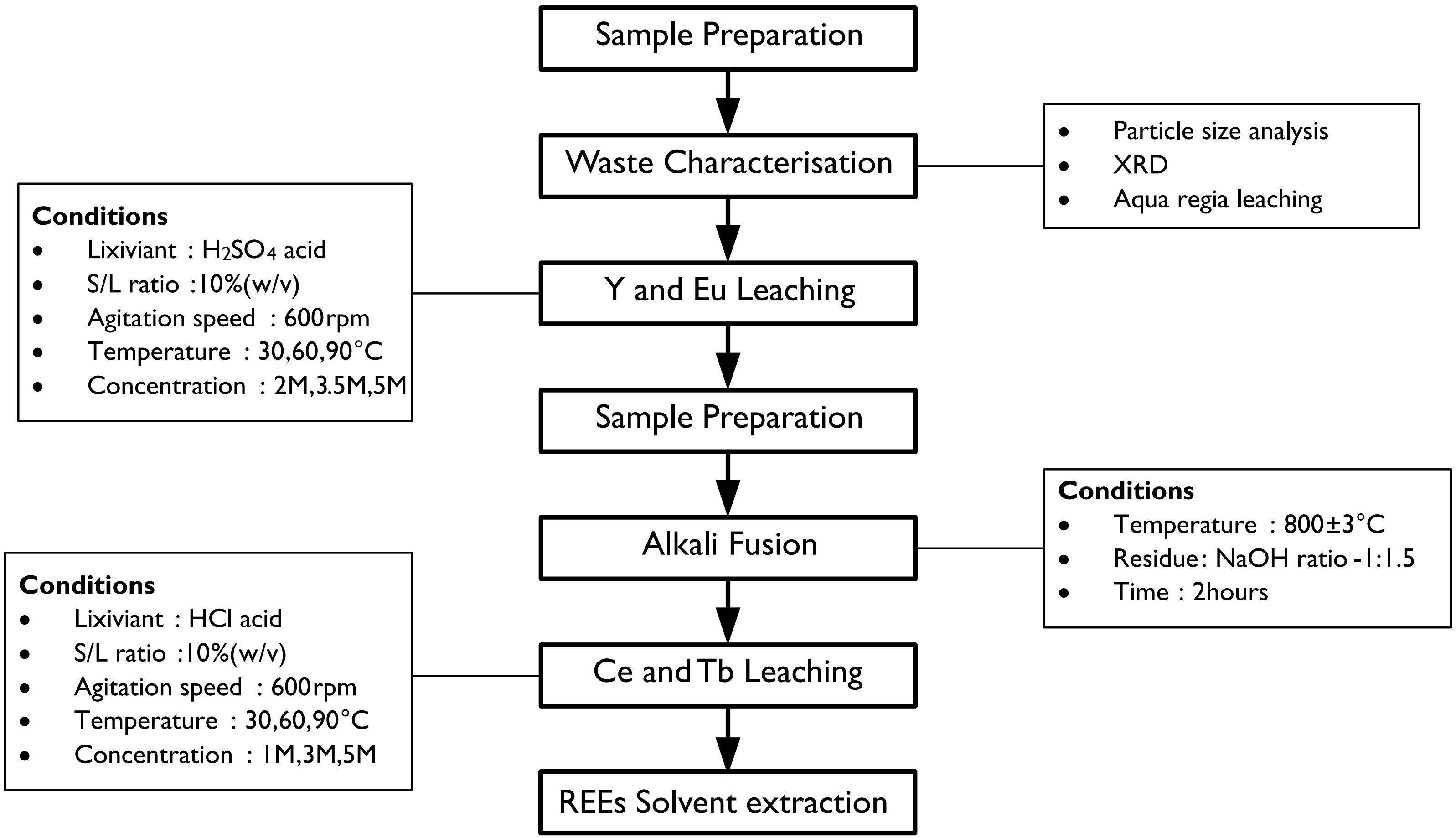
Recycling rare earth elements from fluorescent lamps

- Production and usage of fluorescent lamps rapidly increased over the past decades
- 4,800,000 lamps were scrapped in 2011 (Zhang, 2012)
- Fluorescent lighting relies mainly on six REEs: Y, La, Eu, Ce, Tb and Gd
  - 0.2-2.3 g/lamp
  - ±7,650,000 kg REO applied in fluorescent powders annually
  - Rare earth elements (REEs) used in alloys, magnets, batteries, lasers, glasses…
    - Chinese production accounts for >85% of global REE market
    - China restricts supply through quotas, licences, taxes
- Less than 1% of REE recycled in 2011 (Binnemans and Jones, 2014)
- Most preferred method of recovering REEs from powders is hydrometallurgy

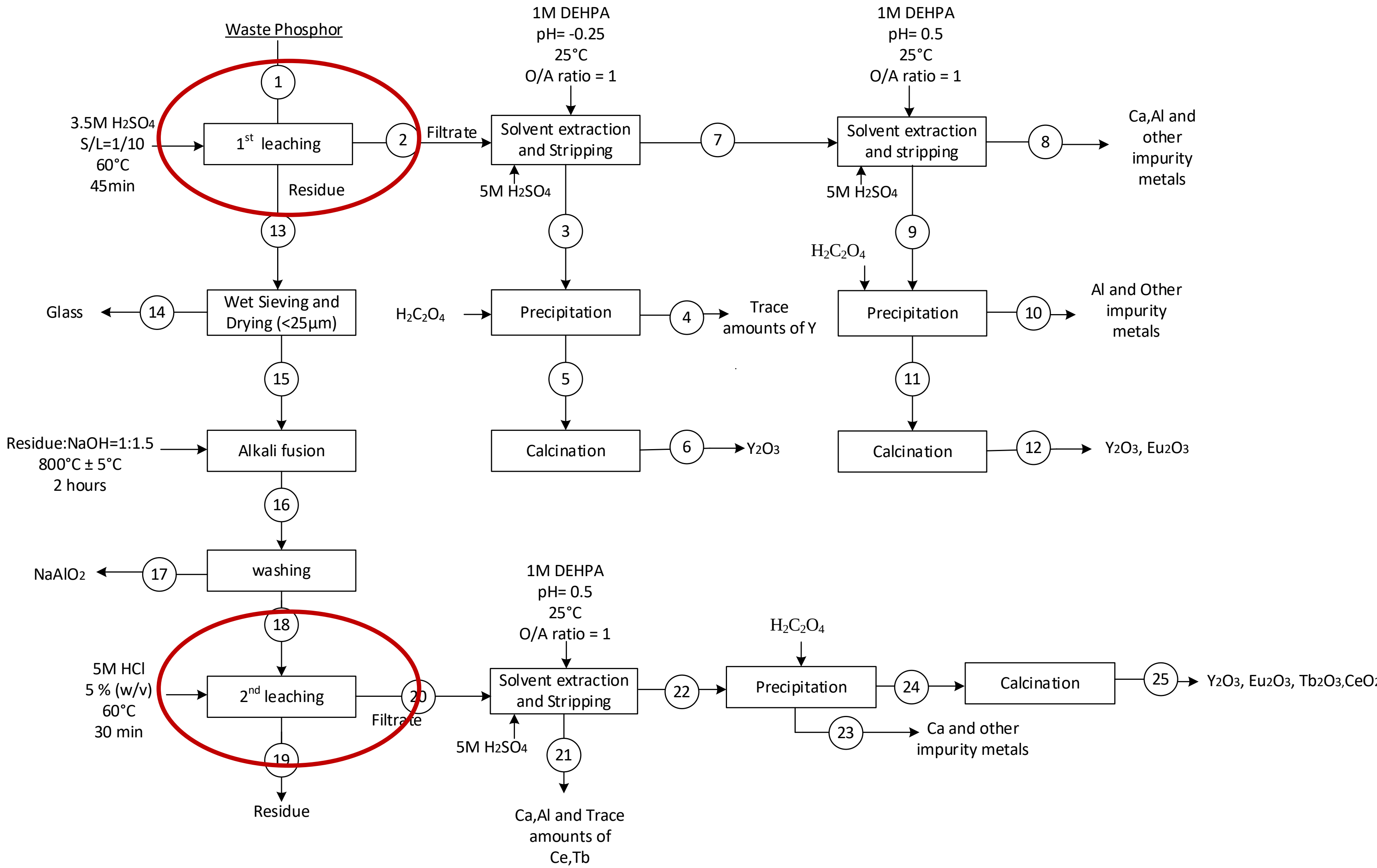
REEs in fluorescent lamps



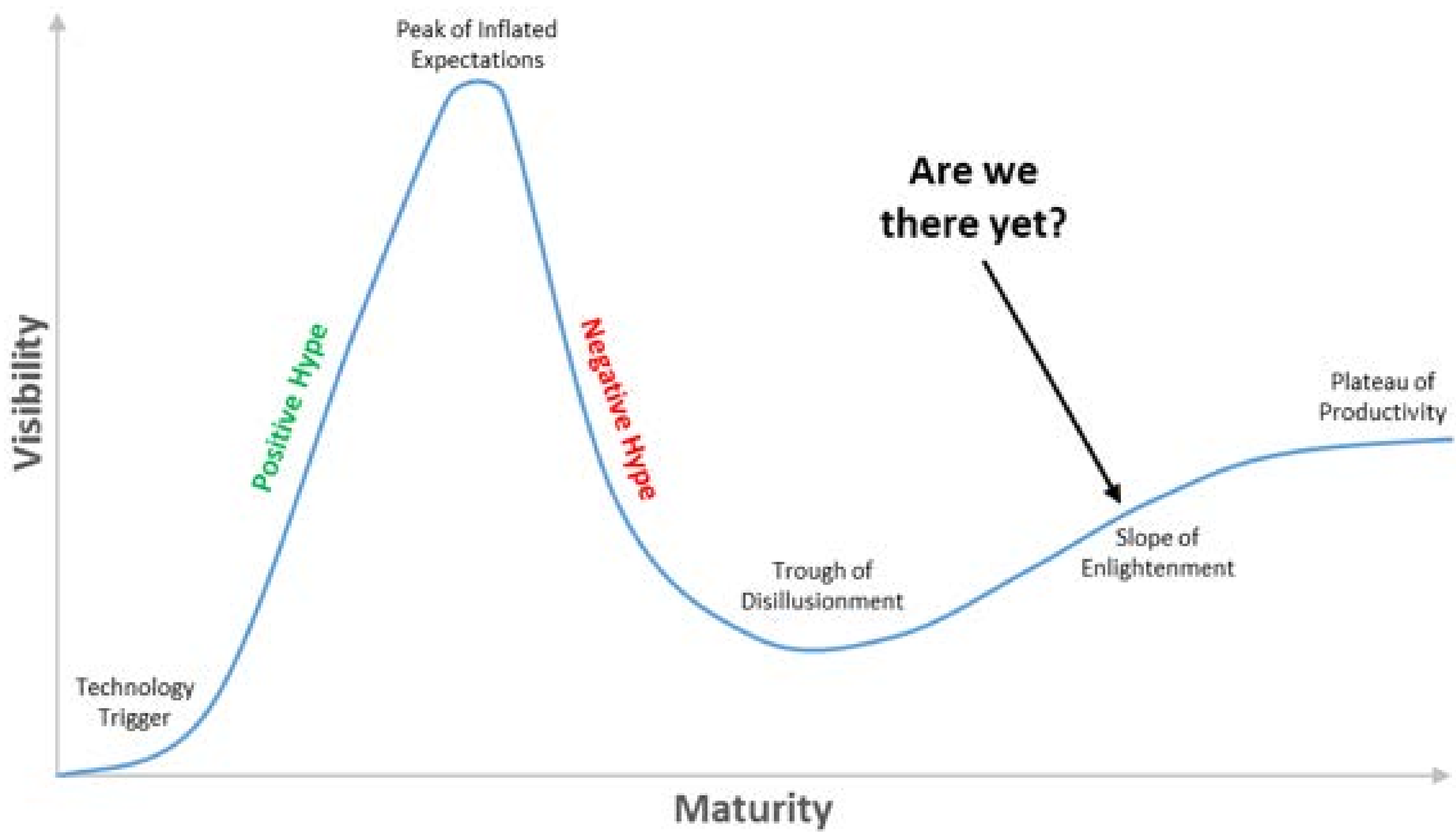
REE Extraction



Proposed flowsheet



Business models for gold recovery from WPCBs



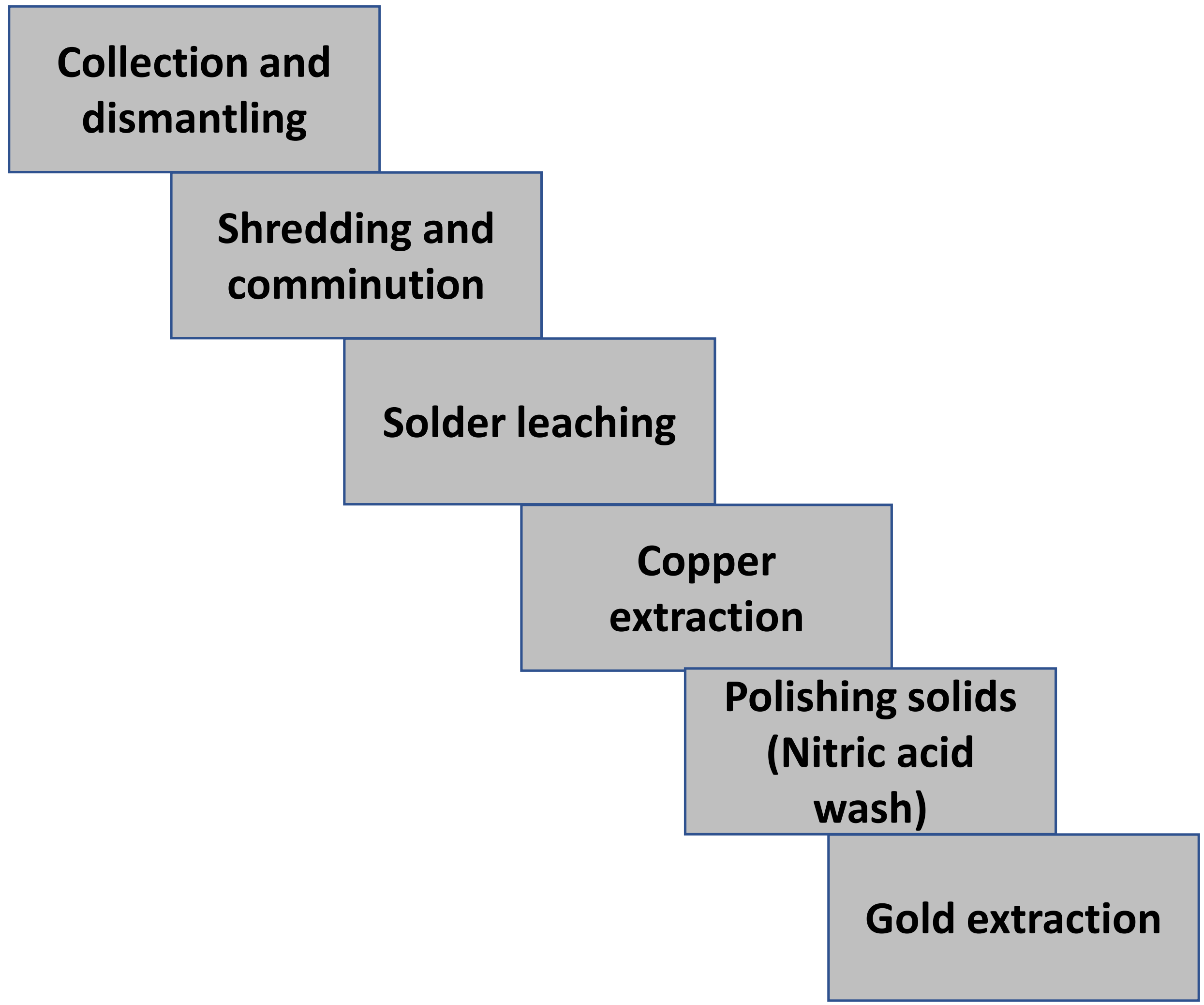
Product	Content of mother-board in product [%]	Metal concentration in PWB (g/t PWB)				Mass of equip-ment [kg]
		Ag	Au	Pd	Pt	
Computer key-board	2 – 2.1	700	70	30		
LCD monitor	4 – 7.8	1300	490	99		
Computer mouse	8 – 8.2	700	70	30		
DVD player	10 – 16.2	700	100	21		2.95 – 3.4
Hi-fi unit	8 – 10.6	674	31	10		4.15 – 5.05
Laptop	15 – 17.1	1000	250	110		
Speaker	2	674	31	10		
Mobile phone	22 – 22.1	3573 – 5540	368 – 980	285 – 287	7	
PC	8.9 – 13	600 – 1000	81 – 600	90 – 110	40	
Printer/fax	6.6 – 8	350	47	9		
Radio set	20 – 20.5	520	68	8		5.13 – 6.2
Telephone	21.9 – 22	2244	50	241		
Video recorder	10 – 14	674	31	10		4.0 – 6.4
Audi & video		674	31			

UNEP (2013) Metal Recycling: Opportunities, Limits, Infrastructure, A Report of the Working Group on the Global Metal Flows to the Inter- national Resource Panel. Reuter, M. A.; Hudson, C.; van Schaik, A.; Heiskanen, K.; Meskers, C.; Hagelüken, C.

Business scenarios

1918 · 2018

- 400 tonnes/yr recycling WPCBs
- Medium grade WPCBs (250 g/t Au)
- Tax 28%
- WACC 12.6% (South African Reserve Bank statistics, 2018)
- Project life 20 years
- 312 days/annum



Business scenarios

Operations based

1- All operations done in-house

2- Only size reduction is outsourced

3-Only collection and dismantling is outsourced

4-Collection & dismantling and size reduction outsourced

Product based

a-Copper cathode & Gold sludge

b-Copper liquor & Gold liquor

c- Copper liquor & Gold sludge

d-Copper cathode & Gold liqour

CRITERIA	Product based classification	a	b	c	d
Operations based classification	Matrix				
1		1a	1b	1c	1d
2		2a	2b	2c	2d
3		3a	3b	3c	4c
4		4a	4b	4d	4d

Key findings

- All business models displayed great sensitivity to :
    - Gold content in WPCBs
    - Operating costs
    - Gold revenues and recoveries
    - Operating below name plate capacity
- At 250 g/t under conditions studied all models remained unviable
    - Additional metals recovery unviable
- Secure a reliable source of high grade WPCBs for this process
- Prioritise collection of e-waste
- Consider having a central distribution system
- Homogenise pricing and classification in the country

Mineral processing done better?

- Yes
  - Better data, better experts, better methods, better performance
  - New recycling technologies, recyclable products, smaller footprint, enhanced sustainability

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