



Making Techno-Economic Assessments Work For You

Tim Bartholomew
August 7th, 2025

Process systems engineer supporting R&D



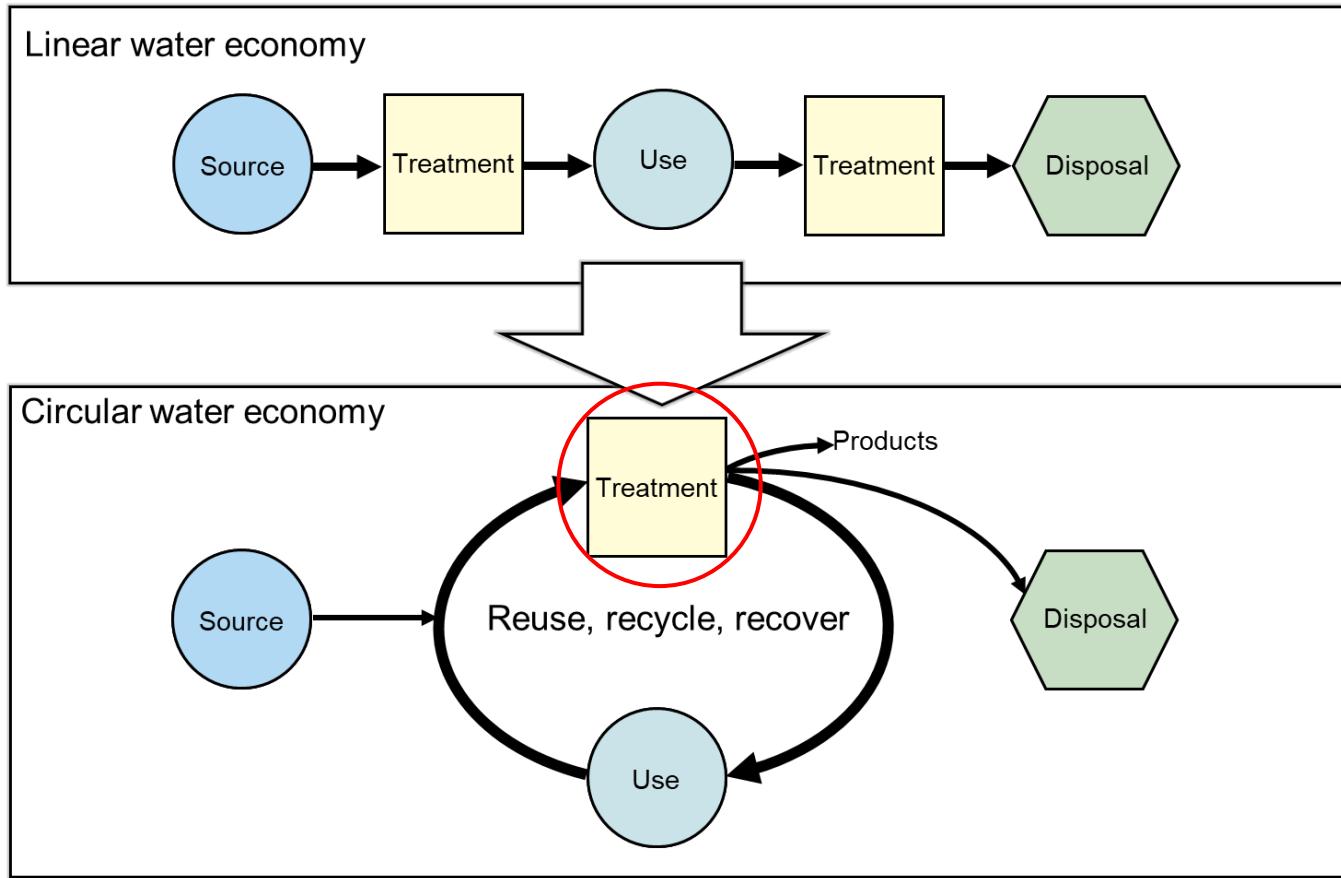
- Expertise:
 - Detailed process modeling, techno-economic assessment, and mathematical optimization
 - Emerging water treatment and desalination technologies
- Education background:
 - Ph.D. Civil and Environmental Engineering from Carnegie Mellon University
 - B.S. Chemical Engineering from Washington University in St. Louis
- Employment background:
 - National Energy Technology Laboratory (NETL), led development of a National Alliance for Water Innovation (NAWI) funded open-source software tool called **WaterTAP**
 - Horizon Modeling Solutions, cofounded a consulting company for supporting R&D

Carnegie
Mellon
University


Washington
University in St. Louis

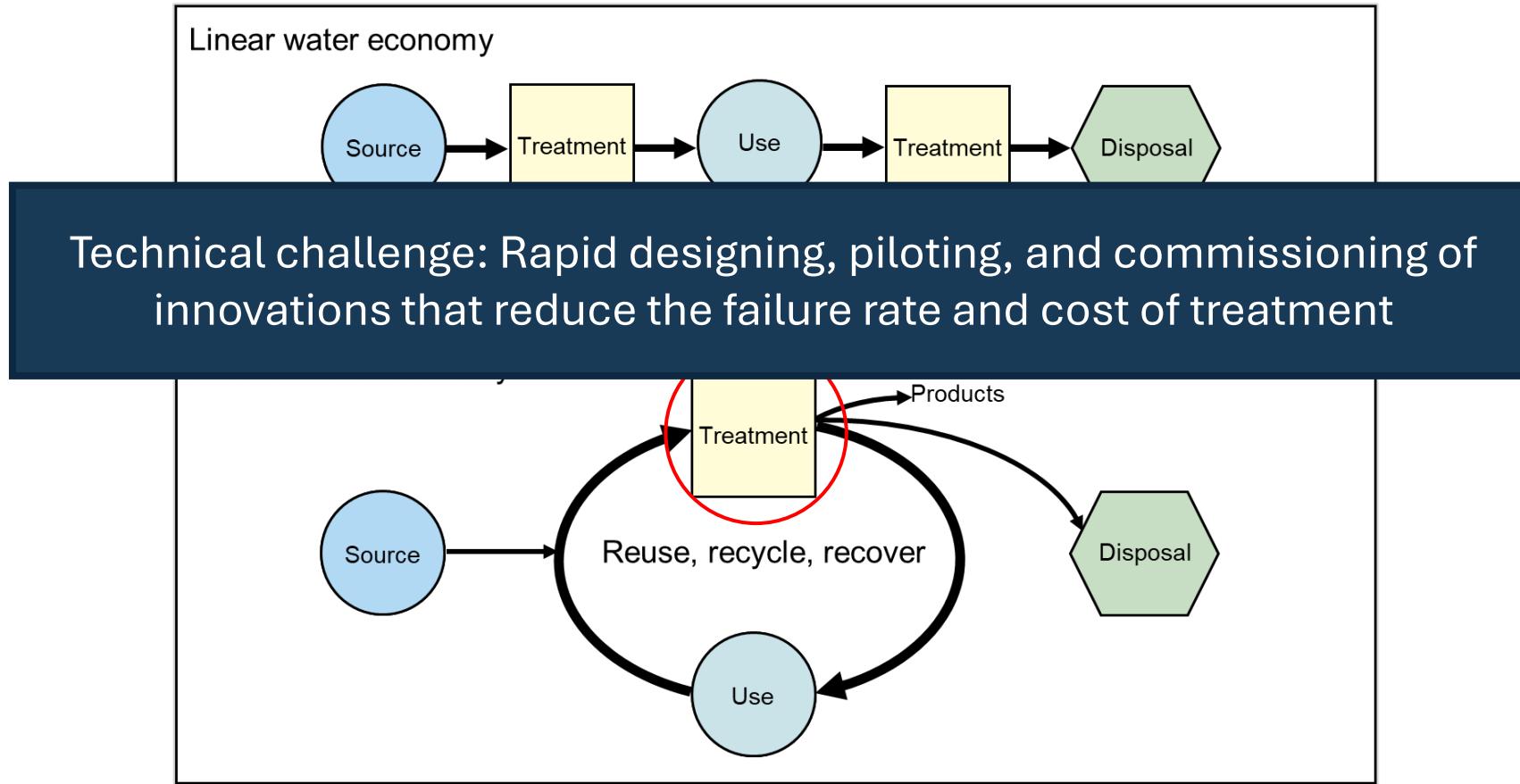
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ENERGY
TECHNOLOGY
LABORATORY 2

A paradigm shift for water management requires advances in treatment technologies



Circular water economy is currently perceived as non-viable because of the **insufficient performance or high cost** of treatment technologies

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TEAs estimate performance and financial metrics

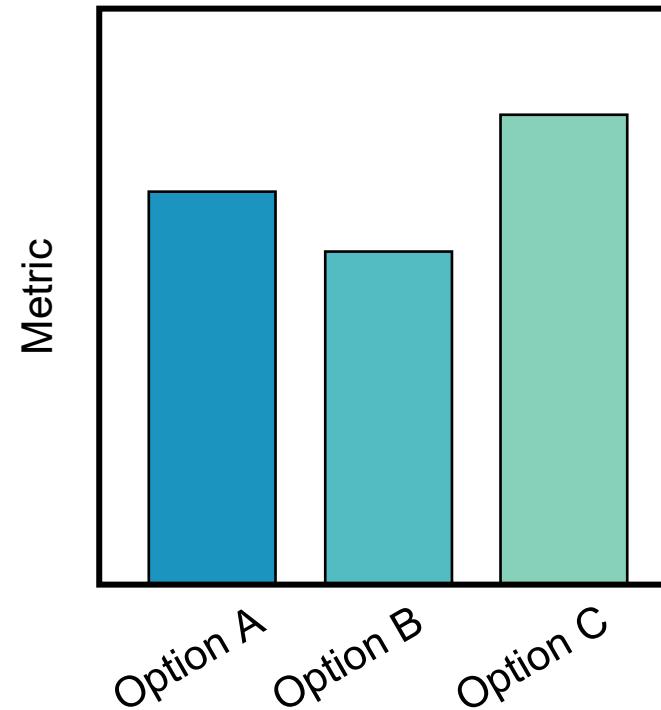
Performance metrics:

- Production or recovery
- Efficiency
- Energy and material consumption
- Waste generation

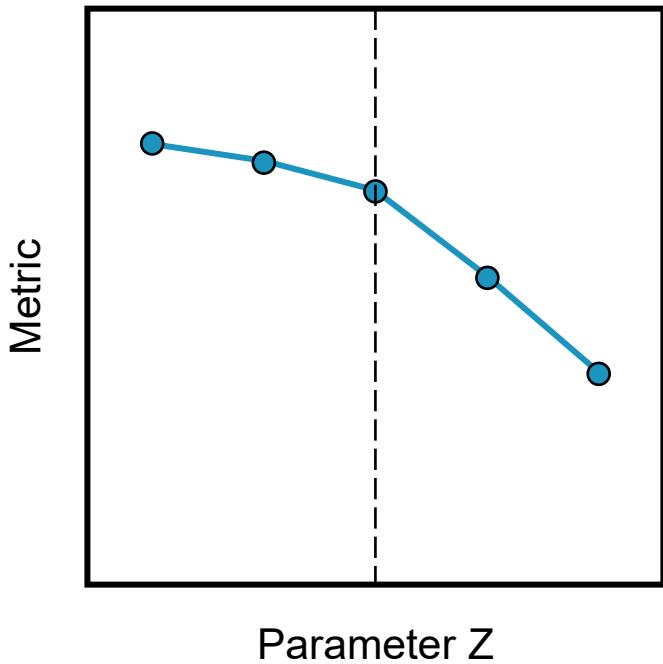
Financial metrics:

- Specific operating cost
- Specific capital cost
- Levelized cost of product or waste
- Net present value
- Internal rate of return

Compare metrics



Quantify the effect of a modeling parameter



There is a wide range of value and detail in TEAs

“All models are wrong, but some are useful”

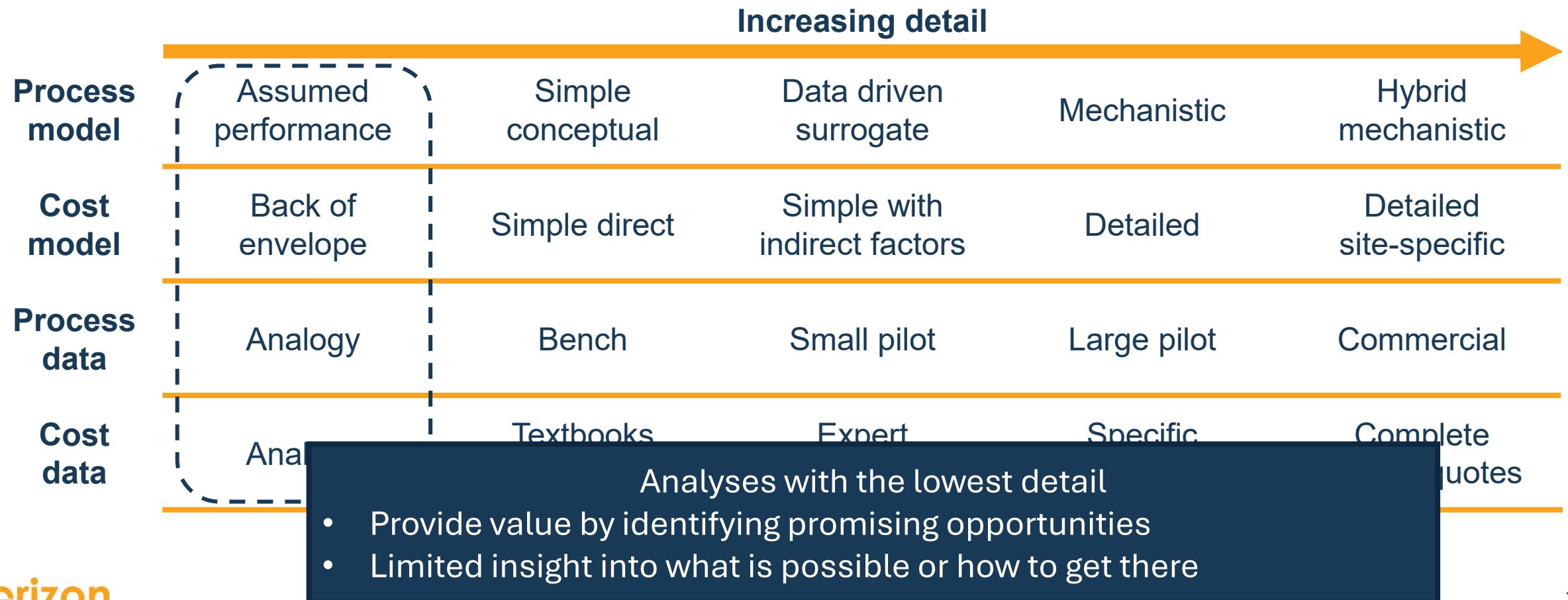
- George Box, British Statistician 1919-2013

	Increasing detail				
Process model	Assumed performance	Simple conceptual	Data driven surrogate	Mechanistic	Hybrid mechanistic
Cost model	Back of envelope	Simple direct	Simple with indirect factors	Detailed	Detailed site-specific
Process data	Analogy	Bench	Small pilot	Large pilot	Commercial
Cost data	Analogy	Textbooks Literature	Expert elicitation	Specific online quotes	Complete vendor quotes

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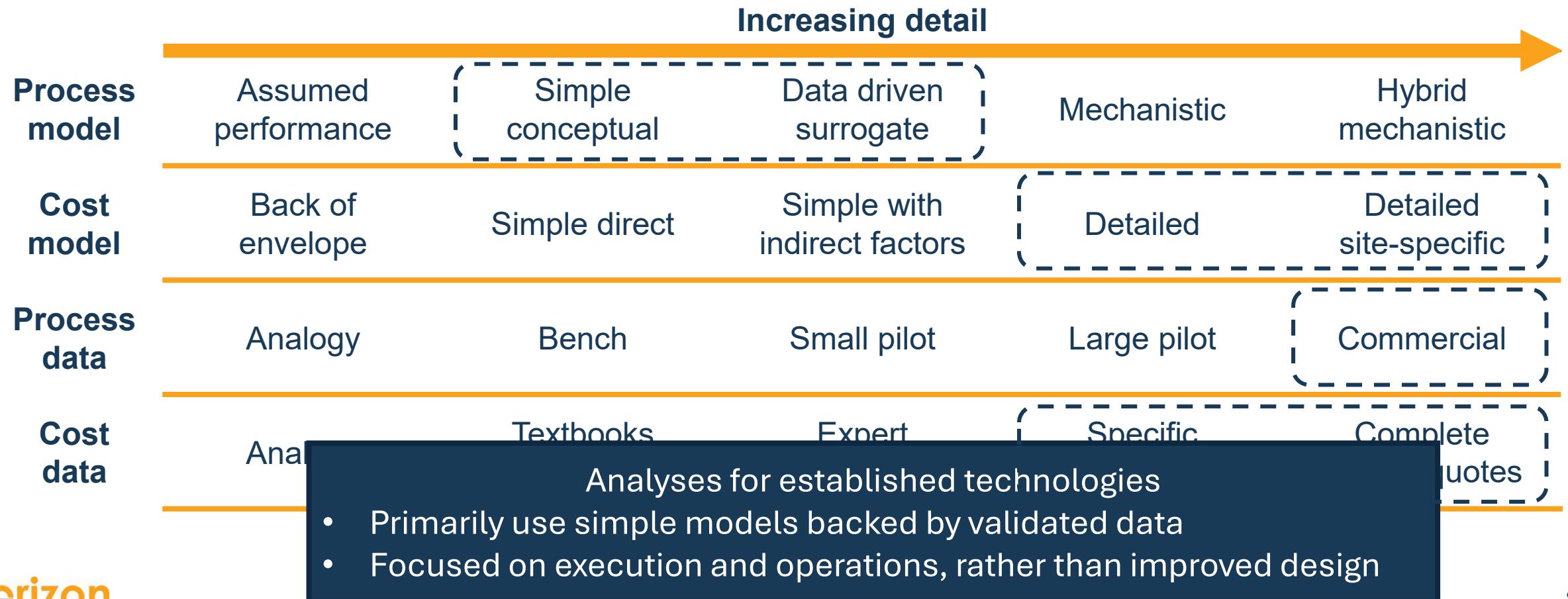
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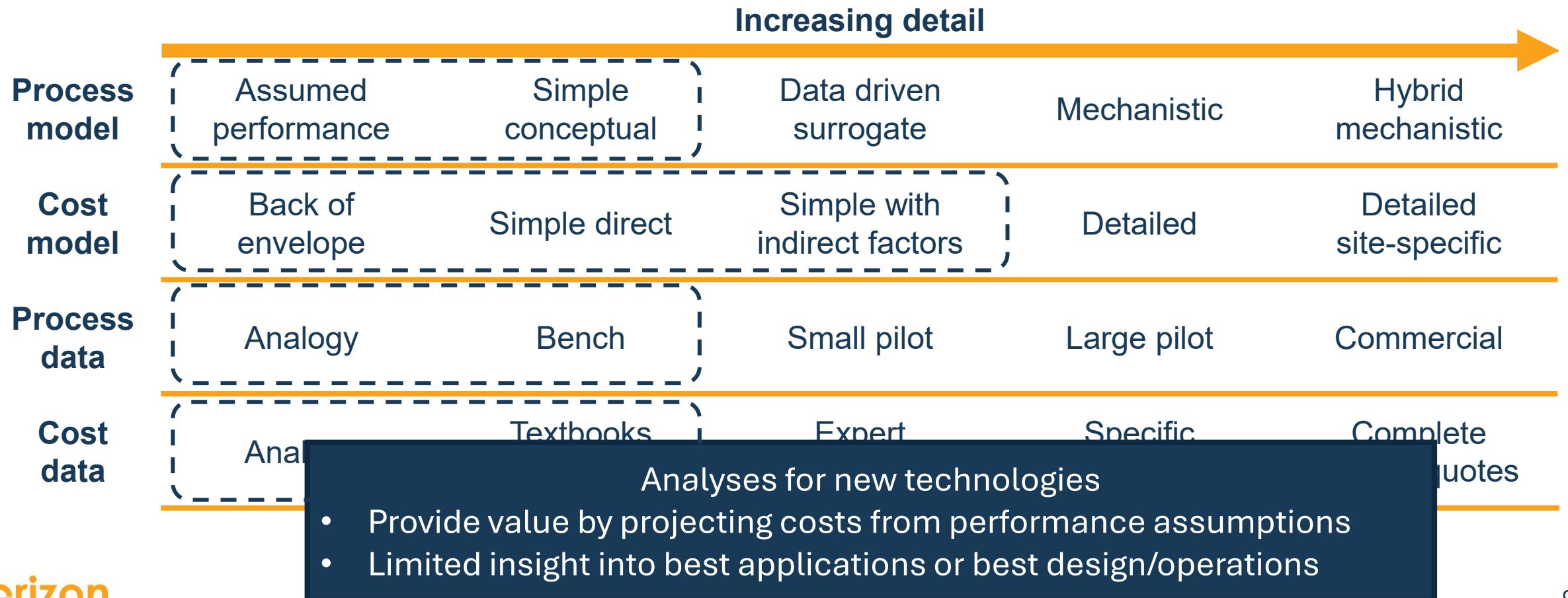
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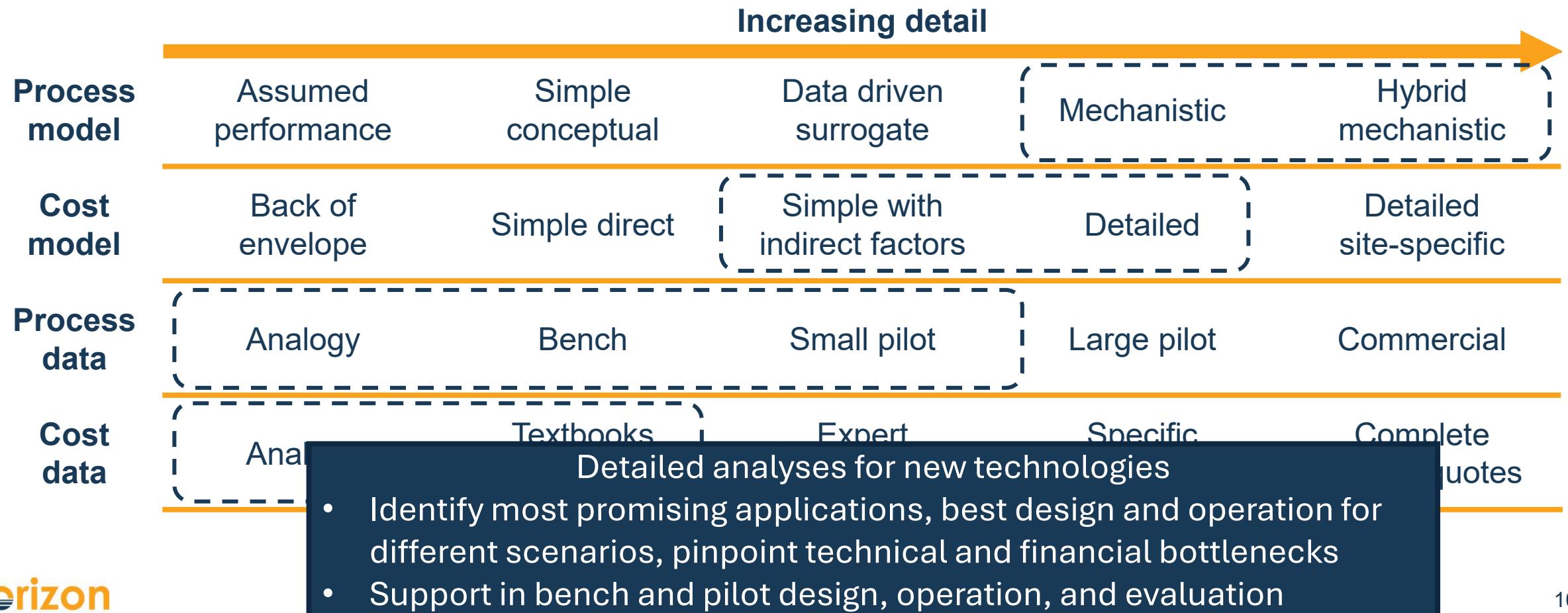
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Conducting a TEA for new technologies can be challenging

Time and skill intensive steps:

1. Scope out relevant system to cover technology benefits and costs
2. Implement or develop predictive models linking decision variables to performance and cost
3. Obtain process and financial parameter values when data is typically limited
4. Determine design and operation without established heuristics

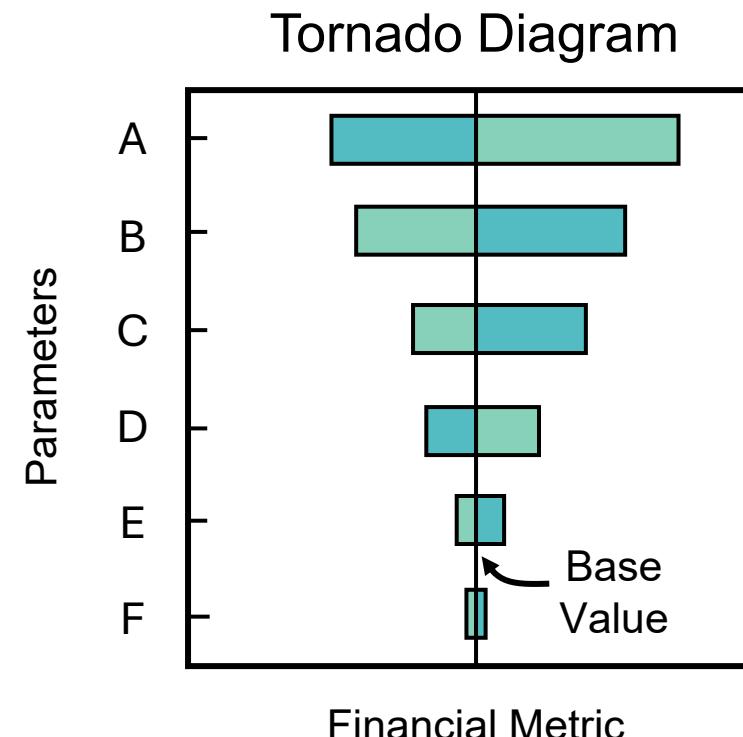
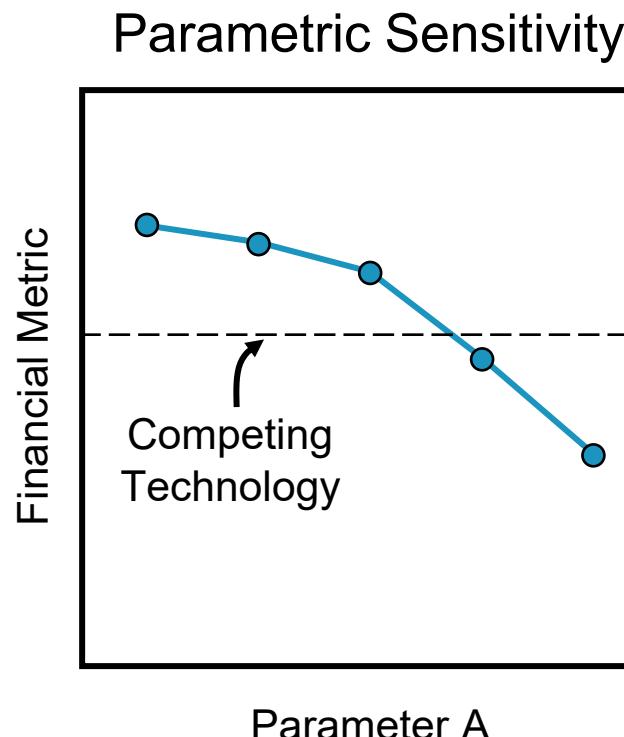
Two overall approaches:

1. Engineers in industry
 - Cobble together available software tools and in-house spreadsheets
 - Inherent limitations for modeling new technologies and incompatibilities due to interfacing between tools
2. Researchers in academia
 - Build models from scratch
 - TEAs have variable quality and can take several months to two years to complete

Start guiding R&D with a cost model and process data

Cost models are required, but predictive process models are optional

- Use an assumed performance process model based on your data or understanding
- Vary the financial and performance parameters to set research goals and priorities



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Cost model can combine engineering handbooks and online resources

- Use costing frameworks in chemical engineering handbooks ([Towler & Sinnott, Seider et al.](#))
 - Tables for generic equipment costs, factors for estimating indirect costs (engineering, siting, etc.)
 - Update to today's dollars with the chemical engineering plant cost index (CEPCI), [blog description](#)
 - Curate online equipment cost quotes and establish a range and/or simple relationship
- Leverage the Activate Technomics course: <https://www.activate.org/technomics>
 - Educational videos, downloadable Excel models with costing framework and parameter ranges
 - Developed by Chris Burk from Burk Techno-Economics with more resources at his [site](#)

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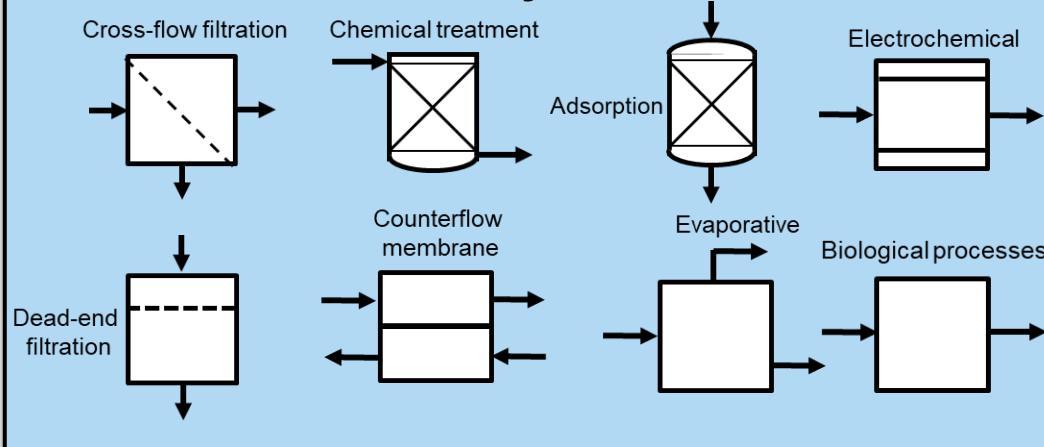
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 - Assumed process models can help set research goals and priorities
 - But they lack insight into whether targets are realistic or how to reach them

WaterTAP provides a platform for improving the quality and decreasing the effort of TEAs



Unified

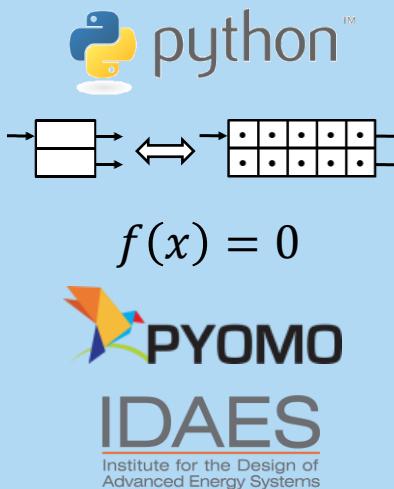
Modular model library:



Flexible

Core attributes:

- Open-source
- Multi-hierarchical
- Customizable
- Equation oriented
- IDAES compatible



Powerful

Software release:

- Publicly accessible on GitHub
- Released every quarter

pip install watertap

<https://github.com/watertap-org/watertap>

<https://watertap.readthedocs.io/en/latest/>



Core capabilities:

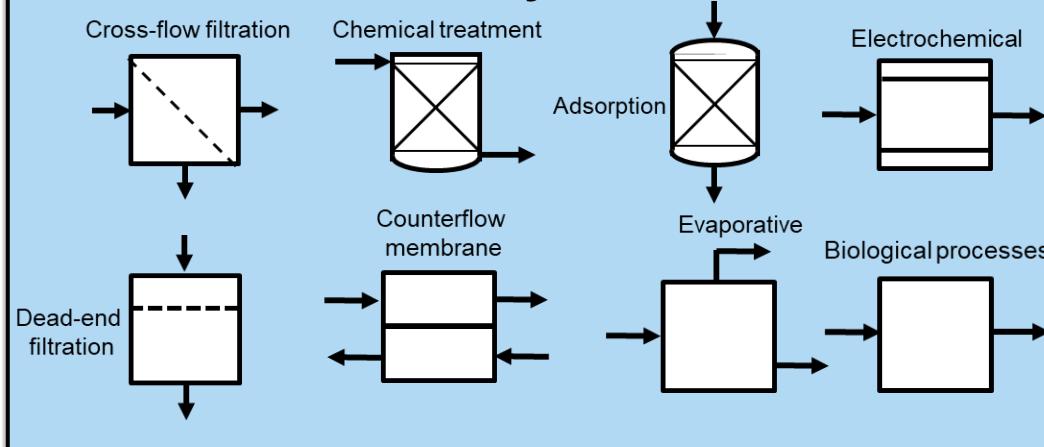
- Simulation to evaluate new device integration
- Optimization to explore complex systems
- Sensitivity analyses to consider uncertainty
- Parameter estimation to fit real-world data
- Data-driven models for complex phenomena

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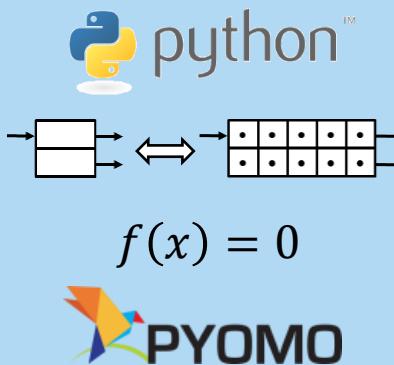
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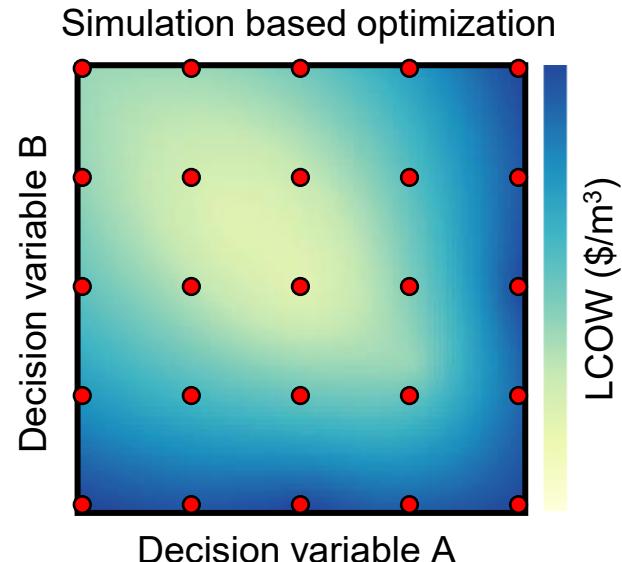
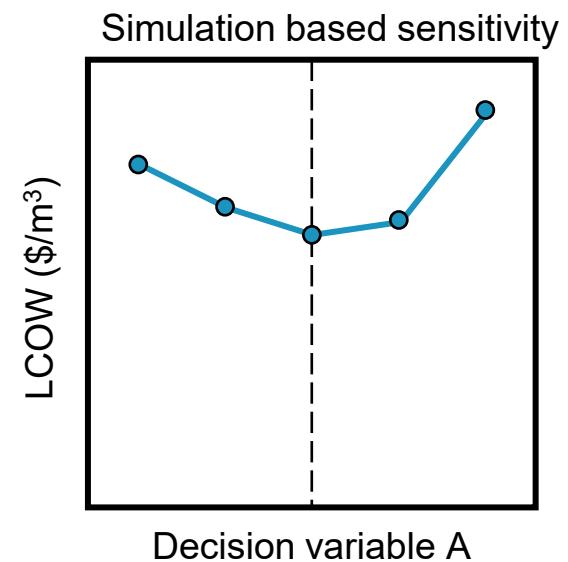
WaterTAP was developed to provide a centralized platform that makes TEAs more transparent, reproducible, comparable, and extendable

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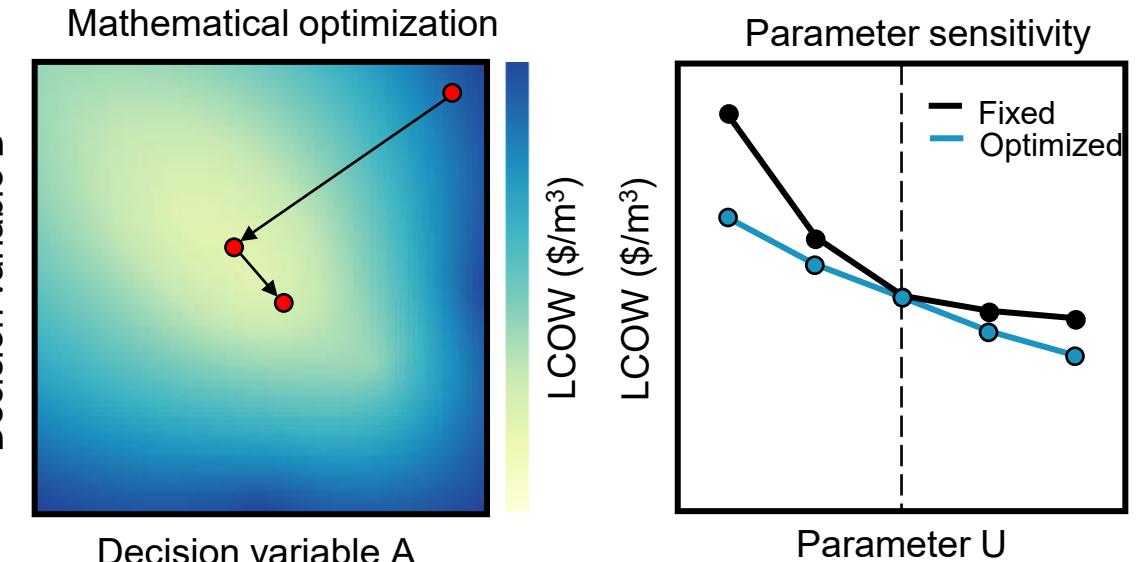
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Mathematical optimization greatly expands TEAs

Simulation based modeling focuses on
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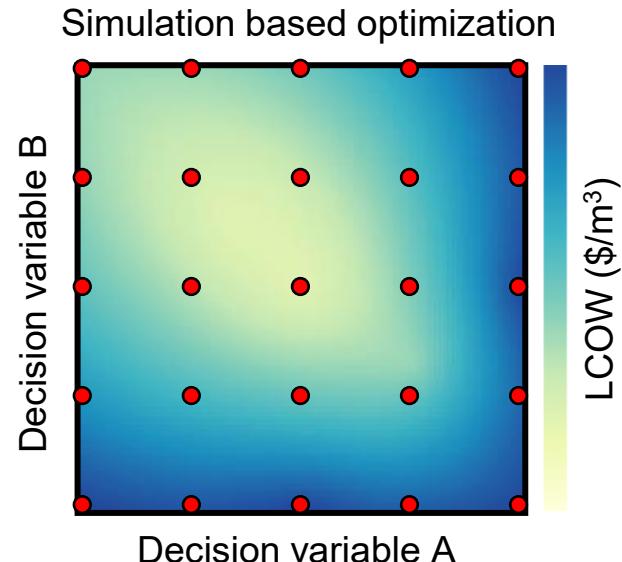
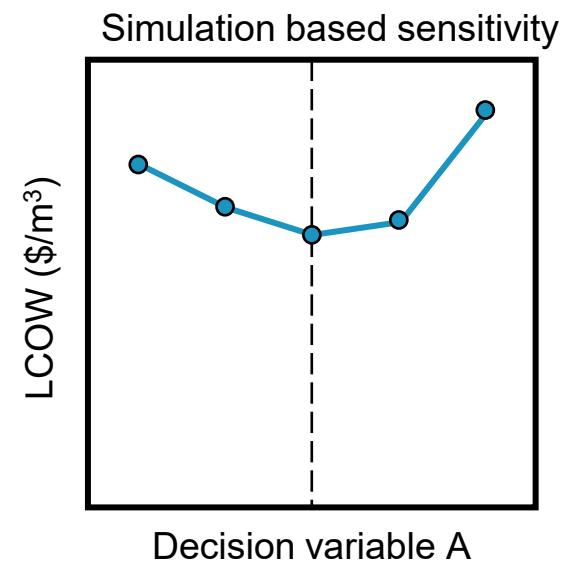


Optimization based modeling focuses on
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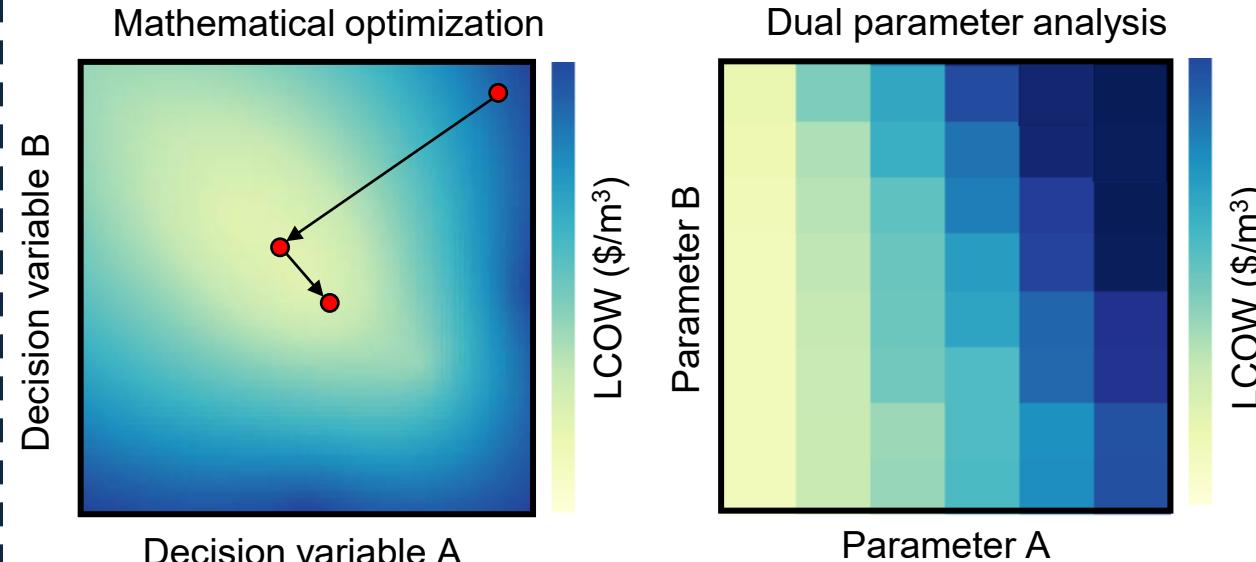


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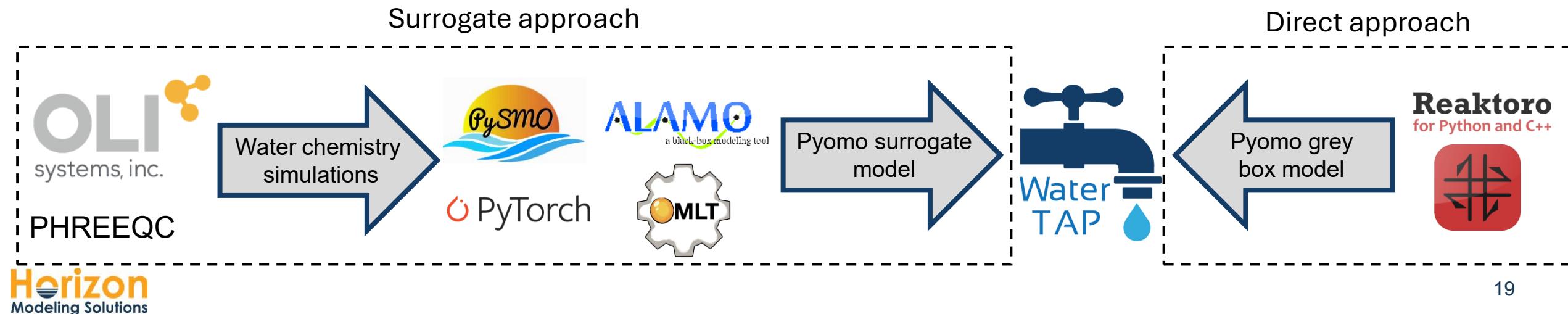


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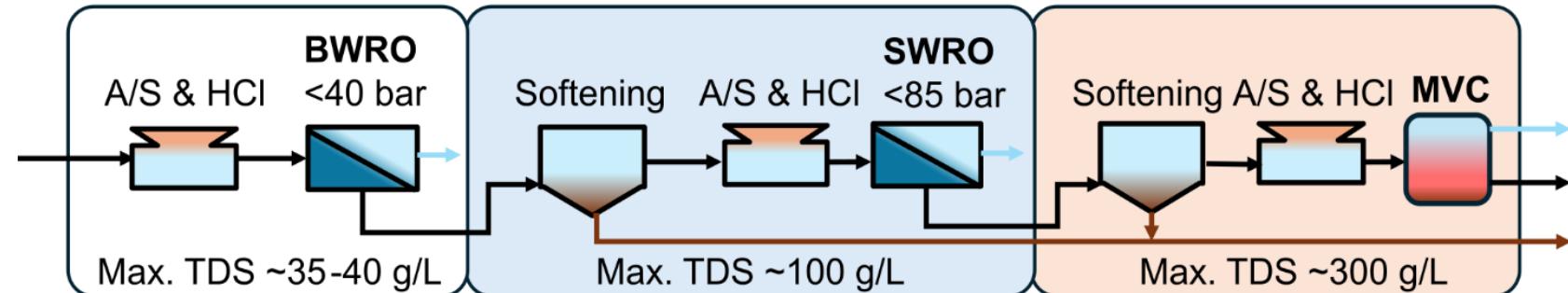
Detailed water chemistry is supported on WaterTAP

- Modeling complex water chemistry is challenging and data intensive
 - Numerous reactions and interactions across aqueous, vapor, and solid species
 - Dependent on concentrations of all species (even very small values)
 - pH, temperature, pressure can all be significant
- Electrolyte theoretical models can be built on the platform (e.g., eNRTL, MSE, Pitzer)
 - Data availability limits the species than can be considered
 - WaterTAP does not currently support a database for these models
- WaterTAP leverages external water chemistry software



Evaluating the potential of a conceptual process

Objective: Model a novel high recovery system using conventional technologies



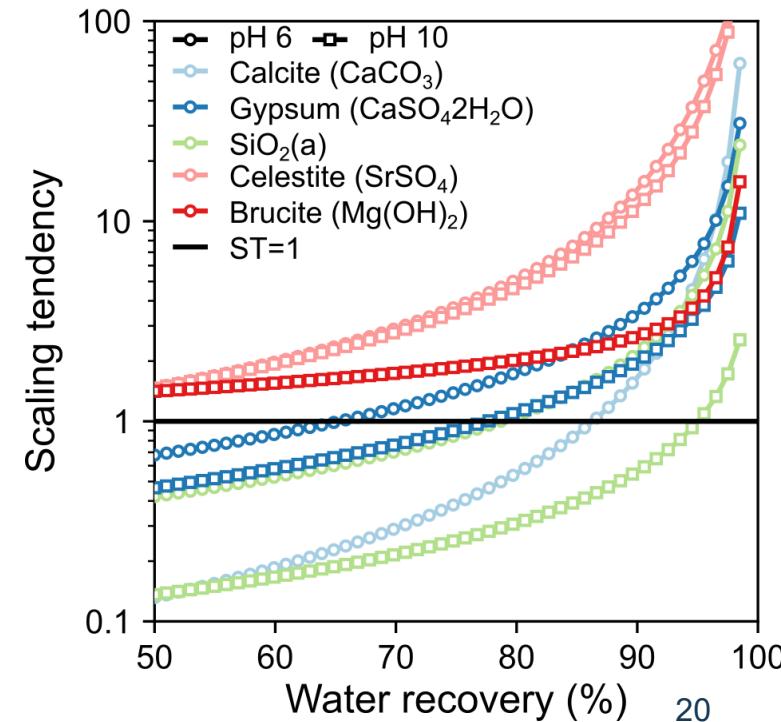
Description:

- 2 membrane and 1 evaporative process
- Constrained by mineral scaling
- Antiscalants, pH control, and softening for interstage precipitation

Approach

- Mechanistic model for desalination processes
- ML model for water chemistry from PHREEQC
- Hypothetical model for antiscalant efficacy

Ion	Conc. (mg/L)
Na	739
Cl	870
K	9
Ca	258
Mg	90
SO ₄	1011
HCO ₃	385
Sr	3
SiO ₂	25
TDS	3397



Evaluating the potential of a conceptual process

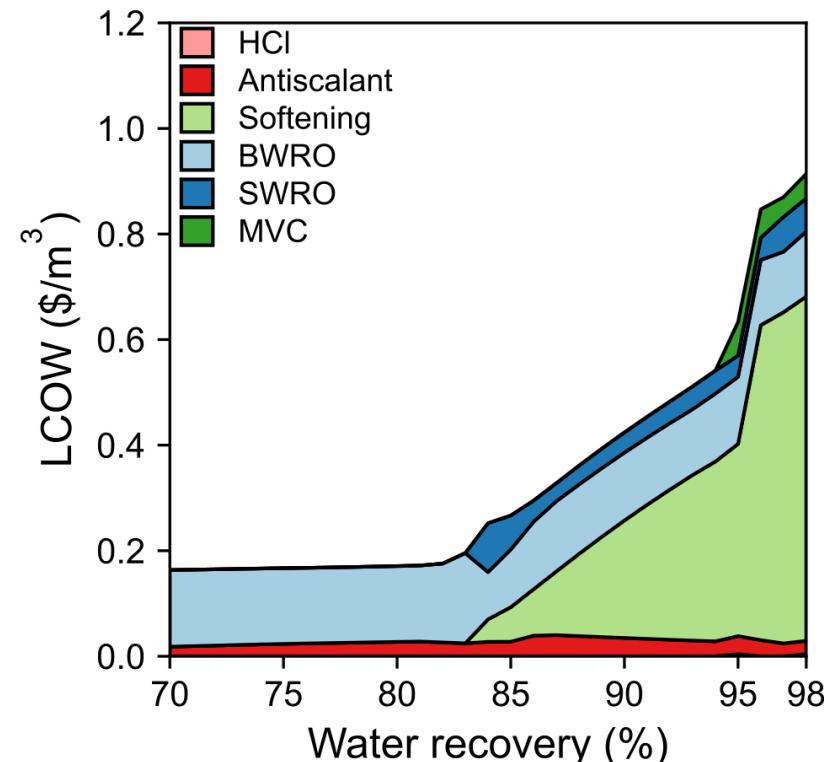
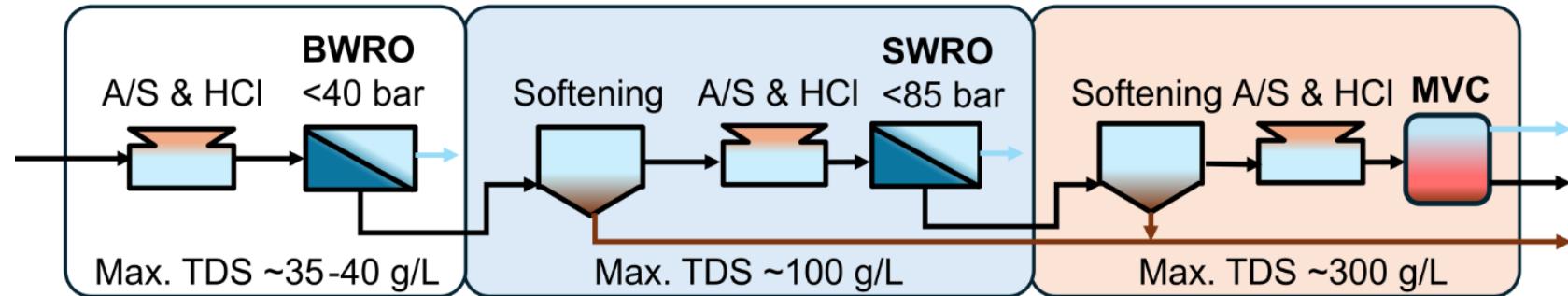
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Surprising results:

- Costs are below \$1/m³
- Recoveries up to 98% recovery

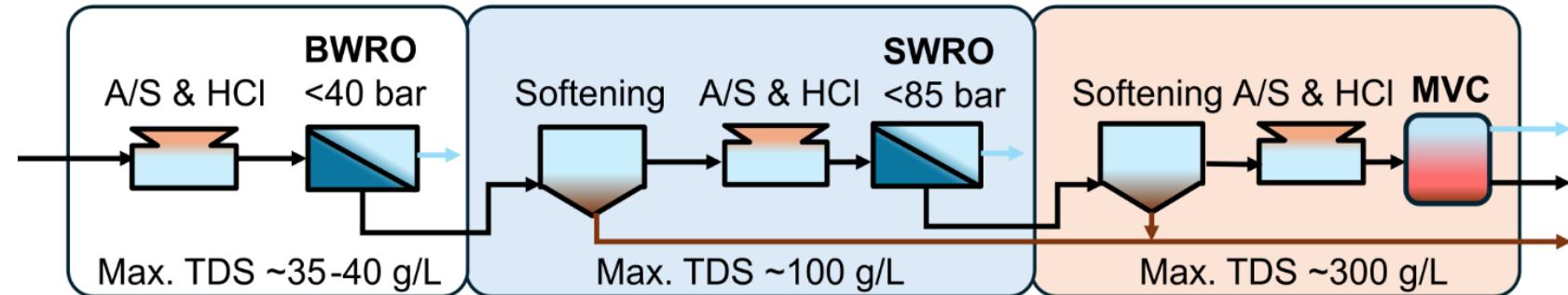
Other results:

- Mineral scaling dictates extent of recovery in each stage
- Higher salinity desalination technologies contribute a small amount to the cost
- Softening cost becomes dominant



Evaluating the potential of a conceptual process

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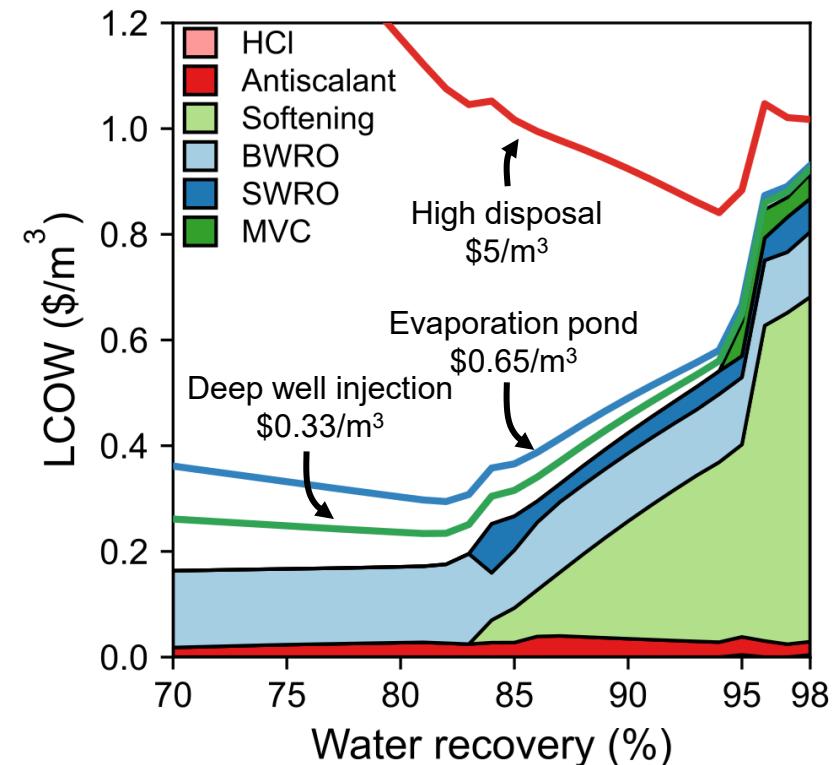


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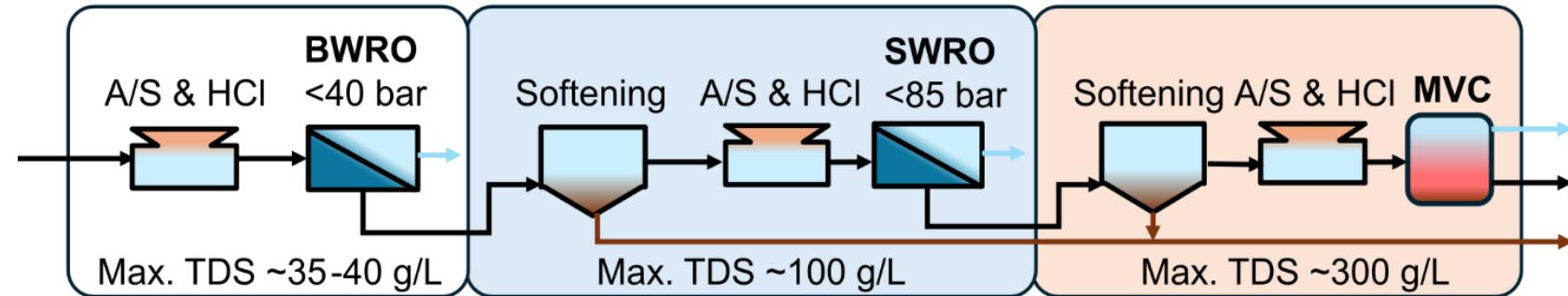
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- Disposal does not raise overall cost significantly, typical disposal costs -> BWRO high disposal costs -> BWRO and SWRO



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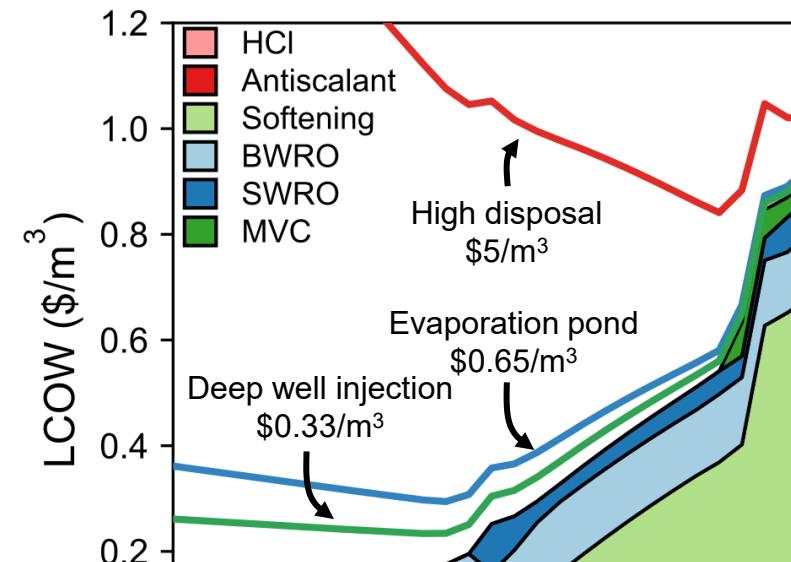
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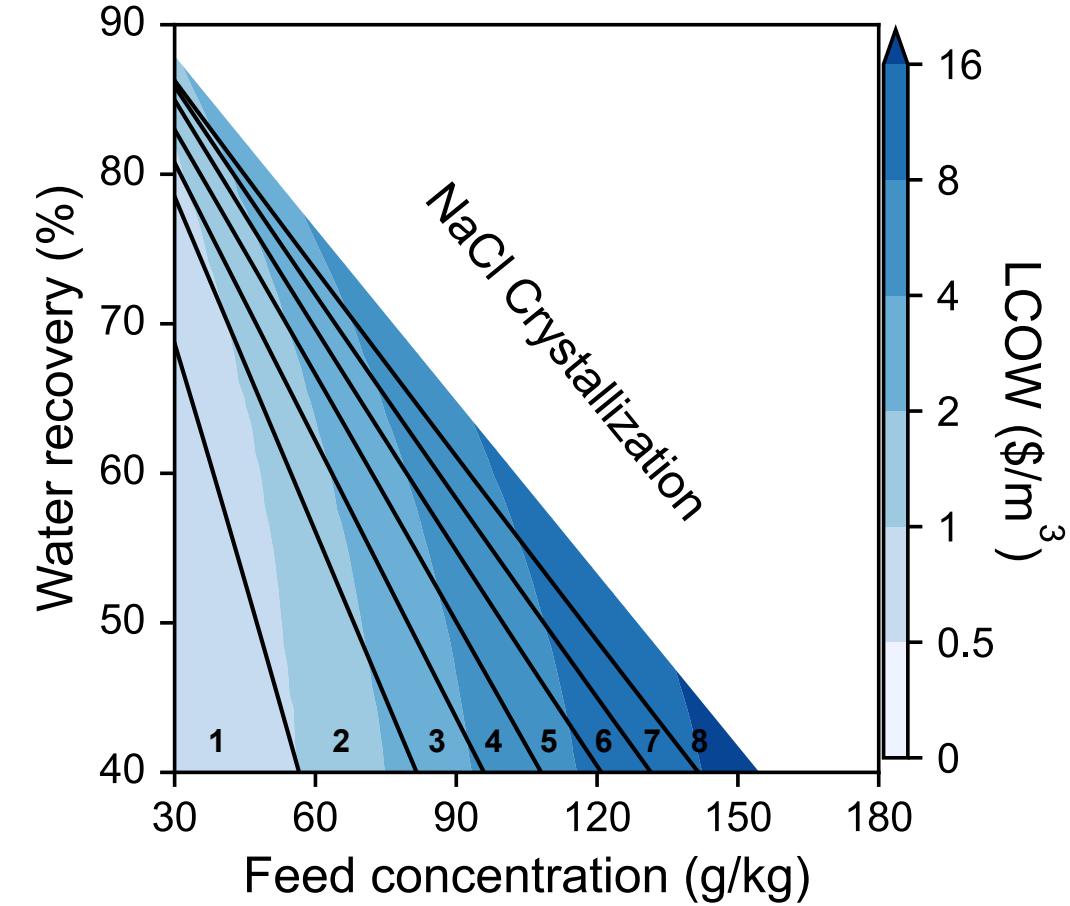
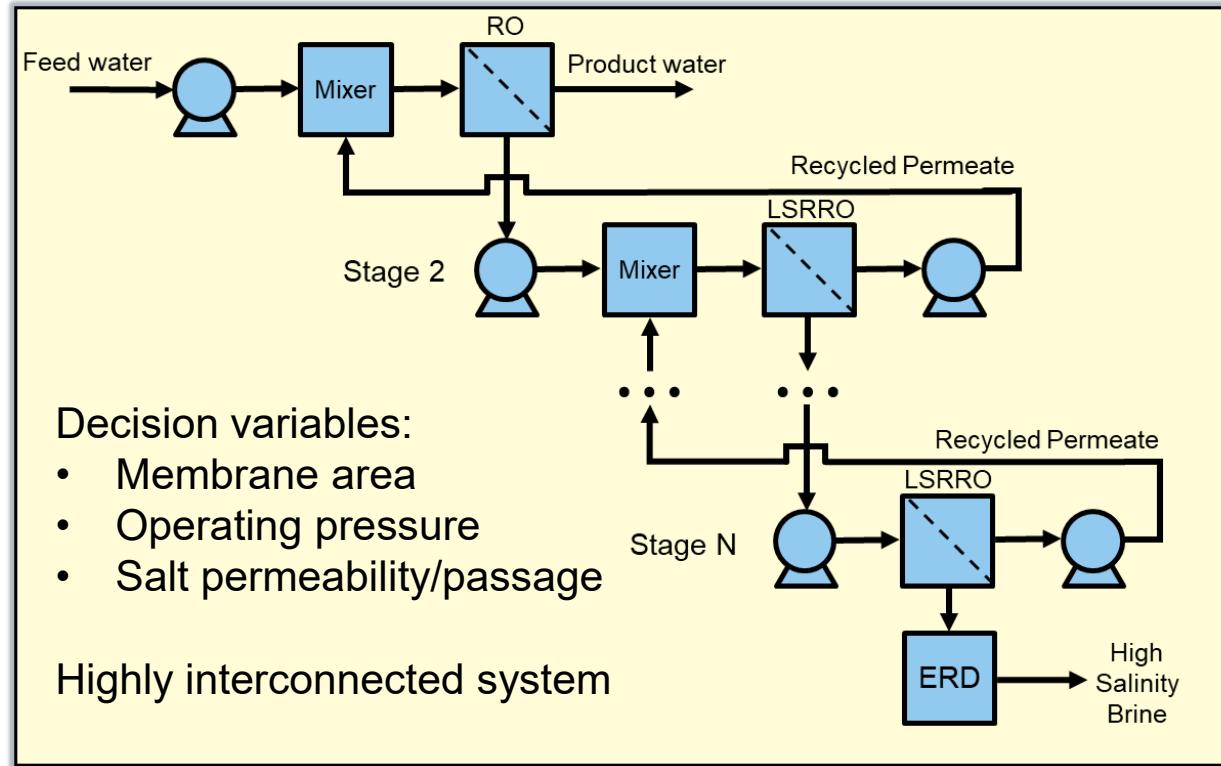
- Antiscalants, acid addition, and softening can likely achieve high recoveries
- Improvements in high concentration desal technologies has limited value



Water Recovery (%)

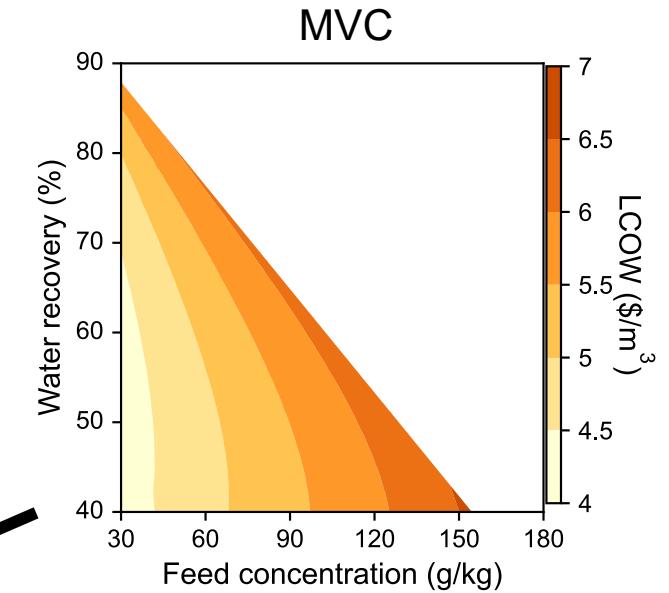
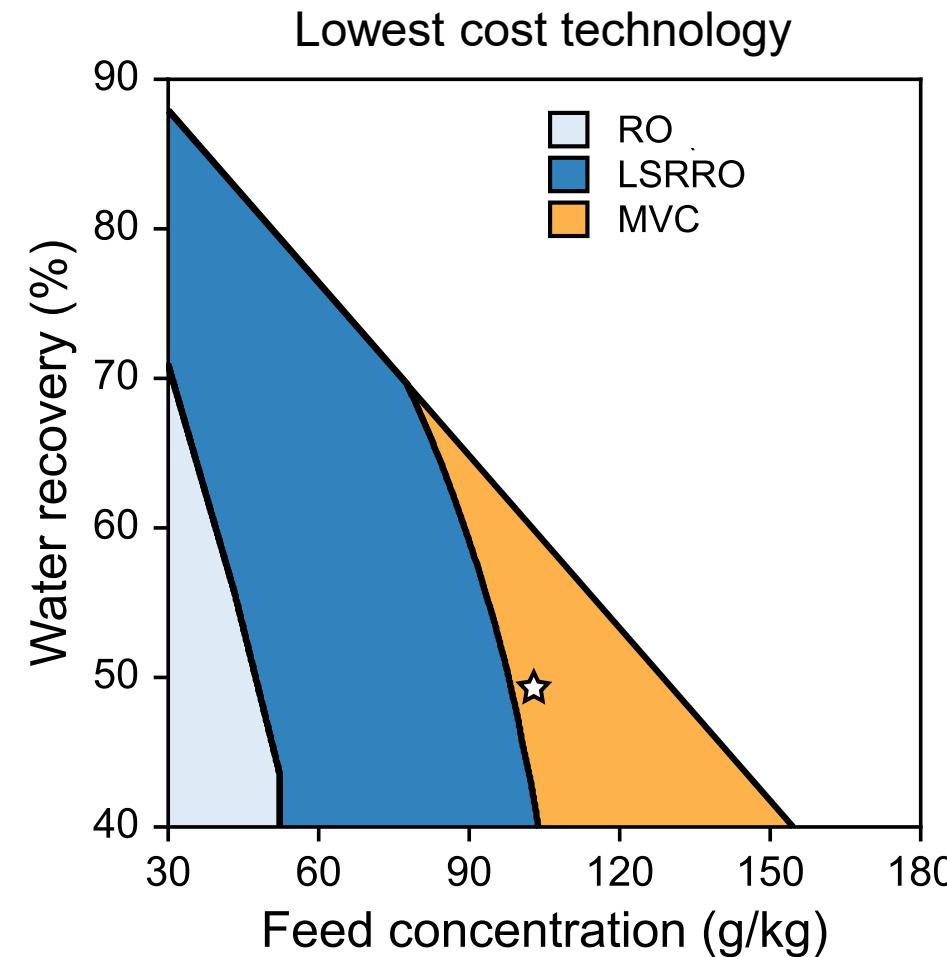
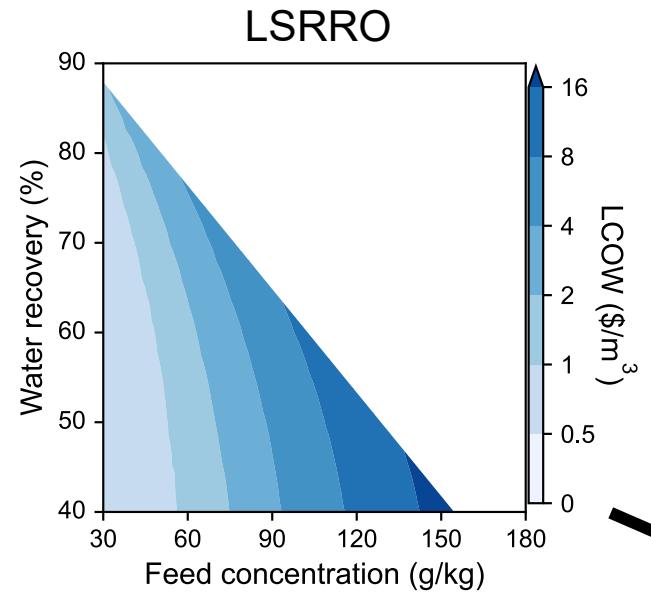
Exploring the potential of a novel membrane process

Low salt rejection reverse osmosis (LSRRO)



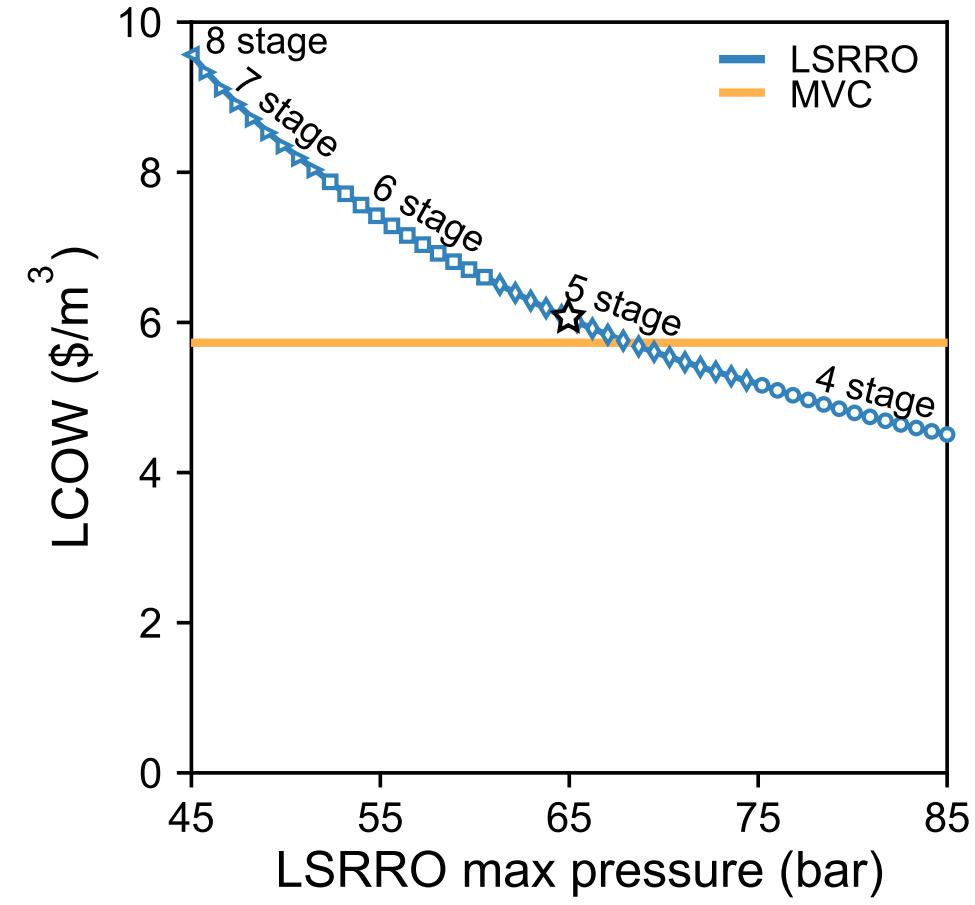
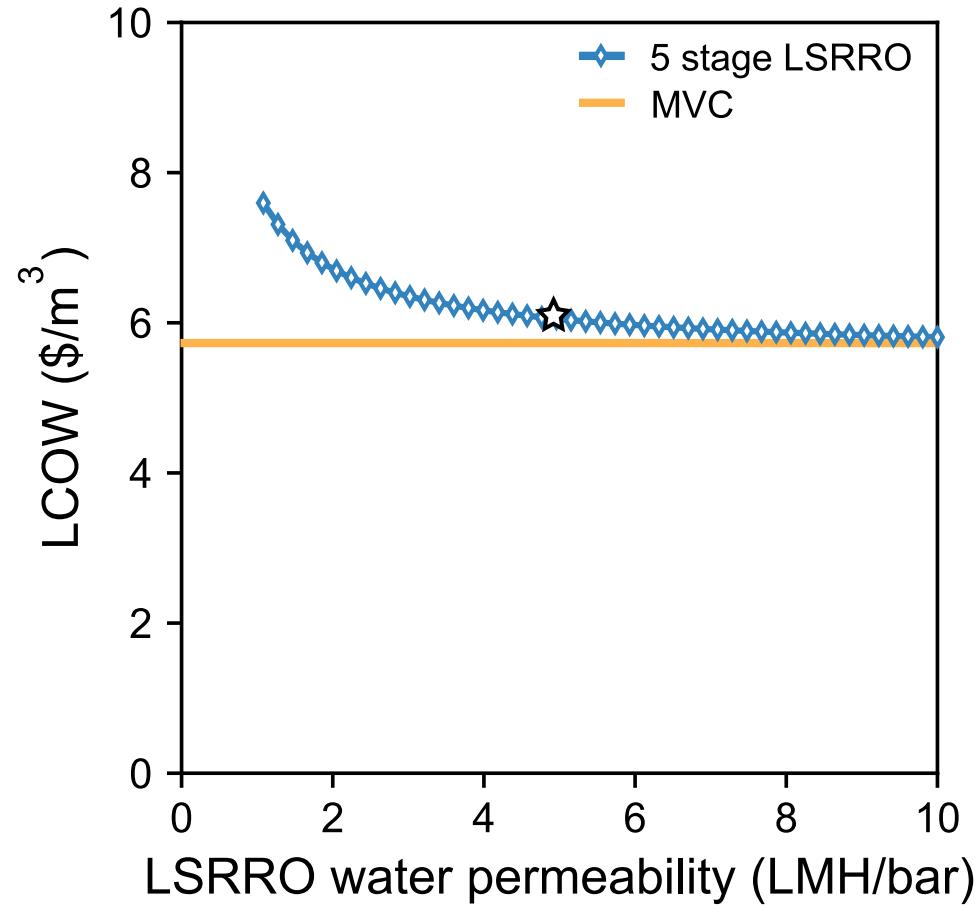
Quantifying technoeconomic viability through comparison

Case: 100 g/kg and 50% water recovery



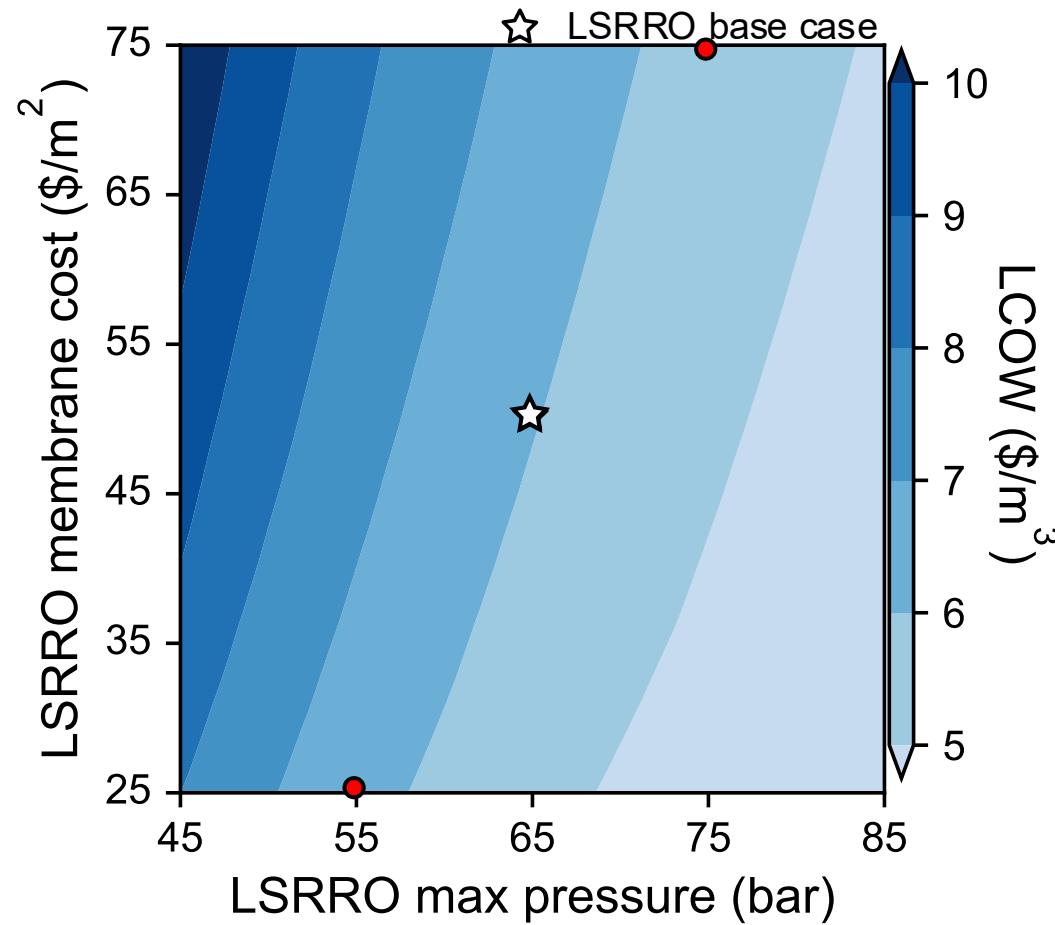
Using sensitivity analysis to prioritize development

Case: 100 g/kg and 50% water recovery



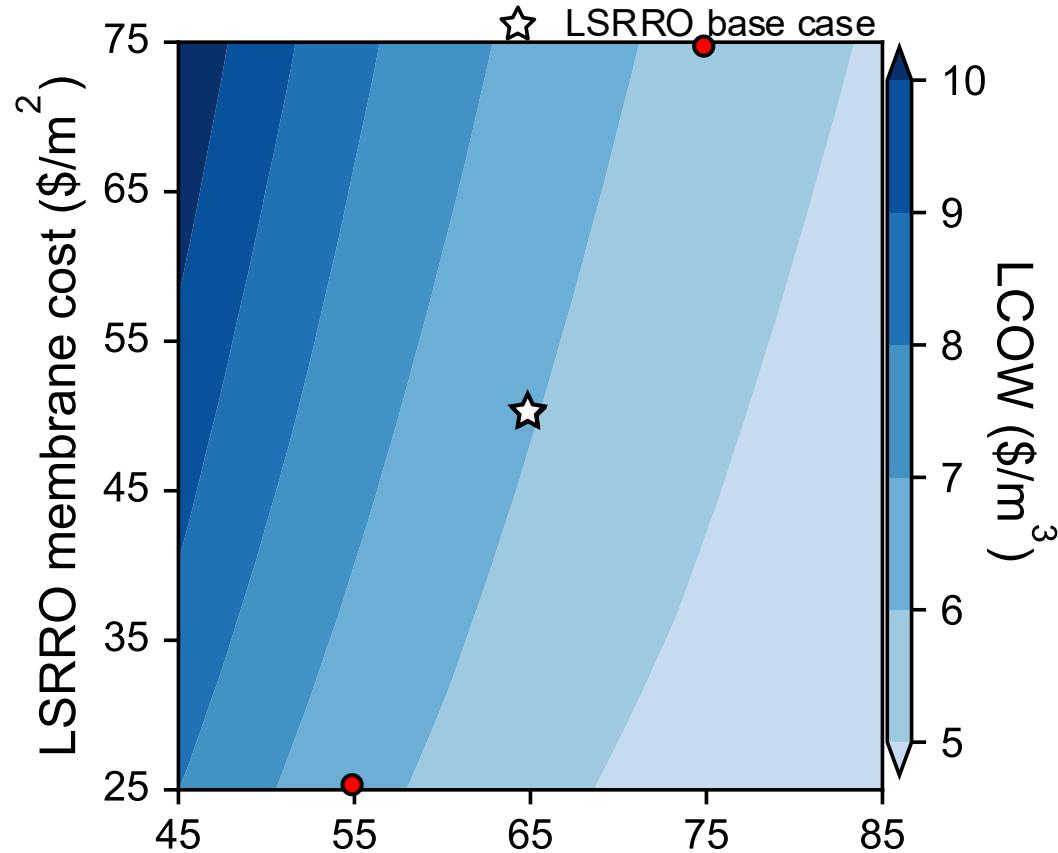
Identifying impactful and viable research targets

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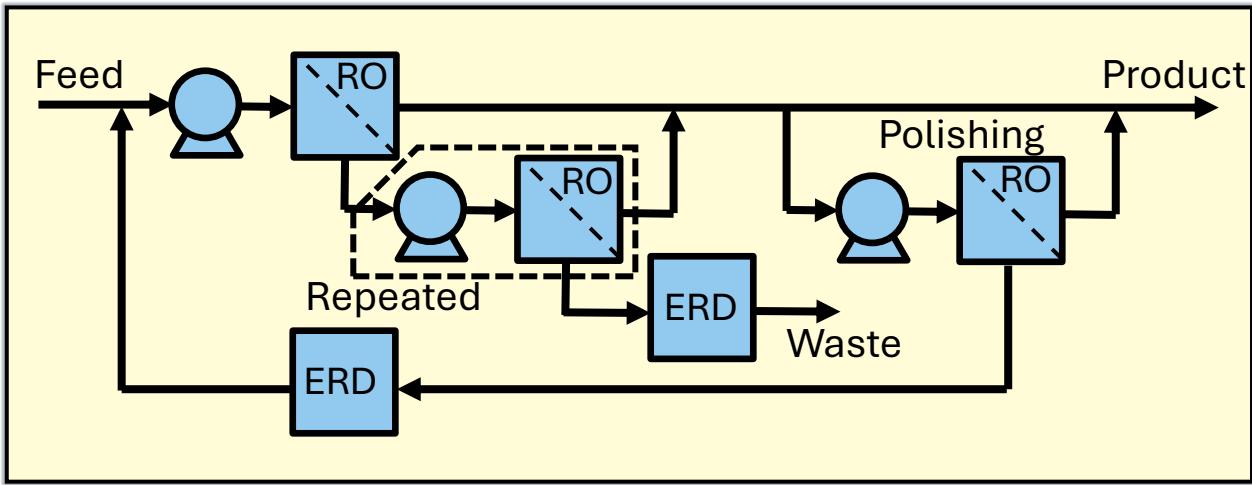
- LSRRO is a promising technology for feed salinities between 35-150 g/L TDS
- R&D should focus on increasing the maximum allowable pressure
- Mathematical optimization expands the analysis for the whole application space

Projecting the implications of bench-scale data



Prof. Eric Hoek

High pressure reverse osmosis (HPRO)

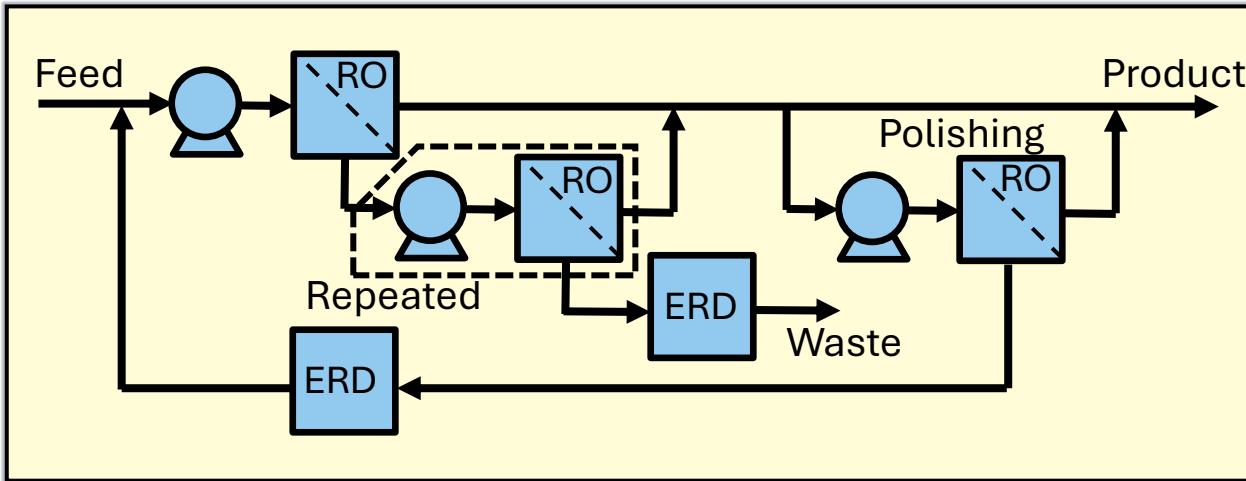


Two known challenges:

- Membrane compaction at high pressures decreases water permeability and increases salt permeability
- Equipment that operates at higher pressures are more expensive

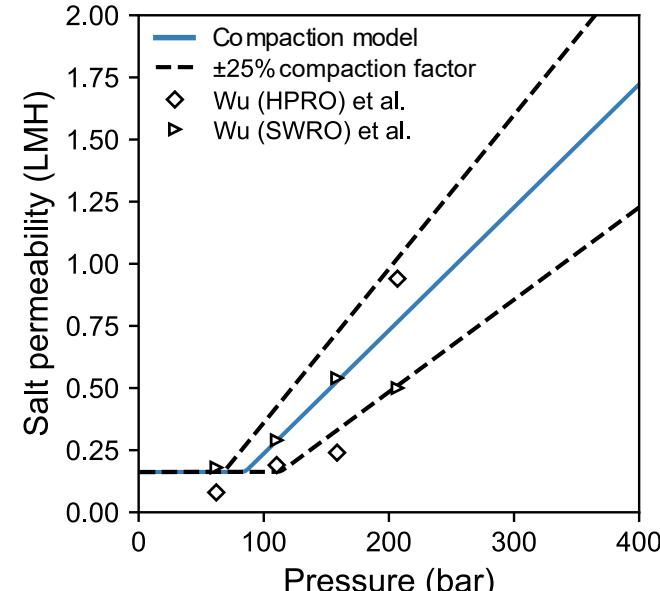
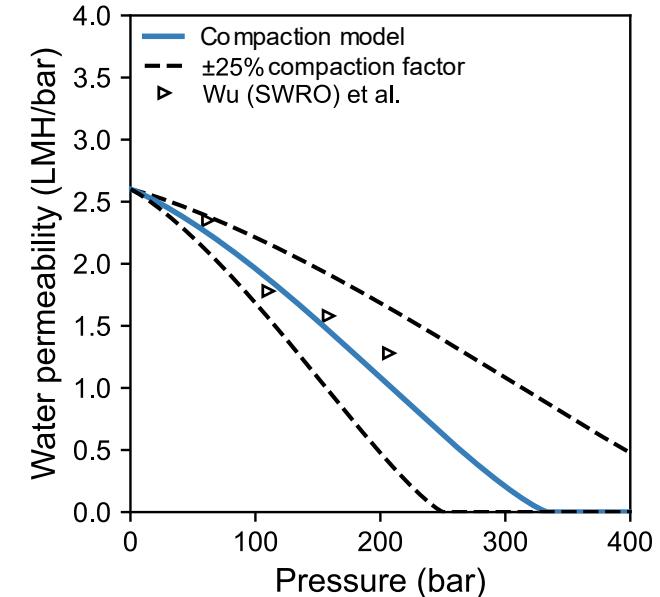
Projecting the implications of bench-scale data

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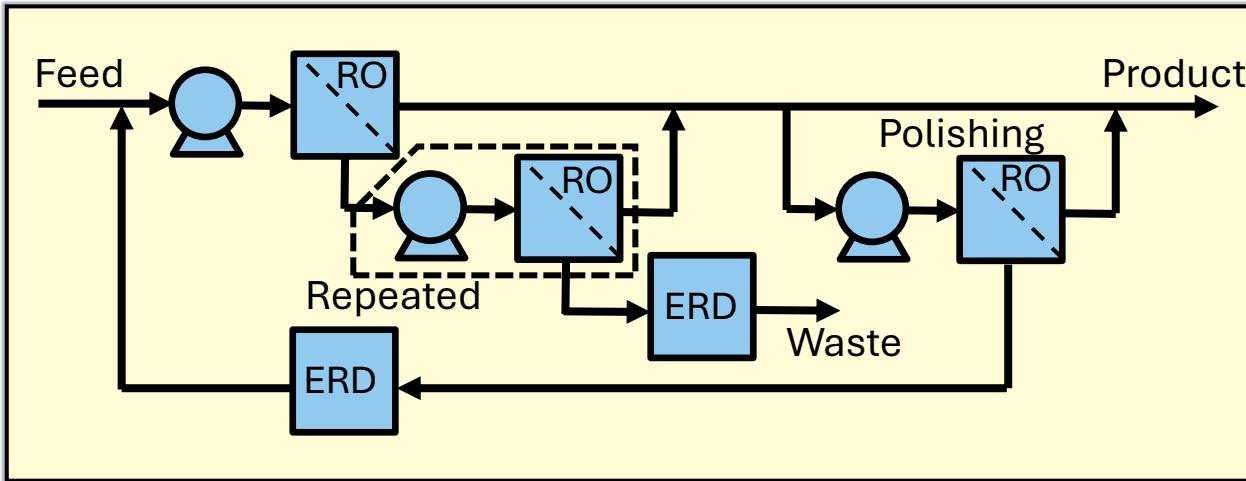
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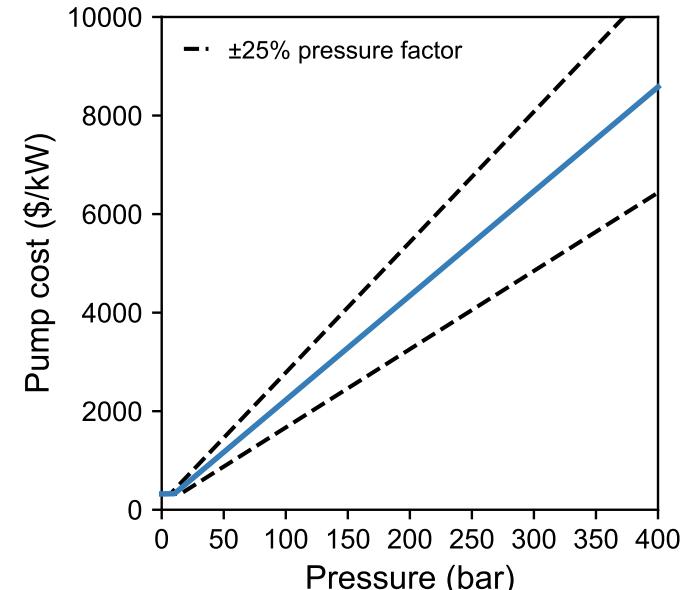
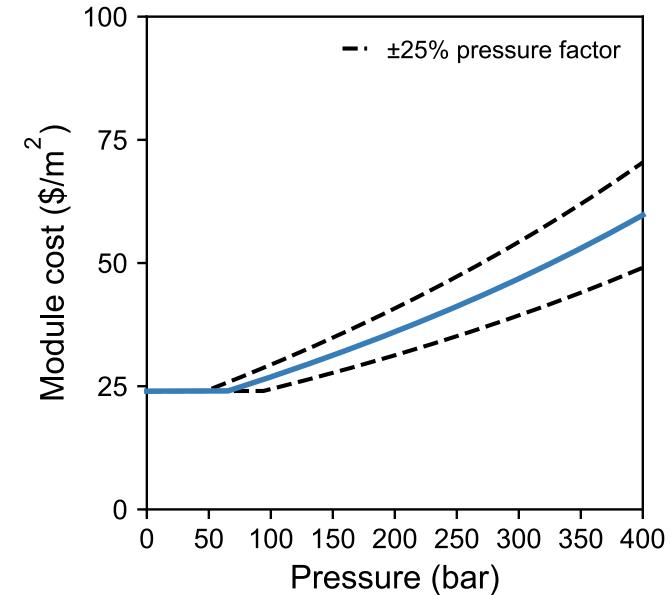
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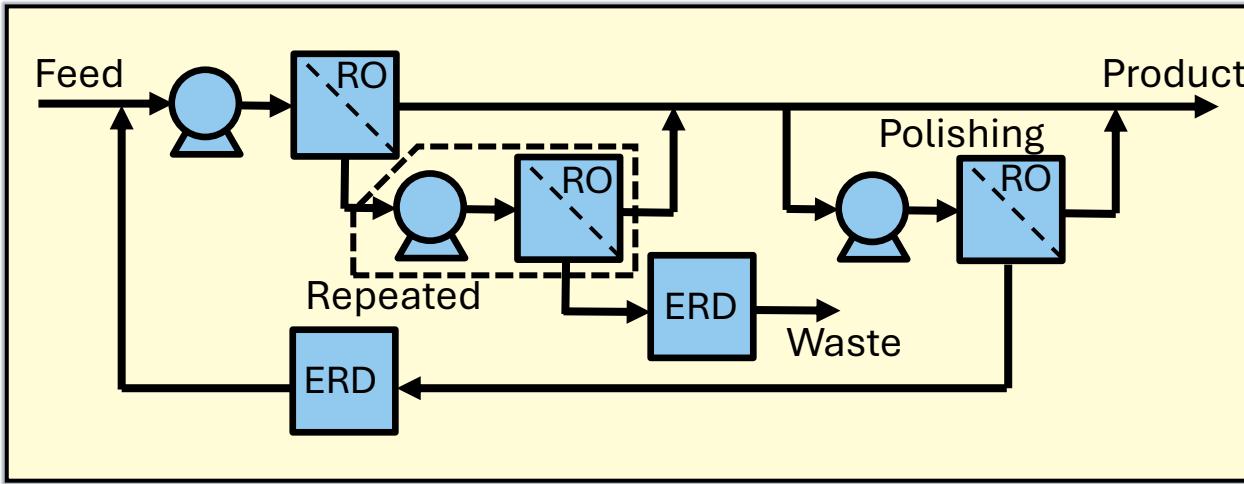
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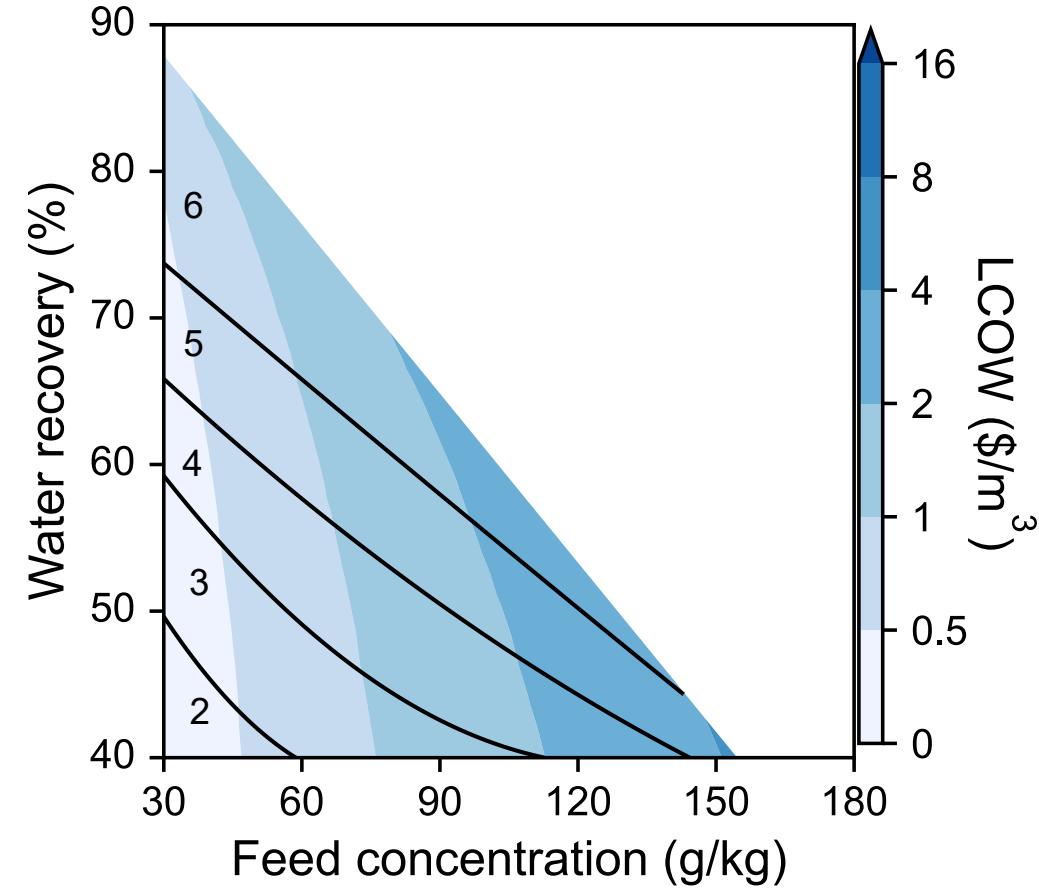
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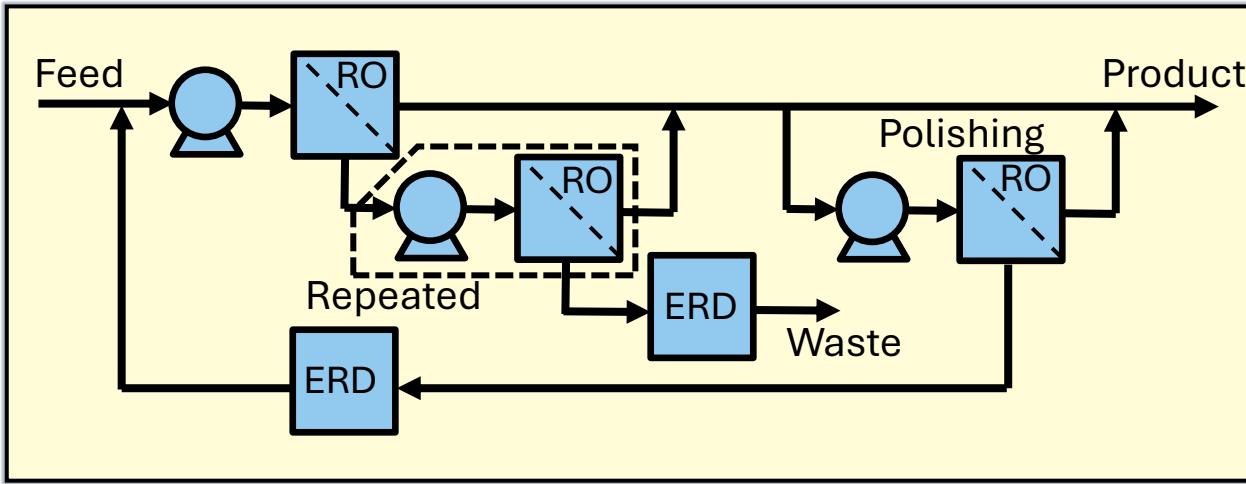
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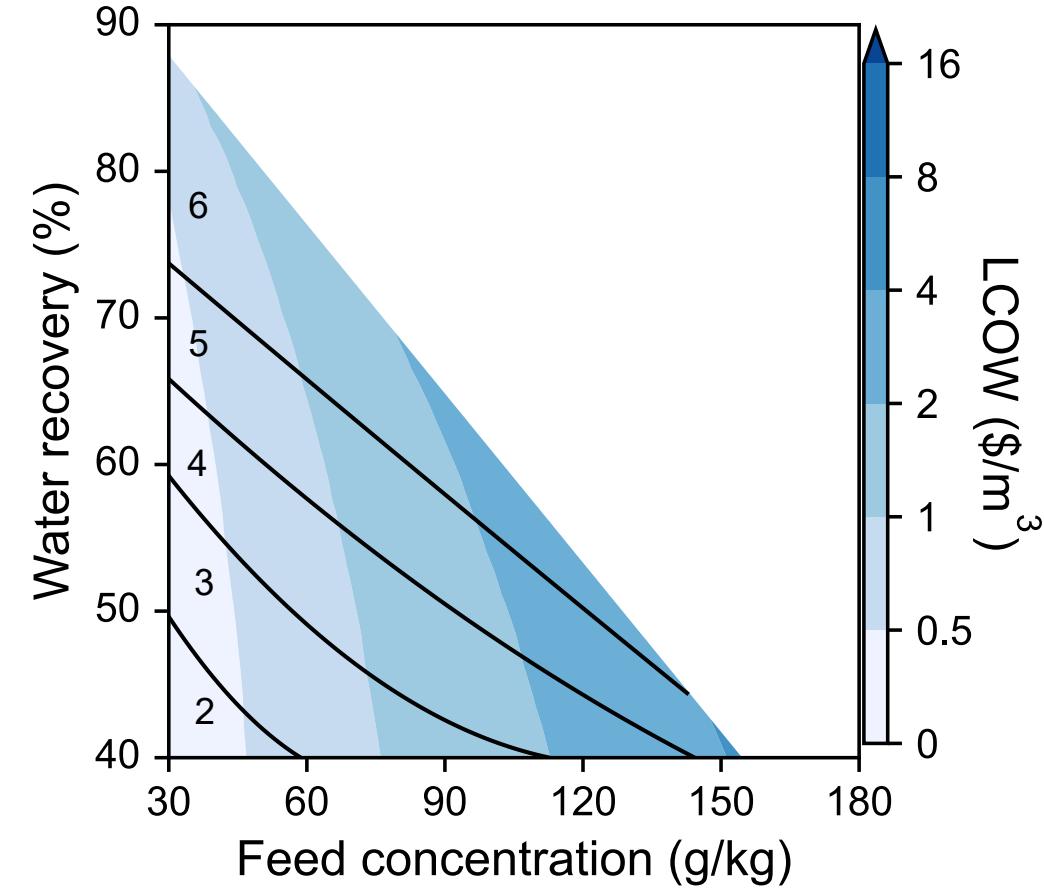
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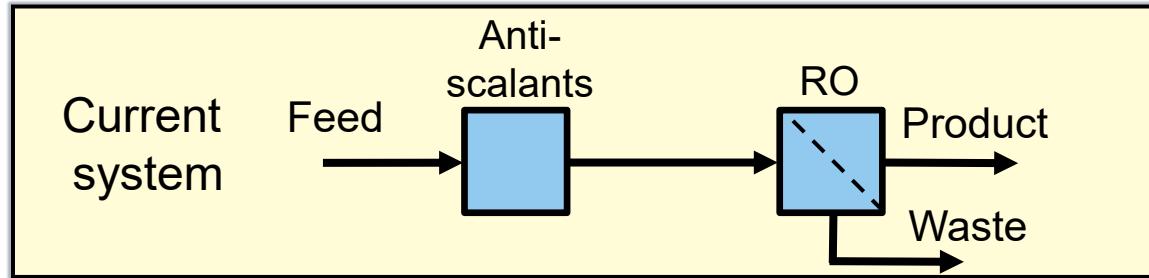
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- HPRO is promising despite membrane compaction and higher component costs
- Modular models enable rapid assembly of different systems (LSRRO and HPRO)

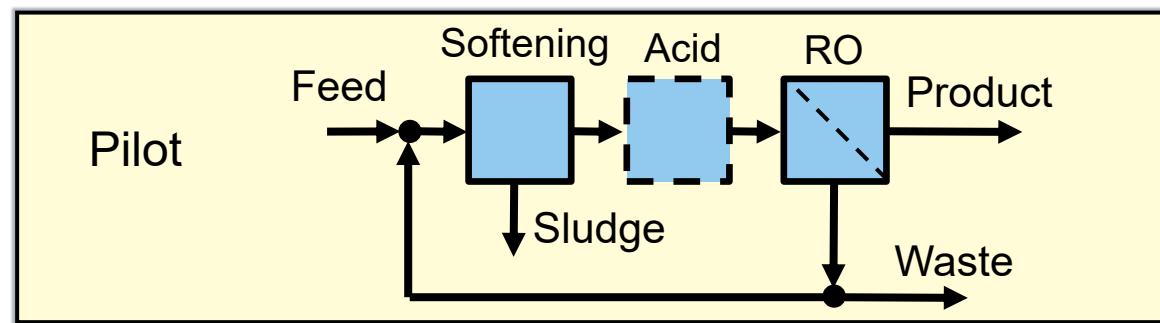
Assisting pilot design and operation

Distributed brackish water desalination in Kenya (off grid and driven by solar power)

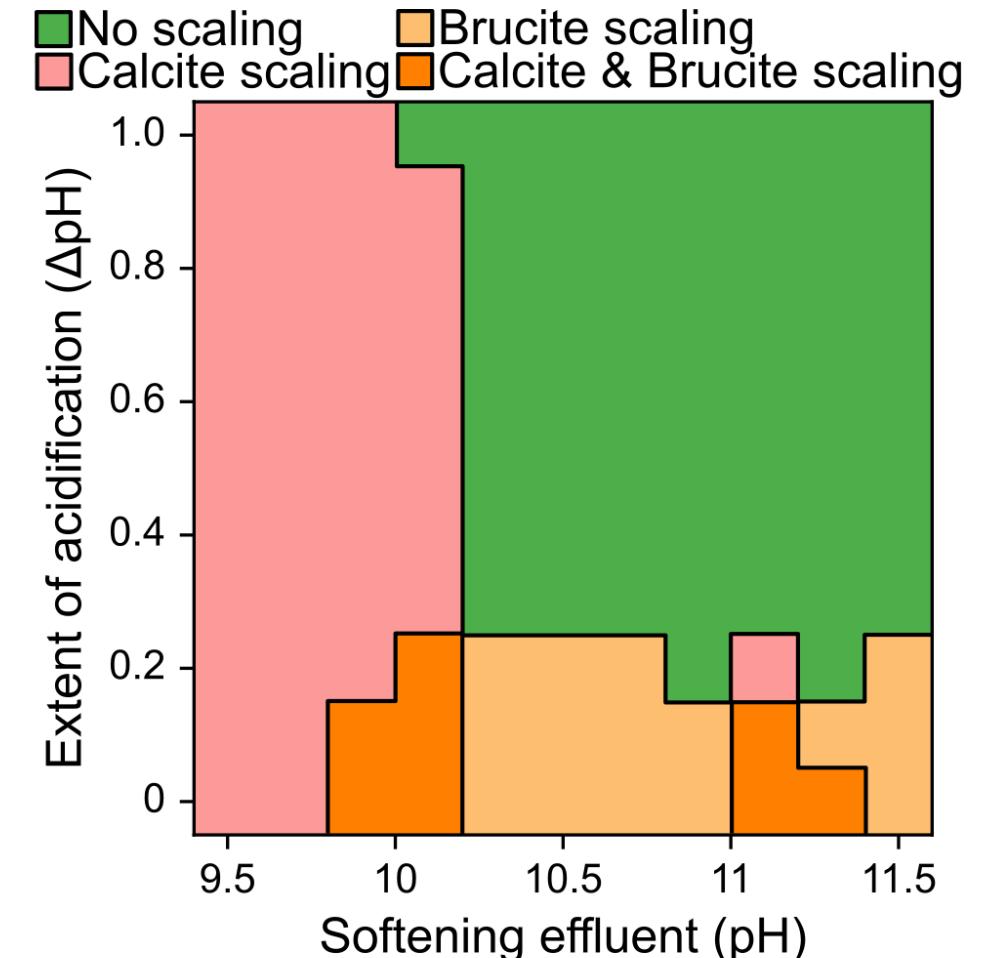


Pilot seeks to address two issues:

- Mineral scaling even with significant antiscalant dosing (at a high cost)
- High disposal volumes with only 50% water recovery

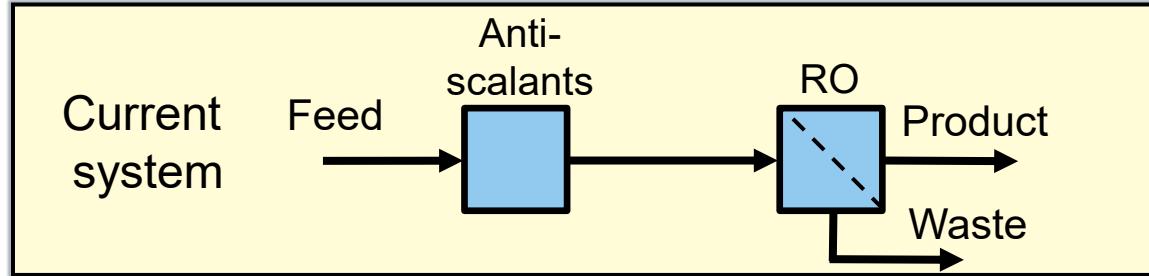


Prof. Manish Kumar



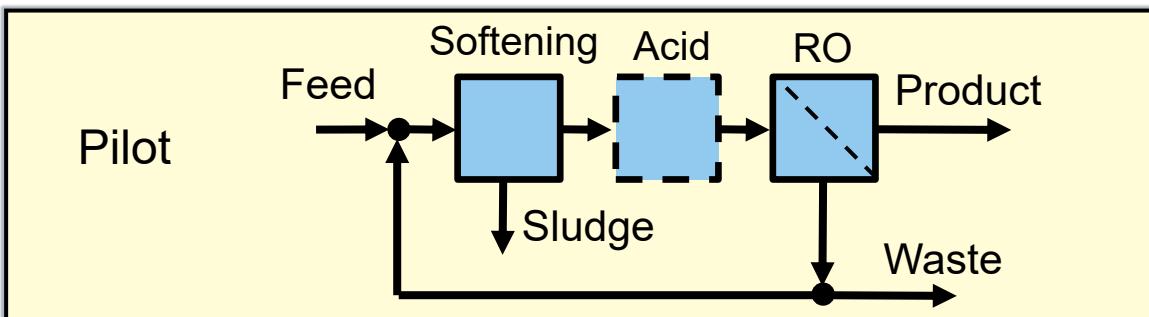
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Before



After



Benefits:

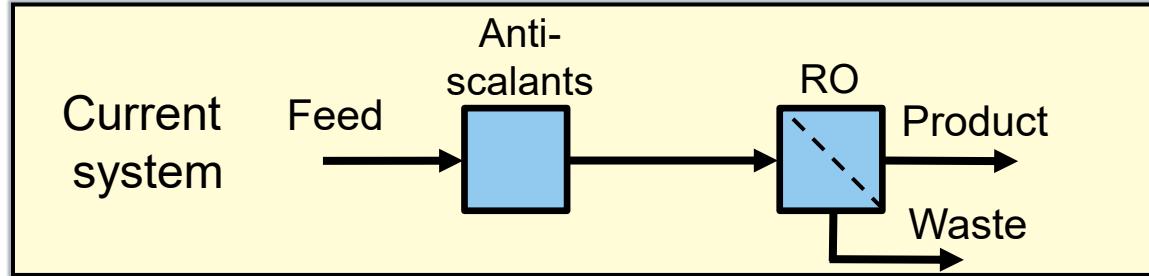
- Reduce brine production by 67.5%
- No use of antiscalants

Cons:

- Lime softening and waste sludge generation

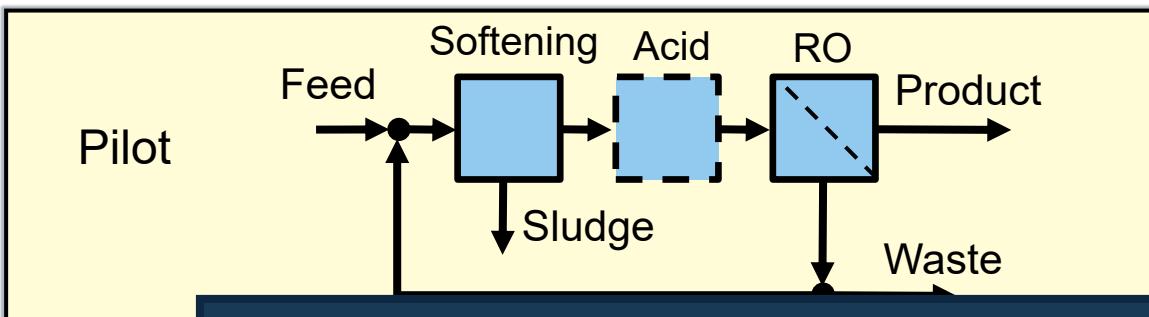
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- Bench-scale testing is extended with detailed process-scale modeling
- Analysis identified a risk for pilot failure and suggested the fix

Before



After



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- No use of antiscalants

Evaluating a potential commercial-scale retrofit

Large groundwater desalination plant

Analysis seeks to evaluate a potential retrofit:

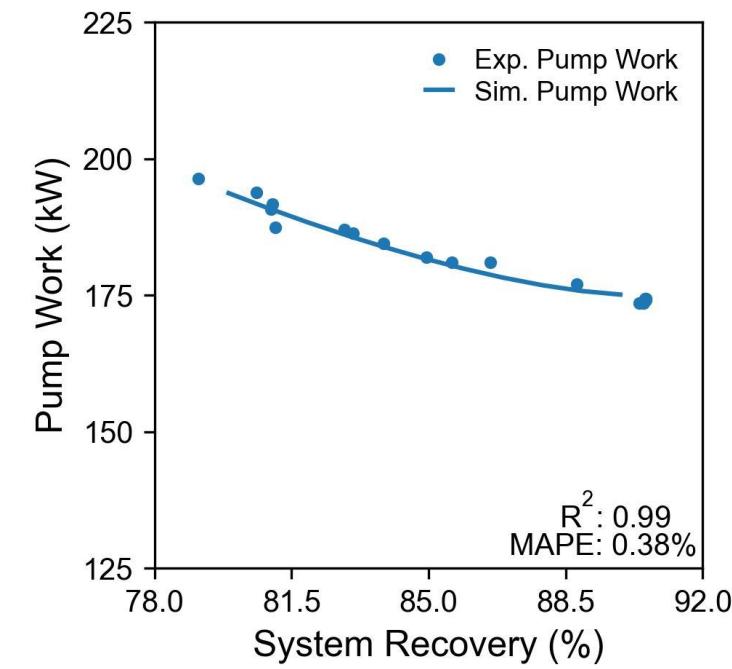
- Reduce disposal costs by increasing recovery
- Potentially add third stage RO with feed flow reversal to mitigate mineral scaling



Chino Basin Desalter



Prof. Mingheng Li



Evaluating a potential commercial-scale retrofit

Large groundwater desalination plant

Analysis seeks to evaluate a potential retrofit:

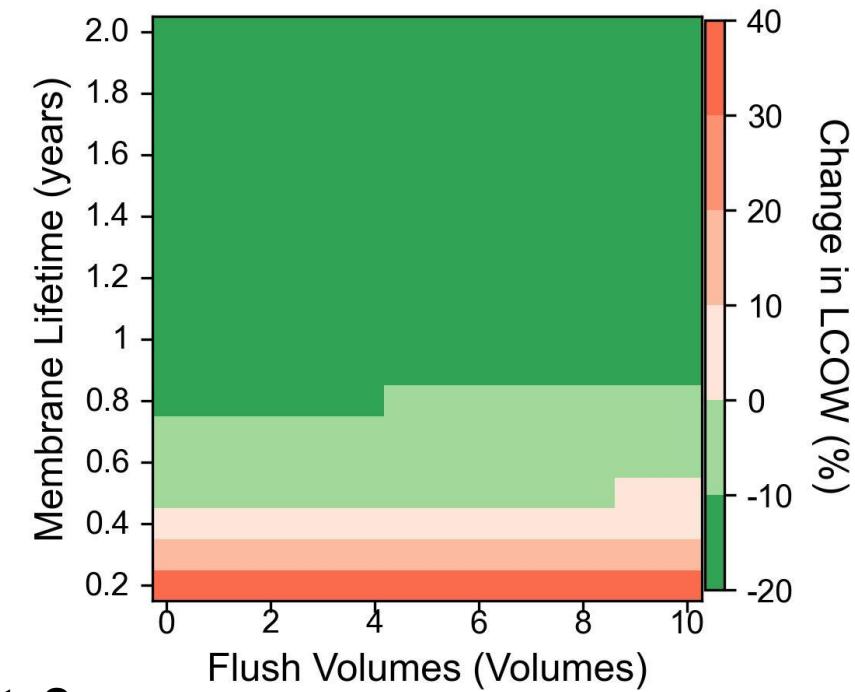
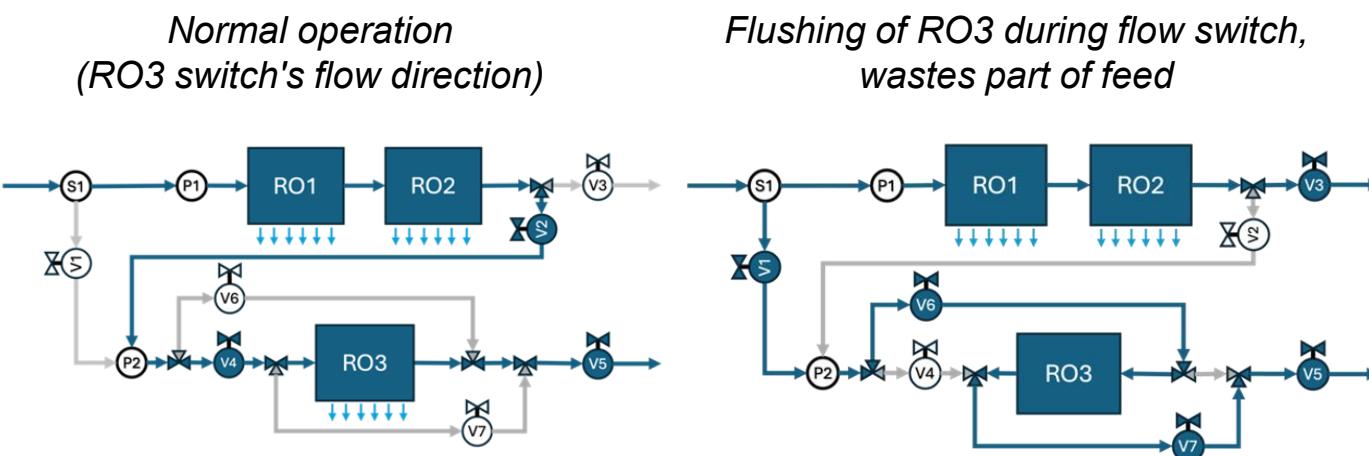
- Reduce disposal costs by increasing recovery
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Chino Basin Desalter



Prof. Mingheng Li



What impact does membrane life and flush volumes have on viability?

Evaluating a potential commercial-scale retrofit

Large groundwater desalination plant

Analysis seeks to evaluate a potential retrofit:

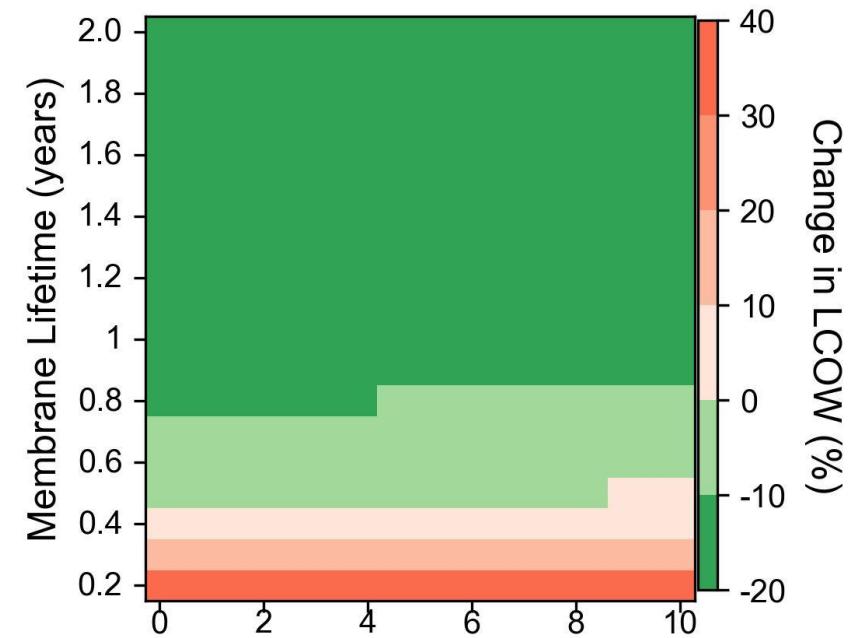
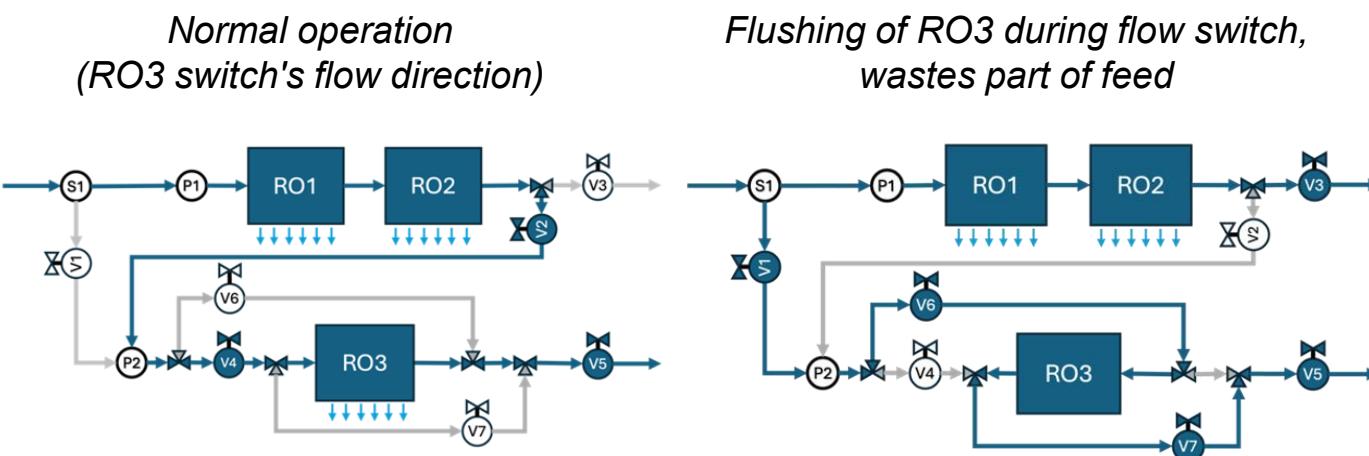
- Reduce disposal costs by increasing recovery
- Evaluate a third stage RO with feed flow reversal to mitigate mineral scaling



Chino Basin Desalter



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What impact

- Significant insight with varying two assumed performance parameters
- Suggests further investigation into membrane lifetime (not necessarily flushing)

WaterTAP has a broad water treatment library

Membrane:

- Reverse osmosis
- Osmotically assisted reverse osmosis
- Nanofiltration
- Membrane distillation

Evaporative:

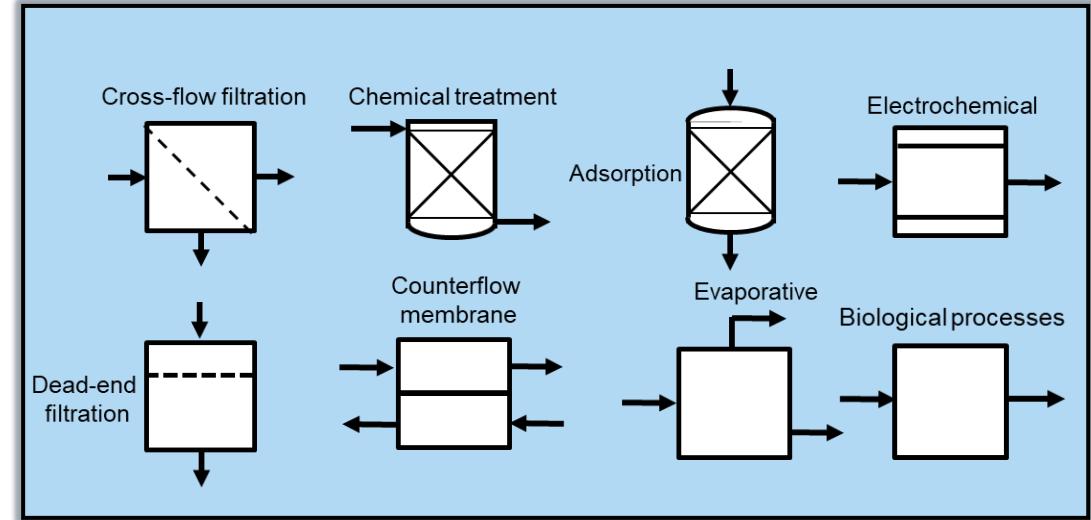
- Mechanical vapor compression
- Multi-effect distillation
- Crystallizer

Electrochemical:

- Electrodialysis
- Electrolyzer
- Electrocoagulation

Chemical:

- Stoichiometric and equilibrium reactors



Ad/absorption:

- Ion exchange
- Granular activated carbon
- Solvent extraction

Biological:

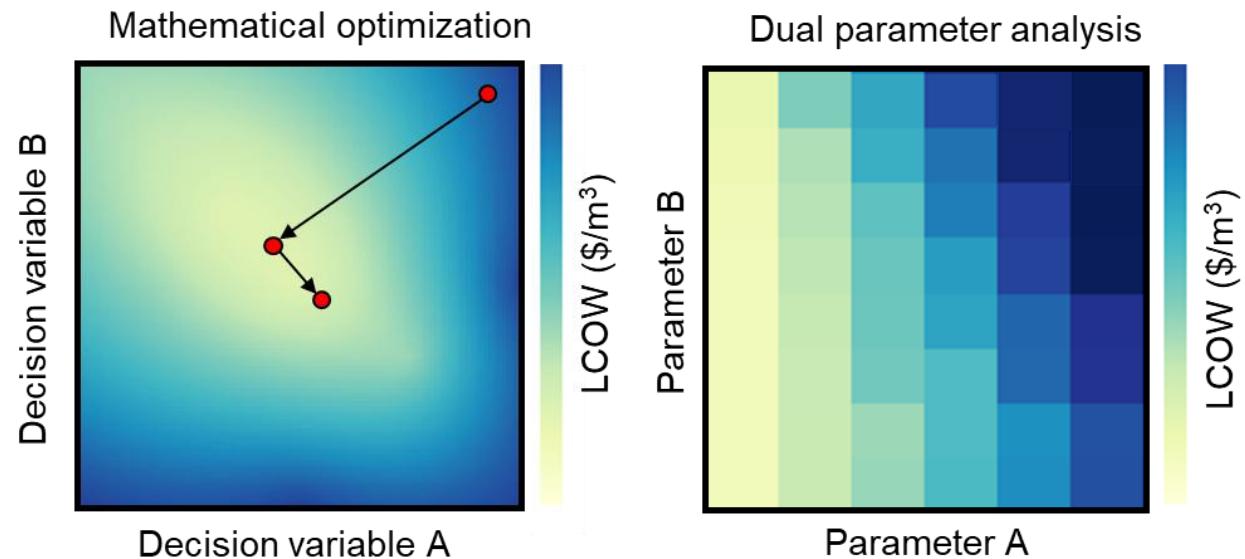
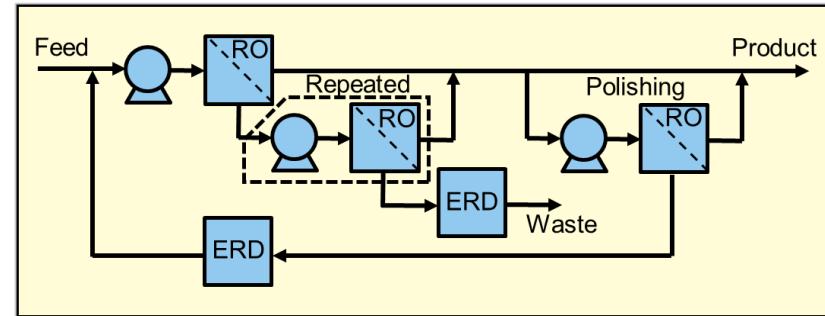
- Activated sludge
- Anaerobic digestor

Auxiliary equipment:

- pumps, heat exchangers, mixers, splitters

Process scale modeling provides value in TEAs

- Use process and cost models that:
 - Link key design and operating variables to the performance and cost
 - Represent the system, not just the technology
- Use mathematical optimization to handle the design and operating variables
- Consider uncertainty through deterministic and stochastic sensitivity analyses
- Incorporate real world data through:
 - Parameter estimation with mechanistic models
 - Hybrid models with data-driven surrogate models



TEA provides quantitative decision support for R&D

Predictive process modeling with optimization transforms TEAs:

- Evaluate full application space and identify most promising ones
- Determine best design and operation for a model and specified parameters
- Focus analysis on modeling assumptions and parameters, not decision variables
- Pinpoint technical and financial bottlenecks and determine priority for development
- If model predictions are shown to be inaccurate, they can be updated with implications assessed quickly

Process systems engineering and TEA can support bench and piloting efforts:

- Plan – support system design and experimental campaign to achieve objectives
- Operate – fault detection and attribution, suggest modifications
- Evaluate – project the implications of the data for commercial scale deployment

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Questions?