Opportunities for Process Intensification with Membranes to Promote Circular Economy Development for Critical Minerals

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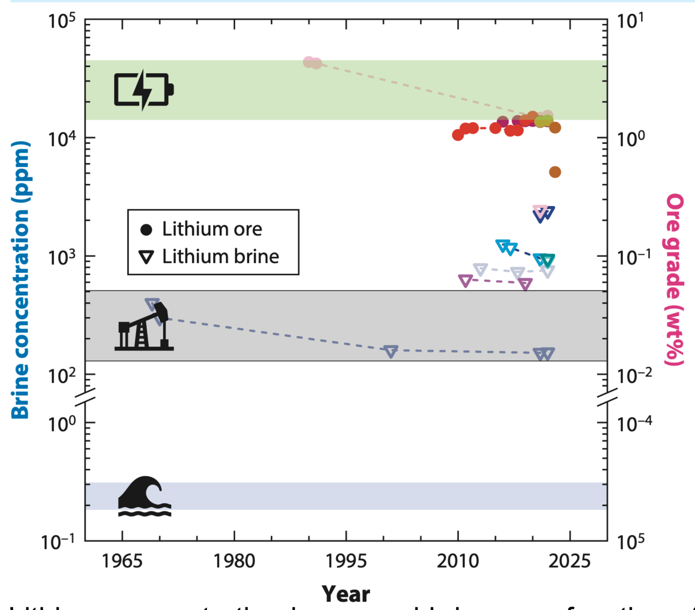
PROMMIS
Process Optimization and Modeling for Minerals Sustainability

Evolving supply chains necessitate revolutionizing critical mineral processing.[1]

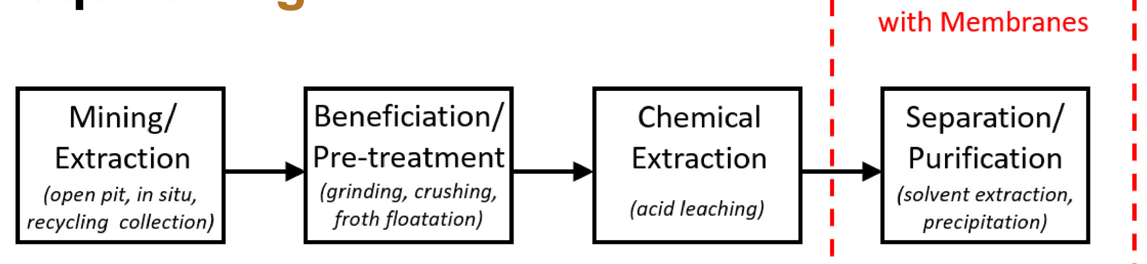


Lithium concentration in ore and brine as a function of time, where the green, grey, and blue bands show lithium concentration ranges in electric vehicle battery packs, oil field brine, and seawater, respectively. Data point colors correspond to geographical locations.[1]

Demand for critical minerals is expected to continue **rising**, and only **5%** of lithium-ion batteries are **recycled** worldwide.[2]

Membranes can offer environmentally responsible processing routes.[1]

Conventional technology requires **significant resources.**



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For more information, please reach out to Thomas Tarka, PrOMMiS Technical Director (Thomas.Tarka@netl.doe.gov)

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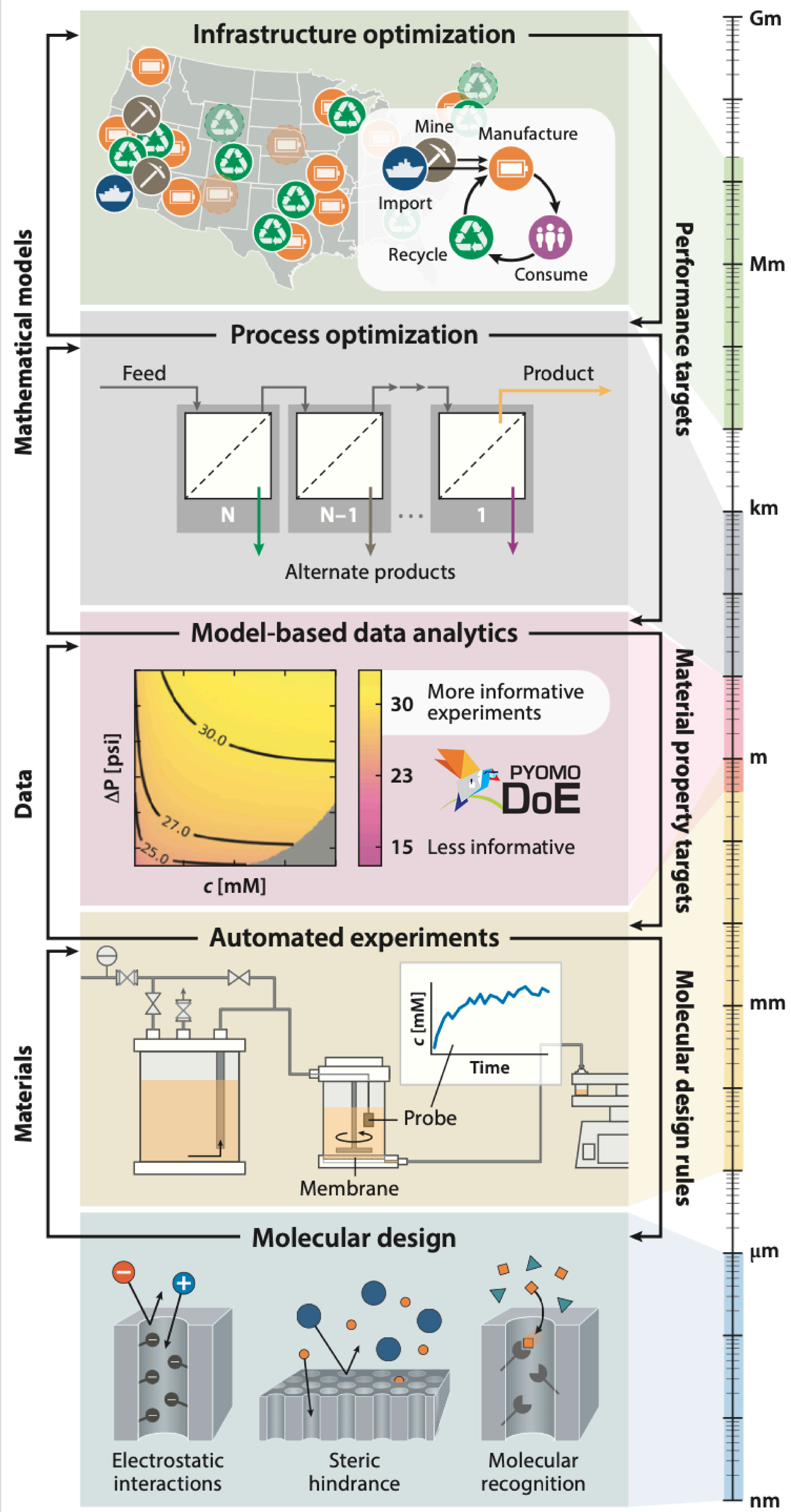
Bi-directional feedback across scales de-risks technology development and scale-up.[1]



Supply Chain Optimization

Stochastic programming incorporates **uncertainty** into optimization with economic and environmental objectives.[3,4]

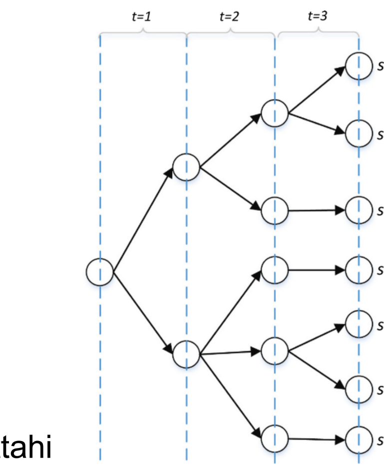


Figure: Fattahi

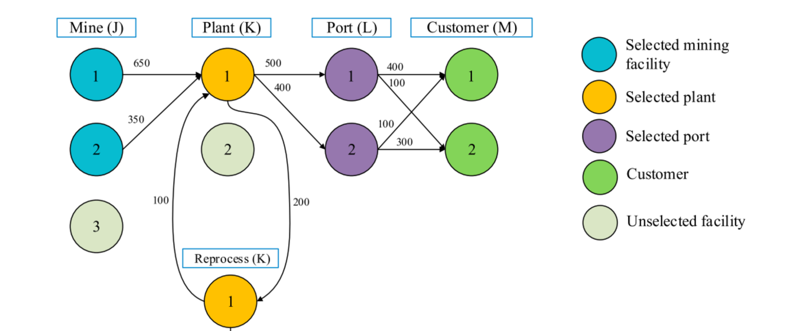
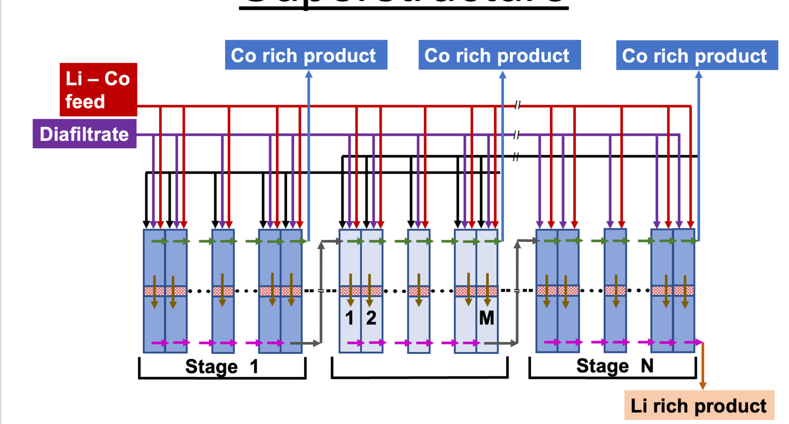


Figure: Canales-Bustos *et al.*

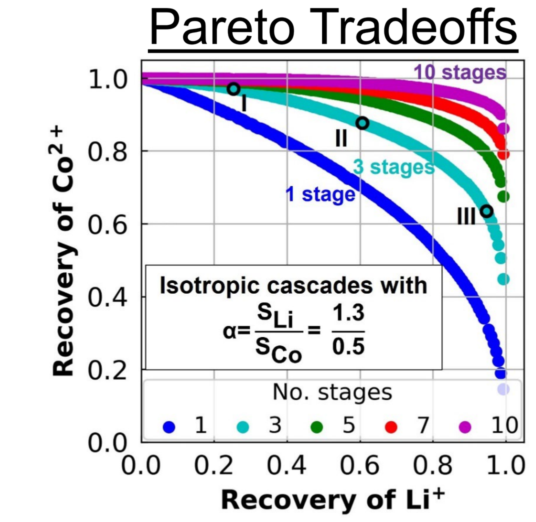
Process Design and Optimization

Superstructure optimization enables rapid design of customizable membrane cascades, simultaneously **evaluating tradeoffs** in ion recovery.[5]

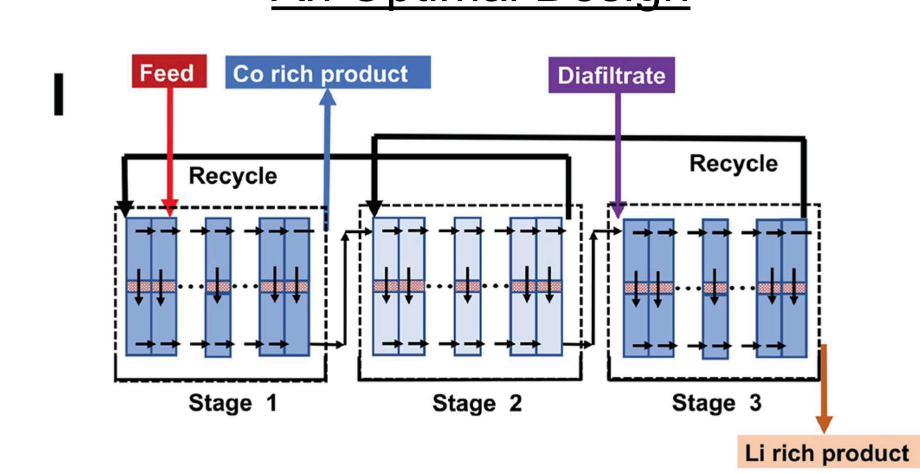
Superstructure



Pareto Tradeoffs



An Optimal Design



Figures: Wamble *et al.*

Increasing Experimental Efficiency

Process systems engineering automation techniques push towards **self-driving laboratories.**[6,7]

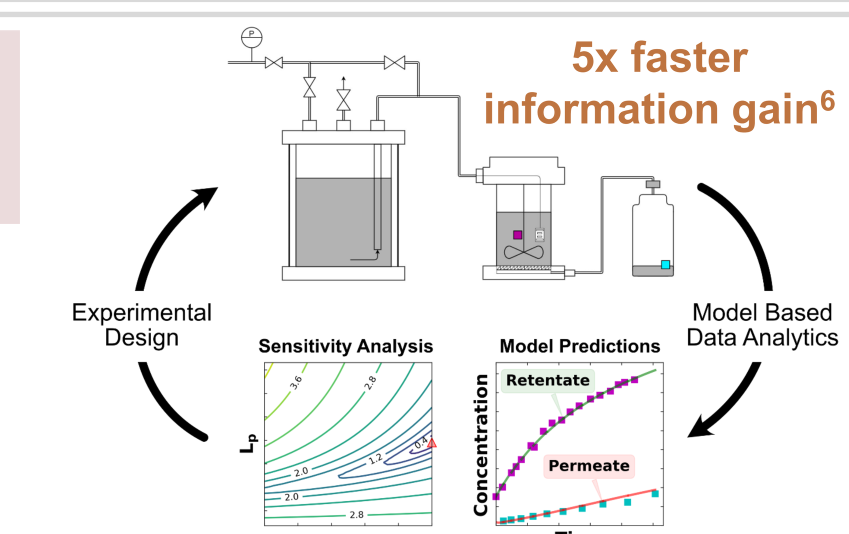


Figure: Ouimet *et al.*

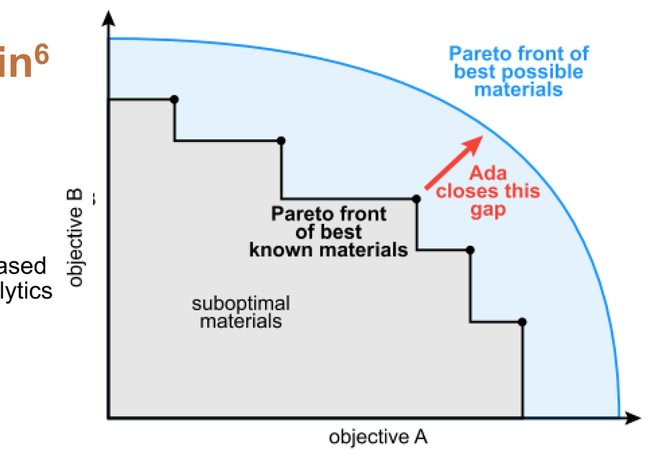
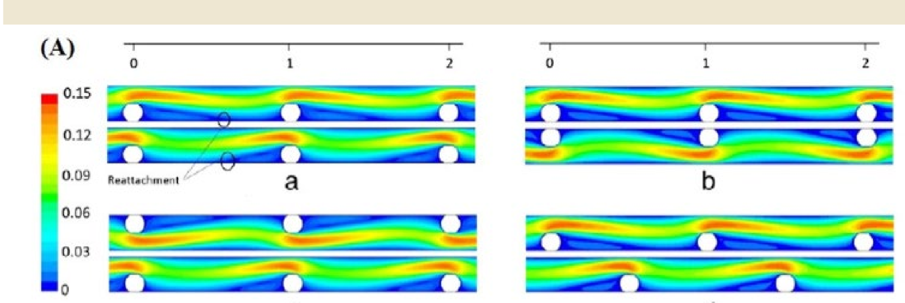
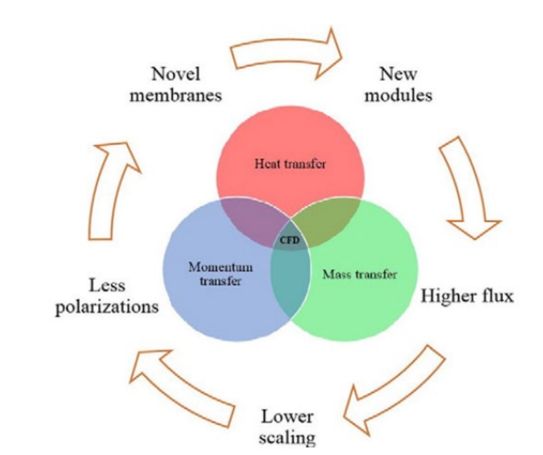


Figure: MacLeod *et al.*

Optimizing Membrane Modules



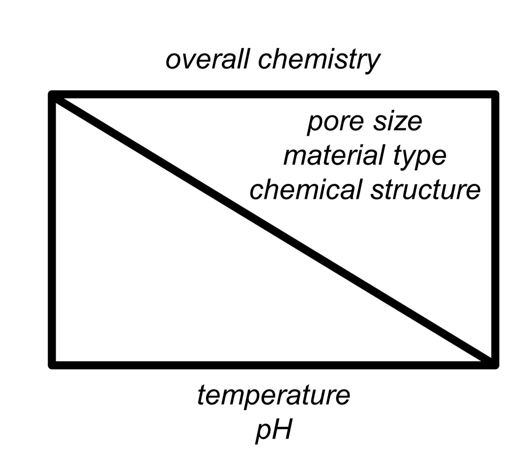


Figures: Shirazi *et al.*

Computational fluid dynamics optimizes the transport and flow profiles within membrane devices.[8]

Machine Learning Accelerating Material Design

The **large design space** of membranes[9] is efficiently explored with **machine learning techniques** such as Bayesian optimization.[10]



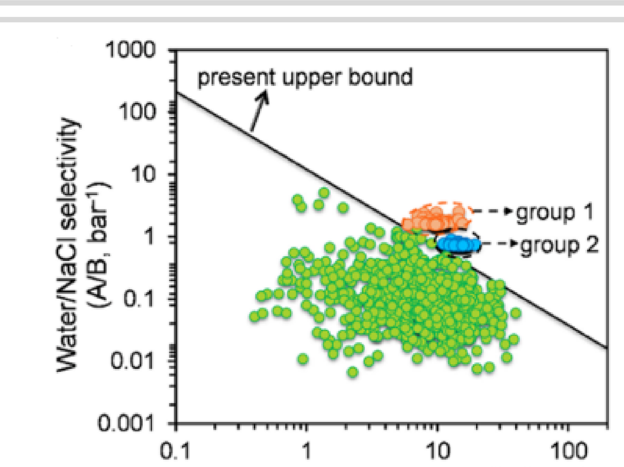


Figure: Gao *et al.*

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