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PrOMMiS: Applying Novel Modeling Methods to Accelerate CMM RD³

Thomas J. Tarka, P.E. *CMM R&D Lead METALLIC Director PrOMMiS Technical Director*

September 18th, 2024

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What is PrOMMiS?

Short Answer: Application of the IDAES Integrated Platform to CMM

Platform to Enable Innovation, Inform DOE Research, & Accelerate Deployment

- Process Modeling Software
	- Process performance modeling
	- Perform TEA and enable LCA
- Optimization Package
	- Process Optimization
	- Multi-criteria Optimization
- Support Commercialization

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PrOMMiS: Process Optimization & Modeling for Minerals Sustainability

Process Optimization and Modeling for Minerals Sustainability

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Objective: Accelerate scale-up and **deployment** of innovative CM & REE processes and establish the toolkit to compress future RD3 timelines by **leveraging IDAES**, **CCSI** and a **decade** of **DOE CM & REE investment**.

Presentation Outline

Process Optimization and for Minerals Sustainability

- The Challenge & Context
- PrOMMiS Capabilities & Project Status
- Framework Development
	- Unit and Property Model Libraries
	- Costing Model Libraries
- Case Study: University of Kentucky Coal Waste Pilot Process
- Case Study: Li/Co Recycling Membrane System
	- Nanofiltration / Diafiltration Membrane Cascade Systems
	- Conceptual Design: Flowsheet Screening with Superstructures
	- Technical Risk Reduction: Robust Optimization
	- Technical Risk Reduction: Model-based Design of Experiments

SHORT TERM 2020-2025

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Process Optimization and Modeling for Minerals Sustainability

Materials have high risk for supply disruption and serve an essential function in one or more energy technologies

MEDIUM TERM 2025-2035

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Challenge: Clean Energy Technologies Drive Demand Growth

Mineral demand for clean energy technologies by scenario

Process Optimization and Modeling for Minerals Sustainability

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Notes: Mt = million tonnes. Includes all minerals in the scope of this report, but does not include steel and aluminium. See Annex for a full list of minerals.

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Source:<https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions/executive-summary>

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Challenge: Large Gaps in Domestic Supply Chain - REE

- Up- and Mid-Stream capabilities **are geographically concentrated** in 1-3 countries
- **Lack of midstream capabilities are a gap** that limits
- growth of upstream supply & downstream manufacturing

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Challenge: Supply Chain Vulnerability – Li-ion Batteries

- Up- and Mid-Stream capabilities **are geographically concentrated** in 1-3 countries
- **Lack of midstream capabilities are a gap** that limits
- growth of upstream supply & downstream manufacturing

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DOE CMM Vision & Strategy

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Vision:

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- **Build** reliable, resilient, affordable, diverse, sustainable, and secure **domestic critical mineral and materials supply chains**.
- Promote safe, sustainable, economic, and environmentally just solutions to meet current and future needs.
- Support the clean energy transition and decarbonization of the energy, manufacturing, and transportation economies.

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- Case Study: End of Life Product Recycling
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PrOMMIS: Process Optimization & Modeling for Minerals Sustainability

Process Optimization and Modeling for Minerals Sustainability

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Guiding Principles & Approach

- **Urgency: Rapidly Establish Capability to Get Early Wins**
	- Learn by Doing Apply to Existing Projects (recently completed or underway)
	- Don't Reinvent the Wheel Leverage Existing Models & Partnerships
	- **Partner with Active Developers**

• **Create A Long-Term Capability!**

- Critical Materials will change over time
- Flexible, Foundational Platform
- Early Stakeholder Involvement and Well-Regarded Leadership Board

• **Maximize Support & Integration with CM and other DOE R&D Portfolios**

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• CM Related: CMC, CMI, BIL Activities, FECM Awarded Projects

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• Adjacent: Water-related (NAWI, PARETO)

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• Inter-Agency: DoD Projects, USGS

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Guiding Principles & Approach

The End Goal is…

Guiding Principles & Approach

The End Goal is…

- **Compress Developmental Timeframes**
- **Innovation Ecosystem**
- **Support DOE Investments & Initiatives**
	- Technology Maturation
	- Unlocking Different Feedstocks
	- Waste Minimization

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PrOMMiS High-level Execution & Capabilities

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Year 1:

- Build capabilities for design, optimization, and scale-up specific to CM & REE processes, enabling technical risk reduction
- \checkmark Evaluate landscape of emerging CM & REE production pathways & solicit input on critical industry needs/gaps
- \checkmark Leverage existing multiscale modeling and optimization capabilities from CCSI & IDAES
- \checkmark Ensure applicability to a range of feedstocks (e.g., mining, waste streams, and recycling end-of-life-products)

Year 2:

- Expand unit model and costing libraries to include other established technologies to use in different case studies
- PrOMMiS will deploy computational capabilities for advanced process design, scale-up, and analysis of the CMM & REE process: Techno-economic analysis, optimization, control, uncertainty quantification, and technical risk reduction through robust optimization approaches.
- PrOMMiS will work directly with initial technology partners to collaboratively support scale-up and integration of novel technologies.

Major Accomplishments

Process Optimization and Modeling for Minerals Sustainability

Created Unit Operation & Property Model library (v1.0) which includes cost data. Successfully developed process flowsheet model for a University of Kentucky REE recovery pilot plant.

Demonstrate effective optimization of candidate flowsheet configurations (conceptual design superstructure) for the selected CM & REE case studies.

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End-of-life magnet recycling model capable of selecting the optimal recovery pathway and most cost-effective technology for different feedstocks.

Established collaborations with key partners.

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Critical Materials Innovation Hub

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Project Overview - Collaborations

The team has established close **collaborations** with several universities:

Framework Development

- What is it?
	- Libraries of models for common unit operations.
	- Includes thermodynamic properties, unit operations and cost estimation.
	- Different levels of rigor to support analyses from conceptual design through to high-fidelity simulations.
- Why do we care?
	- Facilitates rapid assemble of process models from modular components.
	- Will support full optimal design workflow from process synthesis to process control.

A New Domain

- Need new library of models for minerals processing
	- Need both current and future technologies
- Reviewed literature for REE recovery processes
	- Focus on unconventional resources
		- •Coal Waste Products
		- •Acid Mine Drainage
		- •Brines and Produced Water
- •Phosphates and Gypsum
- •End-of-Life Recycling
	- •Batteries
	- •Magnets

- Learning by Doing
	- DOE wants immediate results

Unit and Property Model Libraries

• Goal: Develop a comprehensive library of models for CM & REE processing operations.

• First Year:

- Identify key unit operations and properties from candidate case studies.
- Focus on unconventional feedstocks:
	- Coal ash and waste
		- **Brines**
		- Acid mine drainage
		- Phosphates & gypsum • Battery recycling
			- End-of-life magnets

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Core Model Development

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- Models (contributed to GitHub)
	- Roaster (calcination)
	- Leaching
	- Solvent extraction
	- Solid liquid separation
	- Precipitation
	- Thickener
	- Crushing and Grinding
	- Evaporation
- Property Packages:

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- Case specific properties
- Integration of PhreeqC / Mintec

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- WaterTAP Models
	- RO

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- Ion exchange
- Nanofiltration
- Electrodialysis
- Membrane Distillation

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Core Model Development

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- Case Study Driven
	- External Stakeholders
		- TBD
	- Internal (NETL) Stakeholders
		- Dry Fork Fly Ash (Powder River basin, WY) REEs from coal byproducts
			- Similar to University of Kentucky process
			- Complex leaching process, but lots of data
		- ABLE Lab lithium from produced waters
			- Lab scale testing apparatus
			- Includes RO, NF and IX technologies
			- External stakeholders to bring Direct Lithium Extraction technologies for testing
		- Carbon products
			- Complex process involving both pyro- and hydro-metallurgy
			- Stakeholder concerned about releasing outside NETL

REE Costing Framework **[https://github.com/prommis/prommis/](https://github.com/prommis/prommis/tree/main/src/prommis/uky/costing)**

[tree/main/src/prommis/uky/costing](https://github.com/prommis/prommis/tree/main/src/prommis/uky/costing)

Current Framework Capabilities

- Capital & Operating Costs
- Annualized Costs & Revenue
- Membrane Capital & Operating Costs via WaterTAP
- Custom Costing Models
- Objectives for TEA Net Present Value and Cost of Recovery

Ongoing PrOMMiS Integration

- Bottom-Up Costing for Hydrogen Decrepitation (WVU)
- Economy of Numbers (WVU)
- Costing for Li/Co diafiltration (ND)
- Superstructure UI integration (LBNL)
- Tutorial development (NETL)

Planned Capabilities

- For March 2025:
	- Operation Labor Estimation
	- Tax & Environmental **Incentives**
	- Byproduct Recovery Value
- For EY25:
	- TEA of at least two processes
	- Cost & Price UQ to supplement task 2.4 tools

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PrOMMiS Costing Library

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Case Study: University of Kentucky Coal Waste Pilot Process

UKy Coal Waste Pilot Process

• What is it?

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- Integrated flowsheet for extraction and separation of REEs from West Kentucky No. 13 coal waste.
- Integrates unit and costing models into single model of leaching and separation train.
- Why do we care?

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- Proof-of-concept example of integrating model libraries to simulate real world process.
- FECM funded project with easily available data.

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• Capable of optimizing process for cost and/or chemical consumption.

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Superstructure Optimization for Conceptual Design

Option I Option II Option I Option II Option III Option IV Option I Option II Option III **+ Unit Operation 1 Unit Operation 2 Unit Operation 3 Optimal Design and Configuration Rapid screening 9 disjunctions 18 binary variables 315 choices**

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Superstructure Optimization for Conceptual Design

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Superstructure Optimization for Conceptual Design Process Optimization and for Minerals Sustainabilit

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IDAES Conceptual Design Framework

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PrOMMiS Modeling Framework **Pyomo.GDP Disjunctive Modeling Framework** General GDP Solution Approaches

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• Models built using IDAES framework and process model library

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- High-level representation of superstructure with disjunctions
- Automatic conversion to MINLP with Pyomo.GDP

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Gives access to rigorous, competitive MINLP solvers

Case Study: End of Life Product Recycling

Case Study – End of Life Product Recycling

- Data: Literature, Oak Ridge National Labs, Critical Minerals Innovation Hub
- Example for HDDs:

Iowa U: Patent US 10,648,063 B2 Dissolution and separation of rare earth metals

Process Optimization and Modeling

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2. Literature search: Processing Pathways

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- Most (experimental) efforts focus on advancing part of the REE processing
- How to combine efforts from different groups to find the best processing pathway?

=> Screening via superstructure

optimization for conceptual

Option I **p**otion II Option I Option II Option III Option I Option I Option II Option III **Technology Choice 1 Technology Choice 2 Technology Choice 3** Technologies being developed by different research groups **Processing** sequence

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(Figure: courtesy Prof. Laird)

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3. EoL Superstructure

- Organize existing data in processing stages, identify competitive technology options at each stage
- Identify new connections

3. EoL Superstructure Modeling

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- Superstructures are modeled as networks Technology options \rightarrow nodes \rightarrow binary
	- variable *y =1* if in optimal pathway
	- Arcs: flows of each species
	- Inlet/ Outlet flows \rightarrow MB from simulations

- Allowed connections: logical constraints
- Objective function: NPV

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- CAPEX/OPEX: TEA in the literature or own: APEA, Bhattacharya's group
- Framework: Seider et al.
- Currently updating withTask 2.2 developments

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24. Lyman, J.W., Palmer, G.R.: Recycling of Rare Earths and Iron from NdFeB Magnet Scrap. High Temperature Materials and Processes. 11, 175–188 (1993). https://doi.org/10.1515/HTMP.1993.11.1-4.175

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5. Case Study: Recovery REO from HDDs

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(C. Laliwala, AI Torres, proceedings FOCAPD 2024)

• Optimal pathway

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- Base case: plant recycles 60 % of all available EOL HDDs in the U.S. each year.
- Optimal pathway:
	- Shredding
	- Acid Free dissolution
- NPV negative

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5. Case Study: Recovery REO from HDDs

(C. Laliwala, AI Torres, proceedings FOCAPD 2024)

- Process Optimization and Modeling for Minerals Sustainability
- Optimal solution for different collection rates (from future and past wastes) and REO prices;

Figure 6: NPV for a varying collection rate. The base case is a collection rate of 60% and no recycling of EOL HDDs generated prior to plant production. The NPV break-even point was found to occur at ~360%. Numerical values are not reported to preserve confidentiality.

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Figure 7: NPV for a varying initial collection rate. The base case has a collection rate of 60% and an initial collection rate of 25%. The NPV break-even point was found to occur at ~148%. Numerical values are not reported to preserve confidentiality.

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Figure 8: NPV for varying percentages of the initial REO price projection estimate. The NPV break-even point was found to occur at ~168%. Numerical values are not reported to preserve confidentiality.

• ONL Shredding + CMI acid-free dissolution always optimal pathway

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5. Case Study: Recovery REO from EV/HEV

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(C. Laliwala, AI Torres, proceedings ESCAPE/PSE 2024)

• Slightly different superstructure;

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- Process Optimization and Modeling for Minerals Sustainability igan upun mahali uliu wake dha coovi for Minerals Sustainability
- Base case: plant recycles 10 % of all EOL EVs and HEVs in the U.S. each year.
- Optimal pathway:
	- Automatic disassembly
	- Hydrogen decrepitation
	- Acid Free dissolution
- NPV positive

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5. Case Study: Recovery REO from EV/HEV

(C. Laliwala, AI Torres, proceedings ESCAPE/PSE 2024)

Sensitivity Analysis

• Automatic disassembly, hydrogen decrepitation, acid-free dissolution were always selected as optimal

Figure 3. Sensitivity analysis for the product projected prices, and amount of EOL vehicles available for recycling. Values are reported normalized to the base case optimal solution to preserve confidentiality.

Advanced Optimization Capabilities

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How to systematically explore CM process intensification with membranes?

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interactions

steric

hindrance

recognition

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Infrastructure Optimization

Process Optimization

feed

manufacture

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product

Case Study: Li/Co Membrane System

What is it? Optimization membrane separation cascade to fractionate for Minergls Sustainability Li and Co ions (e.g., battery recycling) as an alternative to extraction cascades

- Reduce the use of environmentally challenging solvents
- More flexible and efficient separations

Why do we care? Highlights benefits of optimization

- Identifies new designs and design rules
- Accelerates process scale-up
- Quantifying separation trade-offs, informs materials and device targets

Motivation: Lithium/Cobalt Fractionation

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Wamble, Eugene, Phillip, Dowling (2022), *ACS Sustainable Chemistry & Engineering*

Case Study: Li/Co Membrane System

Prior work:

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- Demonstrates how optimization identifies new designs, informs material targets
- Bespoke and one-off implementation, 2+ years of student effort

Optimization-based flowsheet screening with superstructures:

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- Automated mixed integer flowsheeting screening, demonstrated on Li/Co example
- [Ongoing] U. Kentucky flowsheet extraction with multiple products and sequencing

Technical risk reduction:

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- Designed processes that are robust to uncertainty (e.g., membrane performance, feed variability)
- [Ongoing] Extend to U. Ky. components, improve design realism, incorporate detailed costing
- [Ongoing] Integrate uncertainty quantification and DoE with robust optimization

Example: Membrane Separation of Li-Co

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- Given known (maybe uncertain) feed characteristics and desired product specifications
- Superstructure formulation to rapidly determine the optimal configuration (# of stages, feed, diafiltrate, reflux connectivity)
- **Co Product Stream** Feed **Diafiltrate Reflux** Retentate ÷ $\ddot{\mathbf{v}}$ ÷ ÷ ÷ ÷ ÷ Permeate $\mathbf{1}$ $\overline{2}$ $N-1$ N Stage 1 Stage K **Li Product Stream**

• Advantage of framework

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- Intuitive to modeler
- Avoid zero-flow issue
- Solution with existing framework

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Figure 2: Superstructure of a generalized membrane cascade

Source: Ovalle D, Tran N, Laird CD, Grossman IE. Optimal Membrane Cascade Design for Critical Mineral Recovery Through Logic-based Superstructure Optimization. FOCAPD (2023)

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Technical Risk Reduction

Chrysanthos Gounaris, Alex Dowling, Anca Ostace

FWP subtask 2.4

Multi-Stage Diafiltration Model

(Based on original model from [1])

Model extensions:

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- **Adjustable number of membrane stages and tube elements** using IDAES unit models
- **Added precipitator units** to isolate Co/Li products and recycle diafiltrate streams
- **Multi-period** model to handle varying process conditions over time
- **Alternative superstructures for mixing of flows** before each stage versus before each tube

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[1] Wamble, NP, Eugene, EA, Phillip, WA, Dowling, AW. Optimal Diafiltration Membrane Cascades Enable Green Recycling of Spent Lithium-Ion Batteries. *ACS Sustainable Chemistry & Engineering*, 10(37):12207–12225, 2022. [2] Ultrafiltration Membrane Skids. Complete Filtration Resources. https://www.gotocompletefiltration.com/wastewater-treatment/ultrafiltration-membrane-skids-2/

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Process Optimization and Modeling for Minerals Sustainability

Robust Optimization

Industrial processes must be able to perform satisfactorily in light of uncertainties .

Potential Sources of Uncertainty

- Location and rate of **membrane fouling**
- **Feedstock** flow rate and solute concentrations
- Membrane **manufacturing variation**
	- Seek to ensure optimal performance for up to *N* membrane tubes underperforming

Two types of DoF in robust process design :

- **Design DoF** (set during construction):
	- Membrane stage length

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- Control DoF (adjustable during operation):
	- Flows (feed, diafiltrate, recycle, products)

Pyomo Robust Optimization Solver (**PyROS**) can obtain robust optimal solutions that are feasible for all realizations of uncertainty $[3,4]$

[3] Isenberg, NM, Akula, P, Eslick, JC, Bhattacharyya, D, Miller, DC, Gounaris, CE. A generalized cutting -set approach for nonlinear robust optimization in process systems engineering. *AIChE Journal,* 67(5):e17175. 2021.

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[4] Isenberg, NM, Sherman, JA, Siirola, JD, & Gounaris, CE. PyROS: The Pyomo Robust Optimization Solver. *Forthcoming*. 2024.

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Pareto Front Comparisons of Robust Feasible **Designs** (3 Stages x 10 Tubes/Stage)

> Deterministic Model Flowsheet (Stage Length: 753m)

Robust Feasible for 50% Underperforming Tube Flowsheet (Stage Length: 785m)

Robust Optimization Across System Sizes

Increasing size of membrane cascades allows for more cobalt to be recovered

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Model Settings:

- Tube-mixing configuration
- \cdot \geq 60% lithium recovery requirement

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• 50% flux decrease in underperforming tubes

Increasing number of underperforming tubes for robust feasible designs comes with a cost of reduced cobalt recovery

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Operational Flexibility Over Multiple Periods

Operational flexibility to achieve requirements under **changing operating conditions**.

Case Study: Upstream plans to increase feed flow rate by 50%. Can we cope with it?

Base case design does not possess sufficient operational DoF to adjust product/recycle flows and cannot maintain lithium recovery requirements

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• Stage-Level Mixing and Tube-Level Mixing configurations can adjust feed/product stream locations to adapt to change.

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Sequential Design of Experiments

Wang, J. & Dowling A. W. (2022). *AIChE Journal*

Open-Source Platform

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- Website:<https://idaes.org/research/application-areas/>
- GitHub repository:
	- <https://github.com/prommis/prommis>
- Documentation:

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- <https://prommis.readthedocs.io/en/latest/>
- Bi-Weekly Software Engineering teleconferences coordinating development
- Targeting quarterly internal/public releases
- IPMP in progress for fully open-source license

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• Overview video: coming soon!

Path 2: create GitHub repository and make idaes-pse and prommis a dependency

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Leverage NAWI/WaterTAP UI infrastructure

- Define key model inputs and outputs
- Distribute UI with PROMMIS flowsheets
- Parallel parameter sweeps (sensitivity analysis)

Gather requirements for UIs specific to WT

• E.g., conceptual design model configuration

Leverage IDAES core flowsheet visualization

- View flowsheet diagrams
- PROMMIS models <- new diagnostics capabilities

Assist team with Jupyter Notebooks and online documentation

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For questions and comments, please contact our Technical Director, Thomas Tarka [\(Thomas.Tarka@netl.doe.gov\)](mailto:Thomas.Tarka@netl.doe.gov).

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Process Optimization and Modelina for Minerals Sustainability

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Technical Risk Reduction

Chrysanthos Gounaris, Alex Dowling, Anca Ostace

Multi-Stage Diafiltration Model

(Based on original model from [1])

Model extensions:

- **Adjustable number of membrane stages and tube elements** using IDAES unit models
- **Added precipitator units** to isolate Co/Li products and recycle diafiltrate streams
- **Multi-period** model to handle varying process conditions over time
- **Alternative superstructures for mixing of flows** before each stage versus before each tube

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Problem Formulation **Stage Level:** max **Cobalt Recovery** \mathcal{R}^{rec}_{n+1} s.t. **Lithium Recovery ≥ Spec Permeate Mass Balances** Interchangeable objectives **Retentate Mass Balances** Tube Level: **Membrane Performance** R^{in} **Equations Stage Connectivity Balances Flow Rates ≥ 0**

Mixing before each stage Mixing before each tube

[1] Wamble, NP, Eugene, EA, Phillip, WA, Dowling, AW. Optimal Diafiltration Membrane Cascades Enable Green Recycling of Spent Lithium-Ion Batteries. *ACS Sustainable Chemistry & Engineering*, 10(37):12207–12225, 2022. [2] Ultrafiltration Membrane Skids. Complete Filtration Resources. https://www.gotocompletefiltration.com/wastewater-treatment/ultrafiltration-membrane-skids-2/

Robust Optimization

Industrial processes must be able to perform satisfactorily in light of uncertainties .

Potential Sources of Uncertainty

- Location and rate of **membrane fouling**
- **Feedstock** flow rate and solute concentrations
- Membrane **manufacturing variation**
	- Seek to ensure optimal performance for up to *N* membrane tubes underperforming

Two types of DoF in robust process design :

- **Design DoF** (set during construction):
	- Membrane stage length
- Control DoF (adjustable during operation):
	- Flows (feed, diafiltrate, recycle, products)

Pyomo Robust Optimization Solver (**PyROS**) can obtain robust optimal solutions that are feasible for all realizations of uncertainty $[3,4]$

[3] Isenberg, NM, Akula, P, Eslick, JC, Bhattacharyya, D, Miller, DC, Gounaris, CE. A generalized cutting -set approach for nonlinear robust optimization in process systems engineering. *AIChE Journal,* 67(5):e17175. 2021.

[4] Isenberg, NM, Sherman, JA, Siirola, JD, & Gounaris, CE. PyROS: The Pyomo Robust Optimization Solver. *Forthcoming*. 2024.

Robust Optimization Across System Sizes

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Increasing size of membrane cascades allows for more cobalt to be recovered

Model Settings:

- Tube-mixing configuration
- \cdot \geq 60% lithium recovery requirement
- 50% flux decrease in underperforming tubes

Increasing number of underperforming tubes for robust feasible designs comes with a cost of reduced cobalt recovery

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Operational Flexibility Over Multiple Periods

Operational flexibility to achieve requirements under **changing operating conditions**.

Case Study: Upstream plans to increase feed flow rate by 50%. Can we cope with it?

Base case design does not possess sufficient operational DoF to adjust product/recycle flows and cannot maintain lithium recovery requirements

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• Stage-Level Mixing and Tube-Level Mixing configurations can adjust feed/product stream locations to adapt to change.

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Sequential Design of Experiments*What is the* Process Optimization and Modeling *uncertainty in the* for Minerals Sustainability *fitted model Which model(s) are most* **PYOMO** *parameters? justified by the data?* **Prior Knowledge Sensitivity & Model(s) Parameter Uncertainty Estimation (Preliminary) Analysis Data** *What is the uncertainty in* **Model-Based** *model predictions?* **Design of** *What data are most* **Experiments PYOMO** *informative to reduce model uncertainty?* Wang, J. & Dowling A. W. (2022). *AIChE Journal* **Carnegie NATIONAL Sandia** UNIVERSITY OF NOTRE DAME **U.S. DEPARTMENT OF** \sim Georgia **Mellon** WestVirginiaUniversity **National** ECHNOLOGY Tech Laboratories **University BERKELEY LAB**

Open-Source Platform

- Website:<https://idaes.org/research/application-areas/>
- GitHub repository:
	- <https://github.com/prommis/prommis>
- Documentation:

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- <https://prommis.readthedocs.io/en/latest/>
- Bi-Weekly Software Engineering teleconferences coordinating development
- Targeting quarterly internal/public releases
- IPMP in progress for fully open-source license
- Overview video: coming soon!

Path 2: create GitHub repository and make idaes-pse and prommis a dependency

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Usability

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Leverage NAWI/WaterTAP UI infrastructure

- Define key model inputs and outputs
- Distribute UI with PROMMIS flowsheets
- Parallel parameter sweeps (sensitivity analysis)

Gather requirements for UIs specific to WT

• E.g., conceptual design model configuration

Leverage IDAES core flowsheet visualization

- View flowsheet diagrams
- PROMMIS models <- new diagnostics capabilities

Assist team with Jupyter Notebooks and online documentation

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Leaching Summary

Feed Composition Data Used

• Coal Composition: UKy Final Report Appendix E, Tables 2 & 6

Model Equations and Data for Unit Process

- Shrinking Core kinetic model
- Operating Conditions: UKy Final Report Tables 3.7.1 & 3.7.2
- Elemental Recovery: UKy Final Report Figures 3.7.4, 3.7.5, & 3.7.6a

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Validation Data Used

• None available

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Additional Data Required

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• Additional experimental data for fitting and validation

Table 6. Mineralogy analysis results from X-ray Diffraction performed on samples obtained from each vertical segment associated with the West $\frac{1}{2}$ and $\frac{1}{2}$ and $\frac{1}{2}$ and $\frac{1}{2}$

Figure 3.7.4. Effect of acid concentration on major REE and contaminants leaching recovery.

Solvent Extraction Summary WVU Team (Prof. Debangsu Bhattacharyya)

Feed Composition Data Used

- Aqueous feed: REESim excel file, buffer tank of cleaner circuit, concentration of components
- Organic feed: REESim excel file, stripping operation of cleaner circuit, concentration of components
- Components considered: Al, Ca, Fe, Sc, Y, La, Ce, Pr, Nd, Sm, Gd, Dy
- Extractant considered: DEHPA

Model Equations and Data for Unit Process

- Komulanein et. al., Hydrometallurgy, 81, 52-61, 2006, Lyon et. al., Industrial and Engineering Chemistry Research, 56, 1048-1056, 2017, and several other papers
- REESim excel file, Phase-1 report, Final phase report,
- Extraction percentage, extractant dosage and pH variation data, feed and product concentration, etc.

Validation Data Used

• Aqueous and organic streams concentration values from REESim excel file, Phase-1 report, and final phase report

Additional Data Required

• Following data are lacking in general in the literature in this area including UKy literature- studies on emulsification, if any, density gradients in the mixer/settler, axial and radial mixing, mass transfer rate, studies on interfaces and continuous and dispersed phase distributions, and ion concentration variation, also dynamic data are mostly lacking.

Solvent Extraction Summary

for Minerals Sustainability

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•First-principles, dynamic model of the counter-current multi-stage, multi-component solvent extraction system followed by stripping •Model results compare well with the data from the UKy pilot plant data.

Solvent Extraction Summary

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- Using the UKy pilot plant data, a data-driven model for the distribution coefficient as a function of pH and extractant concentration.
- Future work will include development of higher fidelity models of the solvent extraction system, inclusion of more solvent materials in the database, validation of the dynamic model of the solvent extraction system, control system development for feed and other disturbance rejection, and development of a model for the membrane solvent extraction system with validation using the NETL in-house data.**Parity plot**

Precipitation Summary

Feed Composition Data Used

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- Input is fed from the solvent extraction system
- Output would need to be validated from inputs and specific pH, acid dosage, and reaction time

Model Equations and Data for Unit Process

- Equilibrium reactor with fixed partition coefficients
- Partition coefficients calculated from data in the literature
- A Hybrid Experimental and Theoretical Approach to Optimize Recovery of Rare Earth Elements from Acid Mine Drainage Precipitates by Oxalic Acid Precipitation, Y. Wang, P. Ziemkiewicz, and A. Noble, Minerals 2022, 12, 236
- One problem is that since it is not a multivariable study, the surrogate model can only be created for one variable

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A Hybrid Experimental and Theoretical Approach to Optimize Recovery of Rare Earth Elements from Acid Mine Drainage Precipitates by Oxalic Acid Precipitation, Y. Wang, P. Ziemkiewicz, and A. Noble, Minerals 2022

Surrogate model results

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Precipitation Summary (Model Validation)

Validation Data Used

- The validation test are based on partition calculated from data
- The model is validated with this data as the surrogate model being built will be based on this data as it is a full data base
- Paper recovery %

Additional Data Required

To build the surrogate and test with UK data, we will require data for:

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- recovery vs pH,
- recovery vs acid dosage
- recovery vs reaction time

Need multivariable data set where (pH, dosage, reaction time, contaminants) are varied

A Hybrid Experimental and Theoretical Approach to Optimize Recovery of Rare Earth Elements from Acid Mine Drainage Precipitates by Oxalic Acid Precipitation, Y. Wang, P. Ziemkiewicz, and A. Noble, Minerals 2022

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REE Oxalate Roaster Summary

Feed Composition Data Used

- Solid feed: PrecipitateParametersData, with optional moisture content
- Gas feed: Generic ideal gas mixture (N_2, O_2, CO_2, H_2O)

Model Equations and Data for Unit Process

- Currently 100% conversion to oxides
- Full species mass balance and energy balance
- User specified solid recovery (default 95%)

Validation Data Used

UKy REESim excel spreadsheet

Additional Data Required

• Conversion and recovery for individual species as functions of temperature and other operation conditions, if available

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- $RE_2(C_2 O_4)_3 \cdot xH_2 O + 1.5O_2 \rightarrow$ $RE_2O_3 + 6CO_2(g) + xH_2O(g)$
- **Impurities:**
- $Fe_2(C_2O_4)_3 \cdot 2H_2O \rightarrow Fe_2O_3$
	- $Al_2(C_2O_4)_3 \cdot H_2O \rightarrow Al_2O_3$

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Ion Exchange Summary

Feed Composition Data Used

• Leaching process outlet from UKy flowsheet

Model Equations and Data for Unit Process

- Modified version of unit model from [WaterTAP](https://github.com/watertap-org/watertap/blob/main/watertap/unit_models/ion_exchange_0D.py) platform
- Data for unit operation and resin from references [1] and [2]

Validation Data Used

• No validation available, but model was tested using batch experimental data from literature (references in unit model)

Additional Data Required

• No additional data required

73

References:

[1] S. Mondal, A. Ghar, A.K. Satpati, P. Sinharoy, D. K. Singh, J.N. Sharma, T. Sreenivas, and V. Kain, Recovery of rare earth elements from coal fly ash using TEHDGA impregnated resin, Hydrometallurgy 185, 2019, 93-101.

[2] Dupont Amberlite XAD(TM)7HP Polymeric Adsorbent. Product Data Sheet Polymeric Adsorbent. February 2023. URL:

[https://www.dupont.com/content/dam/dupo](https://www.dupont.com/content/dam/dupont/amer/us/en/water-solutions/public/documents/en/IER-AmberLite-XAD7HP-PDS-45-D00782-en.pdf) [nt/amer/us/en/water](https://www.dupont.com/content/dam/dupont/amer/us/en/water-solutions/public/documents/en/IER-AmberLite-XAD7HP-PDS-45-D00782-en.pdf)[solutions/public/documents/en/IER-AmberLite-](https://www.dupont.com/content/dam/dupont/amer/us/en/water-solutions/public/documents/en/IER-AmberLite-XAD7HP-PDS-45-D00782-en.pdf)[XAD7HP-PDS-45-D00782-en.pdf](https://www.dupont.com/content/dam/dupont/amer/us/en/water-solutions/public/documents/en/IER-AmberLite-XAD7HP-PDS-45-D00782-en.pdf)

PrOMMiS Subtask 2.2: CM & REE Process Cost Estimation

Brandon Paul, Miguel Zamarripa, Debangsu Bhattacharyya, Alison Fritz

Bottom-Up Costing Approach

- Missing data or capital costing correlations not available for required equipment sizes and process performance.
- New technologies TRL < 3, process technology/process do not exist.
- Leverage existing data to build capital cost based on unit operations in the process or manufacturing steps (i.e., Solvent extraction: vessel, column hydraulics, etc.)

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Cost for processing components and core equipment

Penalize materials of constructions and design factors.

 \overline{a} and \overline{a} Calculate indirect costs (based on existing vendor 100 quotes)

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Bottom-Up Costing Approach: Economy of Numbers

- Due to consistent proficiency improvement, labor hours reduce as the cumulative production quantity rises.
- Following a preliminary CAPEX and OPEX estimate for a hydrogen decrepitation furnace unit, a comprehensive bottom-up cost estimate is underway.

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CM/REE Costing Framework

Capital Cost and Project Cost Calculations

<https://github.com/prommis/prommis/tree/main/src/prommis/uky/costing>

Process Optimization and Modeling for Minerals Sustainability

O&M Cost Calculations

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Supported Unit Operations

- Sourced from Uky REE Recovery Reports $2,3,4$ and literature^{5,6,7}
- Fit capital cost correlations in the form

$Cost = Coefficient * Parameter$ *Exponent*

• Membranes (e.g. nanofiltration, reverse osmosis, ion exchange) costed via WaterTAP

² Keim, Steven Anthony, and Naumann, Hans. Production of Salable Rare Earths Products from Coal and Coal Byproducts in the U.S. Using Advanced Separation Processes (Final Technical Report). United States: N. p., 2019. Web. doi:10.2172/1569277.

³ Honaker, Rick, Werner, Joshua, Yang, Xinbo, Zhang, Wencai, Noble, Aaron, Yoon, Roe-Hoan, Luttrell, Gerald, and Huang, Qingqing. Pilot-Scale Testing of an Integrated Circuit for the Extraction of Rare Earth Minerals and Elements from Coal and Coal Byproducts Using Advanced Separation Technologies. United States: N. p., 2021. Web.

⁴ Honaker, Rick Q., Werner, Joshua, Nawab, Ahmad, Zhang, Wencai, Noble, Aaron, Free, Michael, and Yang, Xinbo. Demonstration of Scaled-Production of Rare Earth Oxides and Critical Materials from U. S. Coal-Based Sources (Final Report). United States: N. p., 2023. Web. doi:10.2172/1971736.

⁵ Garrett, D.E. (1989). Chemical Engineering Economics.

⁶ Ames National Laboratory. (2020, March 26). It's all part of the Grind: CMI's new hard drive Shredder serves up plenty of material for recycling science. Ames Laboratory. https://www.ameslab.gov/news/it-s-all-part-of-the-grind-cmi-s-newhard-drive-shredder-serves-up-plenty-of-material-for

⁷ Loh, H.P., Lyons, Jennifer, White, Charles W.. Process Equipment Cost Estimation Final Report. United States: N. P., 2002. Web.

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PrOMMiS Subtask 2.3: Advanced Optimization Capabilities for End-of-Life Products Ana Torres, Christopher Laliwala

End Of Life Products - Introduction

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- Approach: superstructure-based conceptual design EoL to REO
- Long term goal: EoL feedstock agnostic process

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Activities

- 1. Prioritization of EoL; Quantification of feedstock potential
- 2. Literature Search: processing pathways

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- 3. Superstructure development, modeling, and optimization
- 4. Process flowsheet development, simulation, and economic analysis (if not available in literature)
- 5. Application to 2 case studies: Permanent magnets from HDD EV/HEV

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EoL Products – (1) Prioritization

• Setting priorities

Figure: Dolf Gielen, & Martina Lyons. (2022). *Critical Materials For The Energy Transition: Rare Earth Elements*., IRENA

=> Permanent Magnets

for Minerals Sustainability • Quantification of feedstock potential in the USA

Figures made on the basis of sale projections/ technology adoption/ lifetime/ composition. Lower and upper estimates were obtained.

References:

- Blast et al. (2014). Recycling von Komponenten und strategischen Metallen aus elektrischen Fahrantrieben.
- Alves Dias, P., Bobba, S., Carrara, S., Plazzotta, B. (2020), The role of rare earth elements in wind energy and electric mobility, EUR 30488 EN, Publication Office of the European Union, Luxembourg, ISBN 978-92-79-27016-4.
- Sprecher, B., Kleijn, R., & Kramer, G. J. (2014). Recycling Potential of Neodymium: The Case of Computer Hard Disk Drives. Environmental Science & Technology, 48(16), 9506–9513. https://doi.org/10.1021/es501572z
- Dolf Gielen & Martina Lyons. (2022). Critical Materials For The Energy Transition: Rare Earth Elements.
- LDV Total Sales of PEV and HEV by Month (updated through May 2023). (2023). https://www.anl.gov/esia/reference/lightduty-electric-drive-vehicles-monthly-sales-updates-historical-data

EoL Products $-$ (2) Processing Pathways

- Data: Literature, Oak Ridge National Labs, Critical Minerals Innovation Hub
- Example for HDDs:

EoL Products – (3) Superstructure

- for Minerals Sustainability • Organize existing data in processing stages, identify competitive technology options at each stage
- Identify new connections

EoL – (3) Superstructure Modeling

• Superstructures are modeled as networks

- Technology options \rightarrow nodes \rightarrow binary variable *y =1* if in optimal pathway
- Arcs: flows of each species
- Inlet/ Outlet flows \rightarrow MB from simulations

- Allowed connections: logical constraints
- Objective function: NPV

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- Installed equipment cost and OPEX data: from TEA: existing in the literature or our own (via Aspen Tech)
- Framework: Seider et al.

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EoL – (4) Process flowsheet development and costing

• Only for those for which we could not find TEA in the literature published data

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- **OPEX and CAPEX in literature**
- **Required OPEX and CAPEX estimation**
- **Estimations:**

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• **Aspen Plus flowsheet development**

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• **Aspen Economics: Equipment cost**

Process Optimization and Modeling for Minerals Sustainability

EoL – (4) Process flowsheet development and costing- Example

24. Lyman, J.W., Palmer, G.R.: Recycling of Rare Earths and Iron from NdFeB Magnet Scrap. High Temperature Materials and Processes. 11, 175–188 (1993). https://doi.org/10.1515/HTMP.1993.11.1-4.175

Process Optimization and Modeling for Minerals Sustainability

(C. Laliwala, AI Torres, submitted FOCAPD 2024)

Process Optimization and Modeling for Minerals Sustainability

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• Optimal solution for different collection rates (from future and past wastes) and REO prices;

Base Case $\overline{0}$ $\tilde{\Xi}$ -A $-2A$ $-3A$ 25% 50% 148% 150% **Initial Collection rate**

Figure 6: NPV for a varying collection rate. The base case is a collection rate of 60% and no recycling of EOL HDDs generated prior to plant production. The NPV break-even point was found to occur at ~360%. Numerical values are not reported to preserve confidentiality.

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Figure 7: NPV for a varying initial collection rate. The base case has a collection rate of 60% and an initial collection rate of 25%. The NPV break-even point was found to occur at ~148%. Numerical values are not reported to preserve confidentiality.

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Figure 8: NPV for varying percentages of the initial REO price projection estimate. The NPV break-even point was found to occur at ~168%. Numerical values are not reported to preserve confidentiality.

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• ONL Shredding + CMI acid-free dissolution always optimal pathway

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(C. Laliwala, AI Torres, ESCAPE 2024, accepted)

• Slightly different superstructure;

- **Required in house estimation**
- **Mix of literature and estimation**

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(C. Laliwala, AI Torres, ESCAPE 2024, accepted)

• Slightly different superstructure;

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- Base case: plant recycles 10 % of all EOL EVs and HEVs in the U.S. each year.
- Optimal pathway:
	- Automatic disassembly
	- Hydrogen decrepitation
	- Acid Free dissolution

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• NPV positive

(C. Laliwala, AI Torres, ESCAPE 2024, accepted)

Sensitivity Analysis

• Automatic disassembly, hydrogen decrepitation, acid-free dissolution were always selected as optimal

Figure 3. Sensitivity analysis for the product projected prices, and amount of EOL vehicles available for recycling. Values are reported normalized to the base case optimal solution to preserve confidentiality.

Percent of initial estimate

Future Work

• Symbolic regression

Overview – What You'll Hear

- Coal to Rare Earth Elements University of Kentucky
	- Process Model & Unit Operations
	- Cost Model Development
- Membranes
	- Process Model Development & Application Summary
	- Optimization Cases Studies
	- Enabling Scale-Up: Model-Design of Experiments
- End of Life Pathways Magnets & Hard Drives
	- Process Model
	-
	- Cost Model Superstructure Optimization & Findings
- Ongoing / Parallel Efforts
	- Identifying Model Uncertainty
	- Benchmark Surrogate Modeling Approaches

• Model Usability & Distribution

Open-Source Platform

- Website:<https://idaes.org/research/application-areas/>
- GitHub repository:
	- <https://github.com/prommis/prommis>
- Documentation:
	- <https://prommis.readthedocs.io/en/latest/>
- Bi-Weekly Software Engineering teleconferences coordinating development
- Targeting quarterly internal/public releases
- IPMP in progress for fully open-source license
- Overview video: coming soon!

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Leverage NAWI/WaterTAP UI infrastructure

- Define key model inputs and outputs
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Gather requirements for UIs specific to WT

• E.g., conceptual design model configuration

Leverage IDAES core flowsheet visualization

- View flowsheet diagrams
- PROMMIS models <- new diagnostics capabilities

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Assist team with Jupyter Notebooks and online documentation

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Capital Cost Estimation Approach

PrOMMiS Costing Library (to date)

Process Optimization and Modeling for Minerals Sustainability

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PrOMMiS Costing Library:

$$
SC_i = \alpha_i \cdot R P_i^{Exp_i}
$$

- SC scaled cost
- α reference cost / performance
- RP reference parameter
- Exp exponential factor
- i ith unit operations in the library

References:

² Keim, Steven Anthony, and Naumann, Hans. Production of Salable Rare Earths Products from Coal and Coal Byproducts in the U.S. Using Advanced Separation Processes (Final Technical Report). United States: N. p., 2019. Web. doi:10.2172/1569277.

³ Honaker, Rick, Werner, Joshua, Yang, Xinbo, Zhang, Wencai, Noble, Aaron, Yoon, Roe-Hoan, Luttrell, Gerald, and Huang, Qingqing. **Pilot-Scale Testing of an Integrated Circuit for the Extraction of Rare Earth Minerals and Elements from Coal and Coal Byproducts Using Advanced Separation Technologies.** United States: N. p., 2021. Web. ⁴ Honaker, Rick Q., Werner, Joshua, Nawab, Ahmad, Zhang, Wencai, Noble, Aaron, Free, Michael, and Yang, Xinbo. **Demonstration of Scaled-Production of Rare Earth Oxides and Critical Materials from U. S. Coal-Based Sources (Final Report).** United States: N. p., 2023. Web. doi:10.2172/1971736.

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⁶ Ames National Laboratory. (2020, March 26). It's all part of the Grind: CMI's new hard drive Shredder serves up plenty of material for recycling science. Ames Laboratory. https://www.ameslab.gov/news/it-s-all-part-of-the-grind-cmi-s-newhard-drive-shredder-serves-up-plenty-of-material-for
⁷ Loh, H.P., Lyons, Jennifer, White, Charles W.. Process Equipment Cost Estimation Final Report. United States: N. P.,

2002. Web.

