Direct Repurposing of Spent Battery Electrodes for Water Desalination

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Education

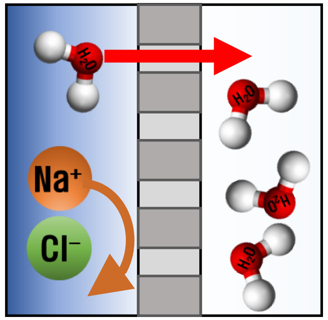
Professional Experiences

B.S.	Ph.D.	Post.Doc.	Res. Prof.	Senior Res. | Assoc. Prof.
Yonsei Univ.	Gwangju Inst. Sci. Tech.	Penn State Univ.	Ulsan Nat'l Inst. Sci. Tech.	Korea Inst. Sci. Tech.
Environ. Eng.	Environ. Eng.	Civil & Environ. Eng.	Urban & Environ. Eng.	Center for Water Cycle Research
	Prof. Heechul Choi	Prof. Bruce E. Logan	Prof. Kyung Hwa Cho	

2006 • 2010 • 2017 • 2020 • 2024

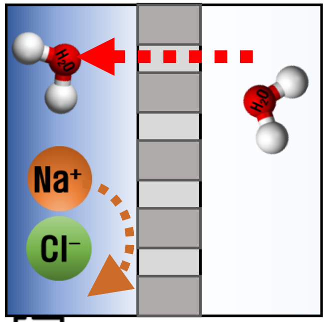
Nano-Membranes

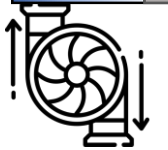
Water | *Energy*



$\Delta P > \Delta\pi$

Reverse Osmosis



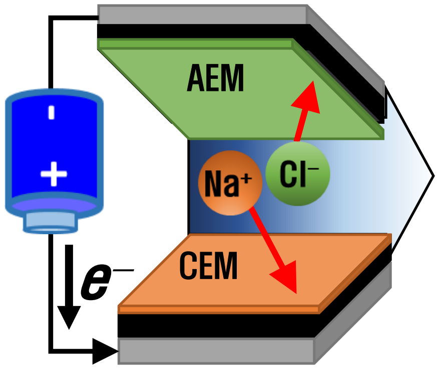


$\Delta P < \Delta\pi$

Pressure Retarded Osmosis

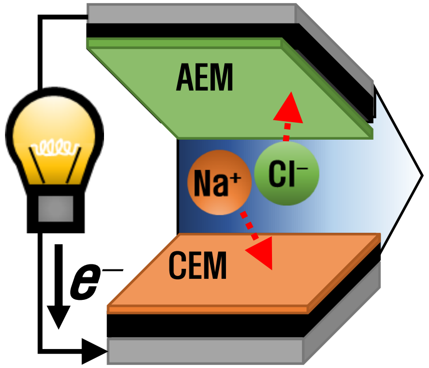
Electrochemical Separations

Water | *Energy*



$E_{applied} > E^0_{cell}$

Capacitive Deionization

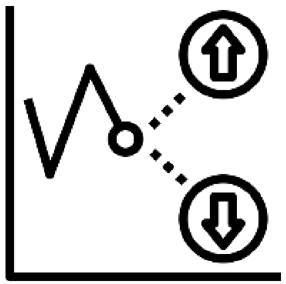


$\vec{F} = E^0_{redox\ or}\ E^0_{chem.\ attrac.}$

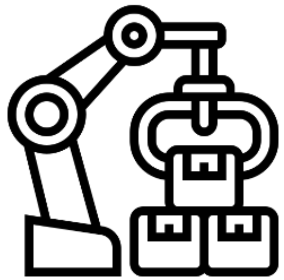
Desalination Battery

Artificial Intelligence

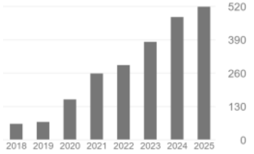
Prediction | *Automation*



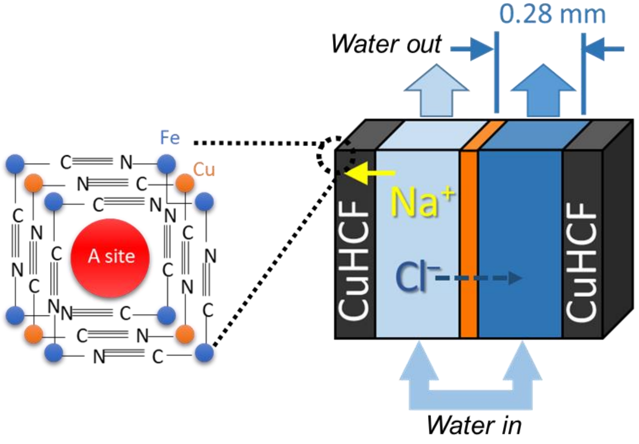
Deep Learning Machine Learning



Reinforcement Learning

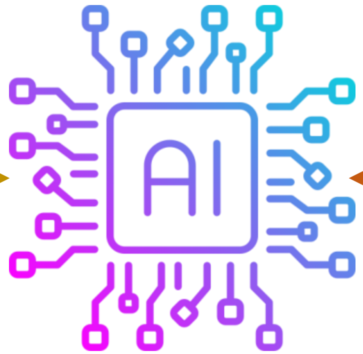


Total Citation: 2325
H10-index: 60
As of Oct., 2025



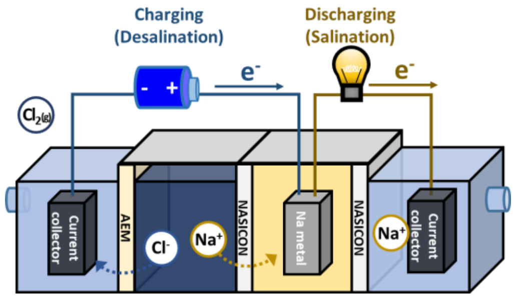
Water

- **Low-energy Desalination**
- **Water Treatment**



Energy

- **Spent Lithium-ion Batteries**
- **Seawater Battery**
- **Urine Power Cell**



- **Explainable AI**
- **Automation**

Waste-to-X

- **Wastewater-to-fertilizer**
- **Wastewater-to-CO_2 capture**
- **Seawater-to-H_2**

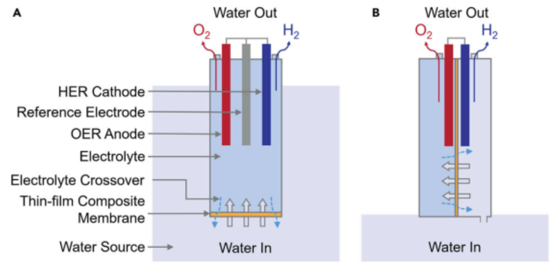
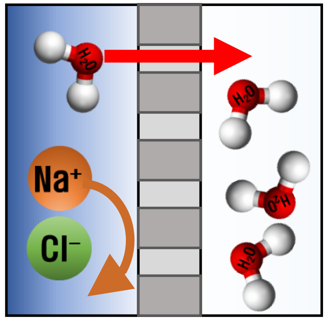


Figure 1. Schematic of the main components for two types of water electrolyzer cells that incorporate forward- or reverse–osmosis-type membranes

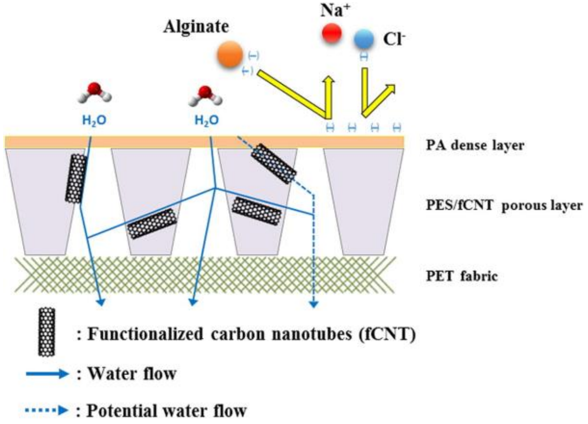
Physical (RO) vs. Electrochemical (CDI)

Artificial water channel



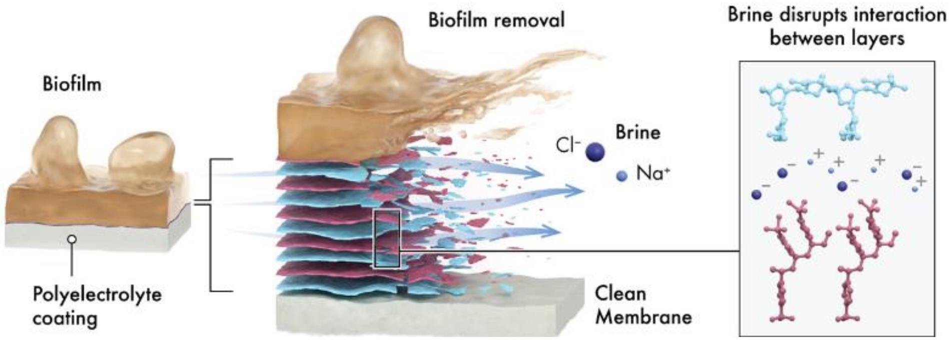
$\Delta P > \Delta\pi$

Reverse Osmosis (RO)

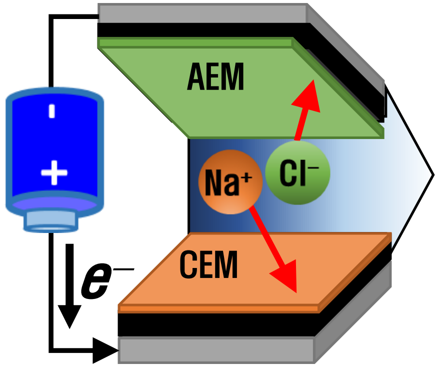


Chem. Eng. J, 2015 & 2016

Replenishable nano-film

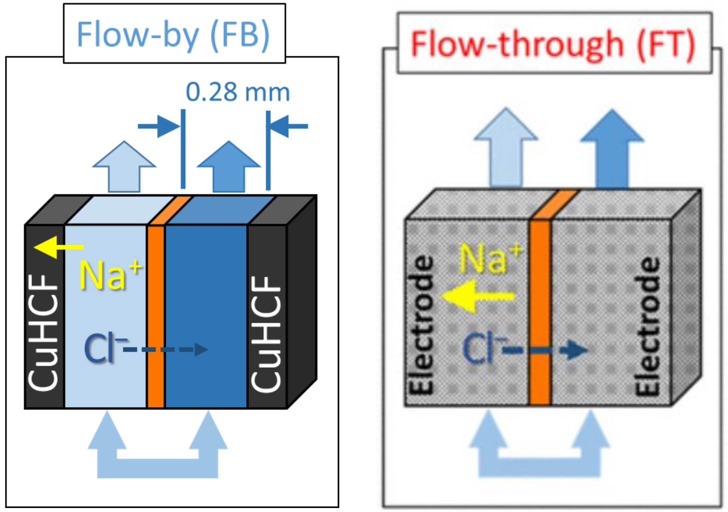


Environ. Sci. Technol. Lett. 2018
Desalination. 2020

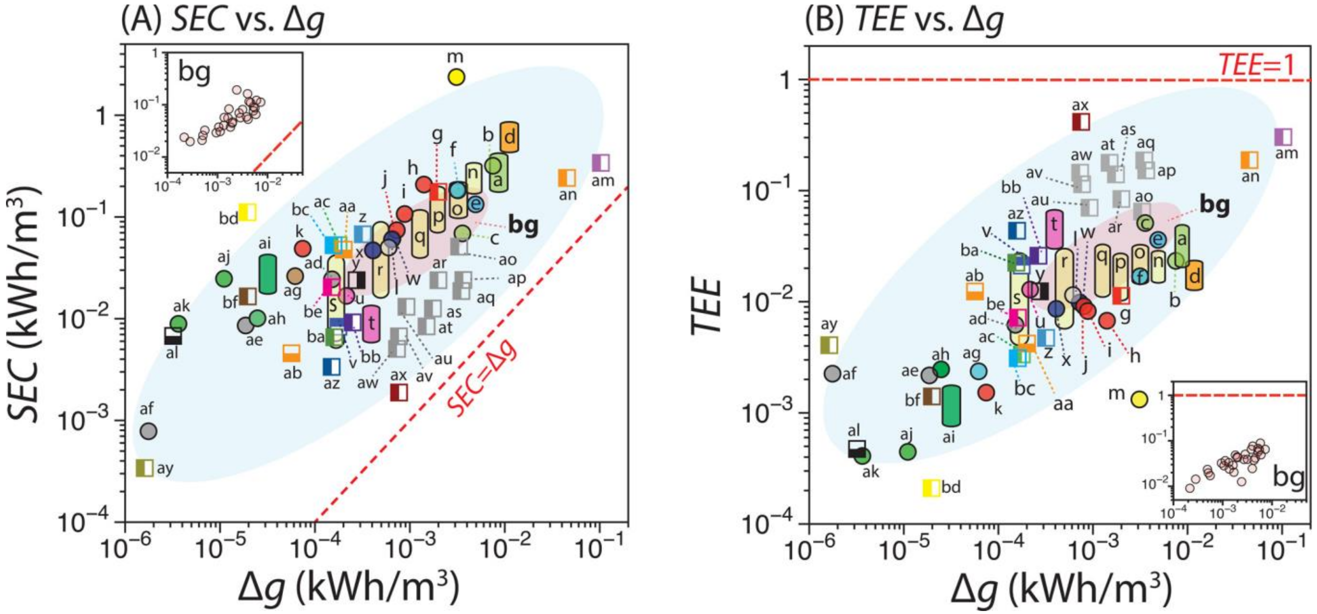


$E_{applied} > E^0_{cell}$

Capacitive Deionization (CDI)



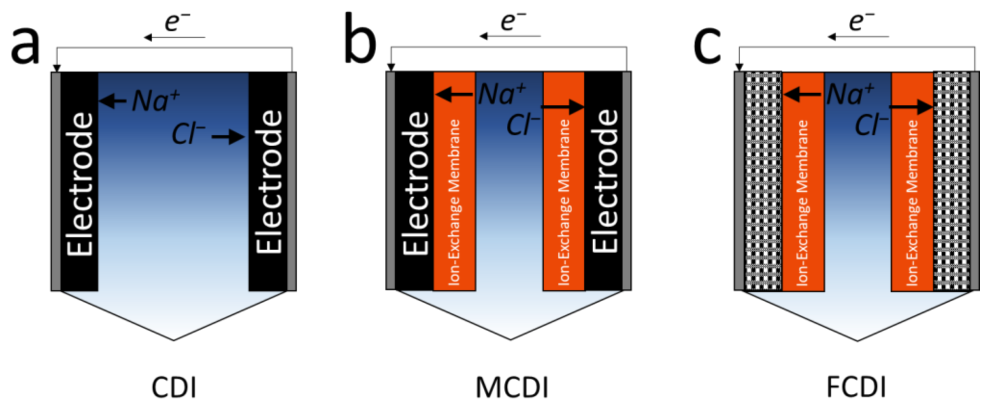
Environ. Sci. Technol., 2020



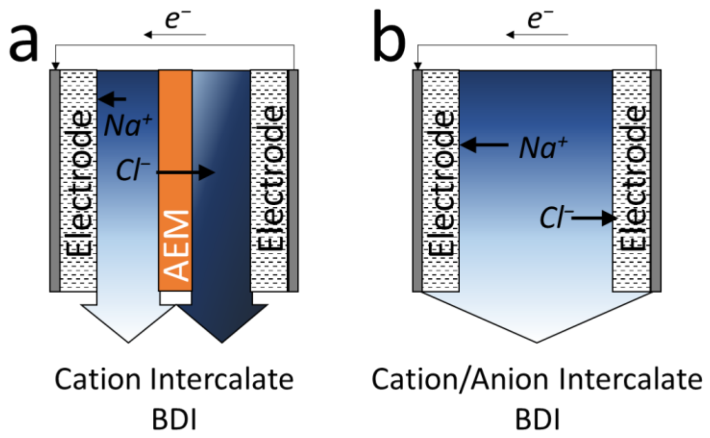
Environ. Sci. Technol., 2019

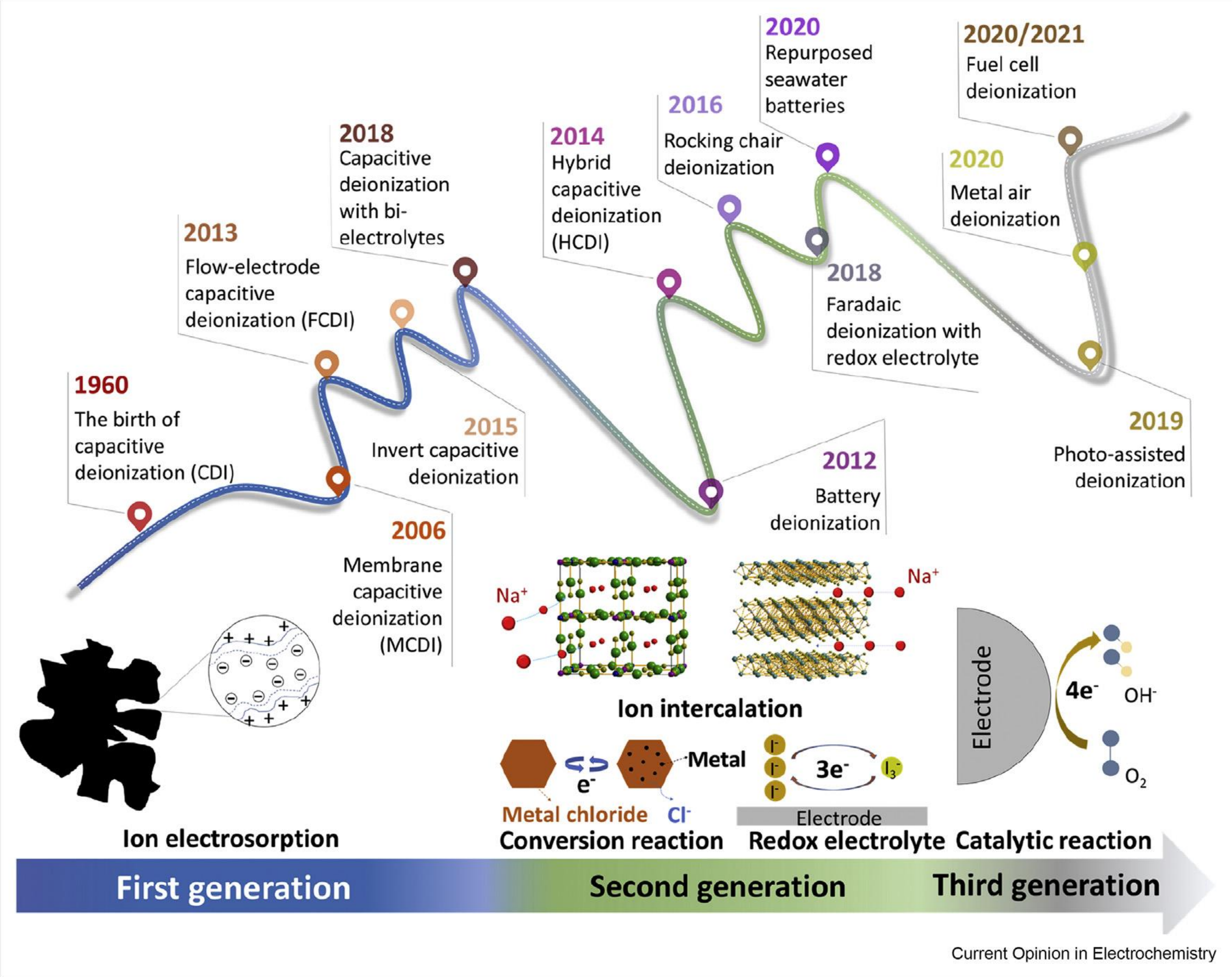
CDI: Electrochemical Desalination

l Ion non-selective (CDI: Capacitive De-Ionization)



l Ion selective (BDI: Battery electrode De-Ionization)

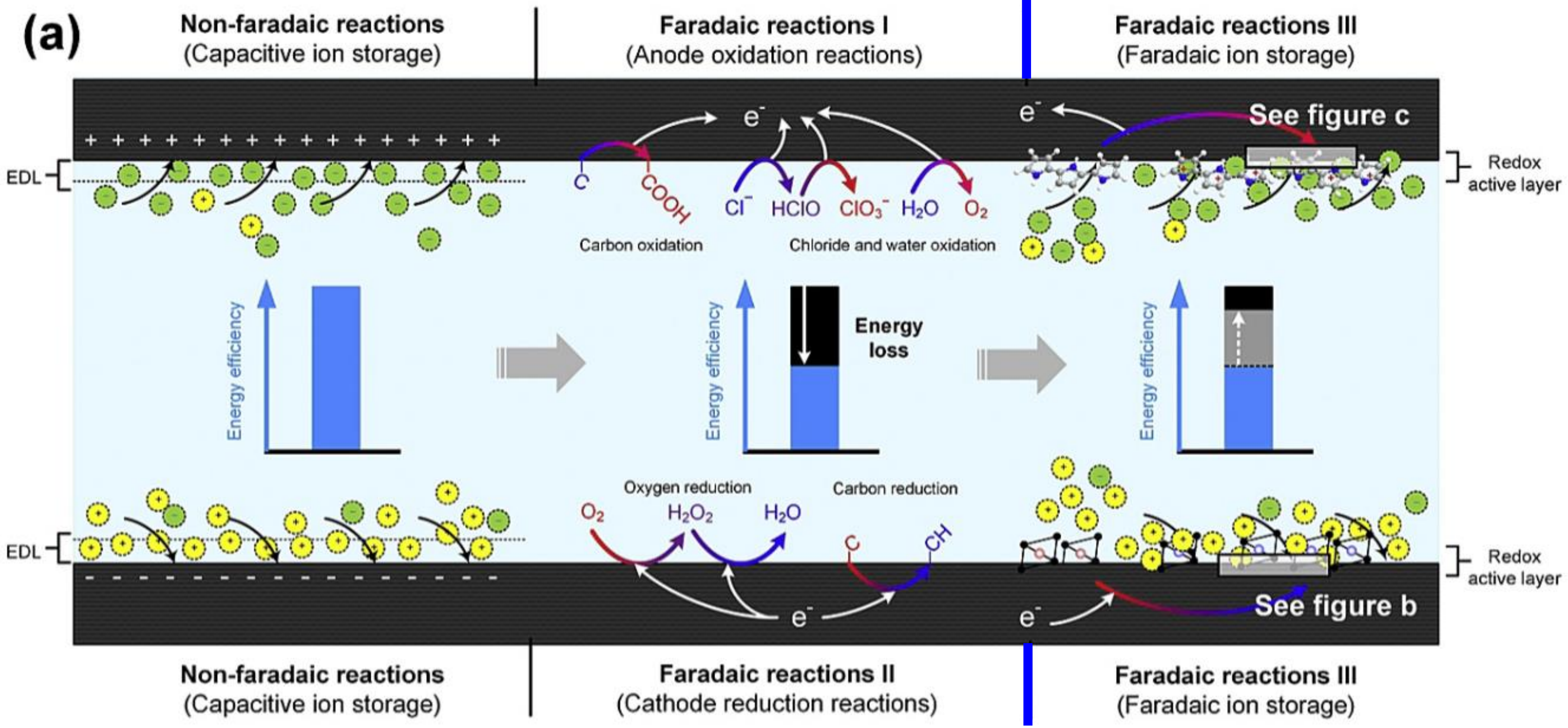




Current Opinion in Electrochemistry, 2021

Challenges in CDI

Conventional Capacitive Deionization (CDI) | Battery Deionization (BDI)

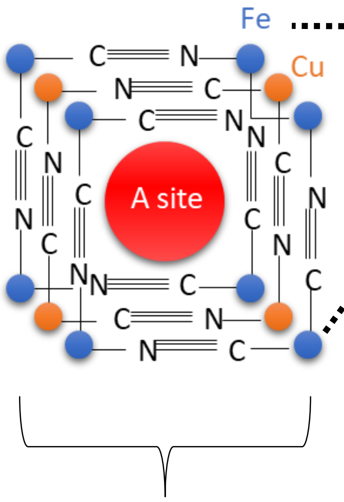


Zhang, Changyong, et al. Water Res. (2018), 128, 314–330
Suss, Matthew E. et al. Joule (2018), 2, 10–15

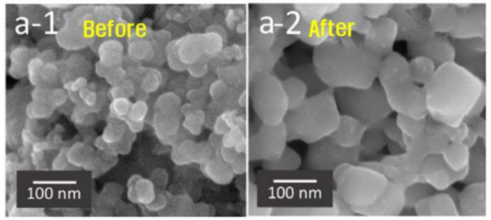
Battery Electrodes for Desalination: BDI

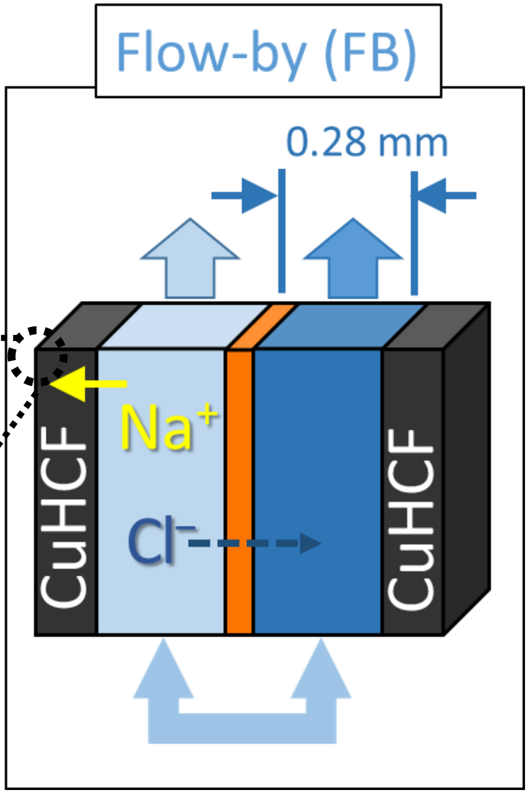
$Na^{+}Cu[Fe^{III}(CN)_6] + xNa^{+} + xe^{-}$

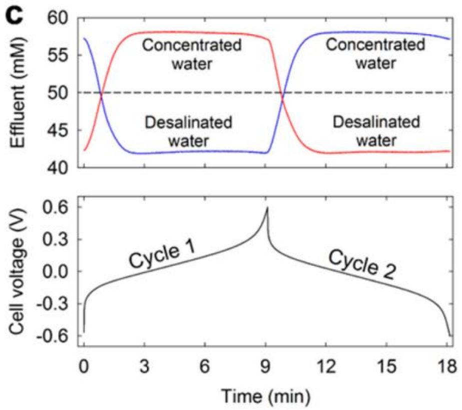
$= Na^{+}_{1+x}Cu[Fe^{II}(CN)_6]_x[Fe^{III}(CN)_6]_{1-x}$



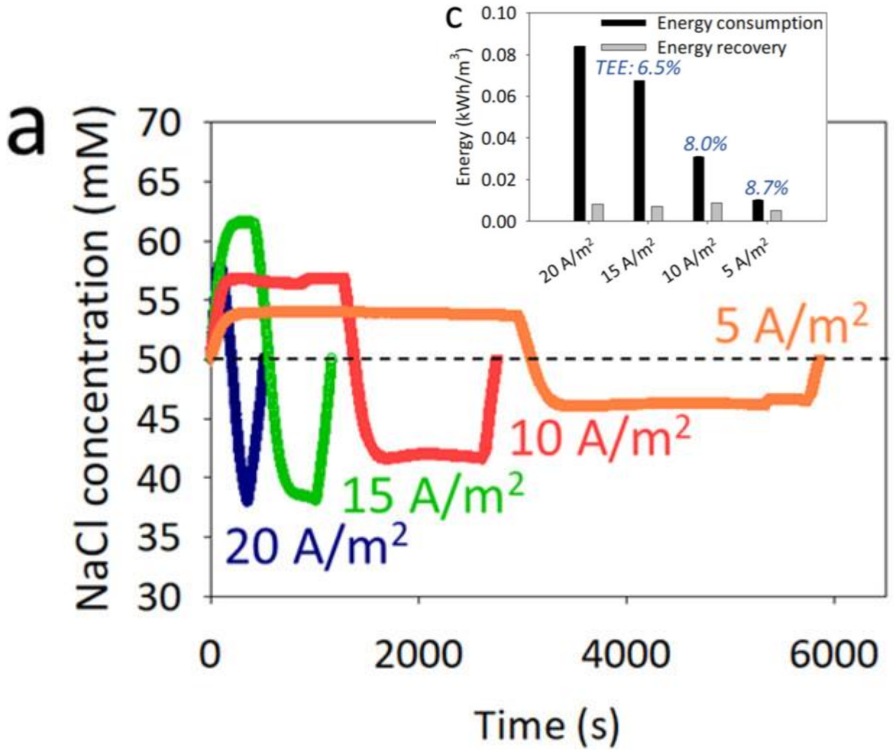
A site: 0.16~0.46 nm
vs.
Na⁺: 0.36 nm (Stokes)





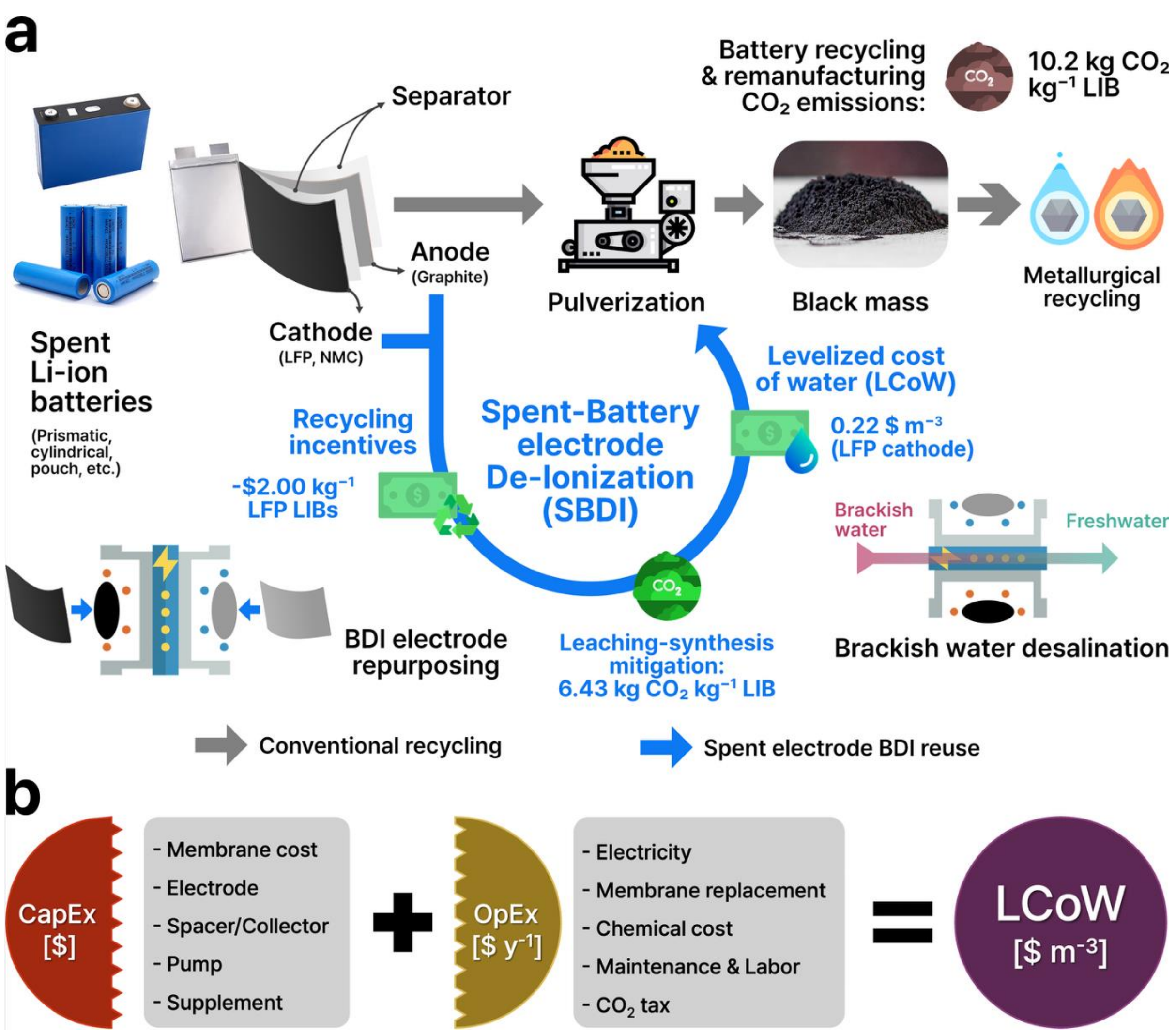


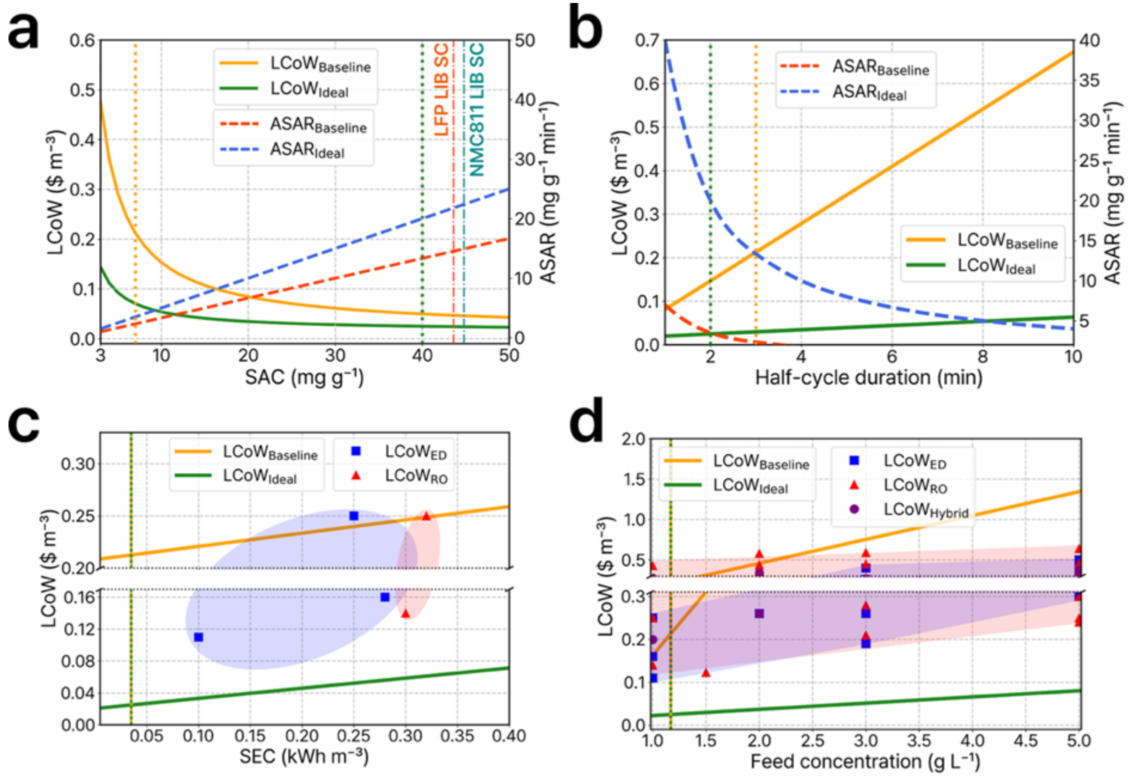
- Ion selective *Brackishwater, ~20% removal
- BDI (0.03 kWh m^{-3}) vs. CDI (0.3 kWh m^{-3}) vs. Reverse Osmosis (3 kWh m^{-3}) **Seawater, ~100% removal



Kim et al., Environ. Sci. Technol. Lett., 2017
Son et al., Environ. Sci. Technol., 2020

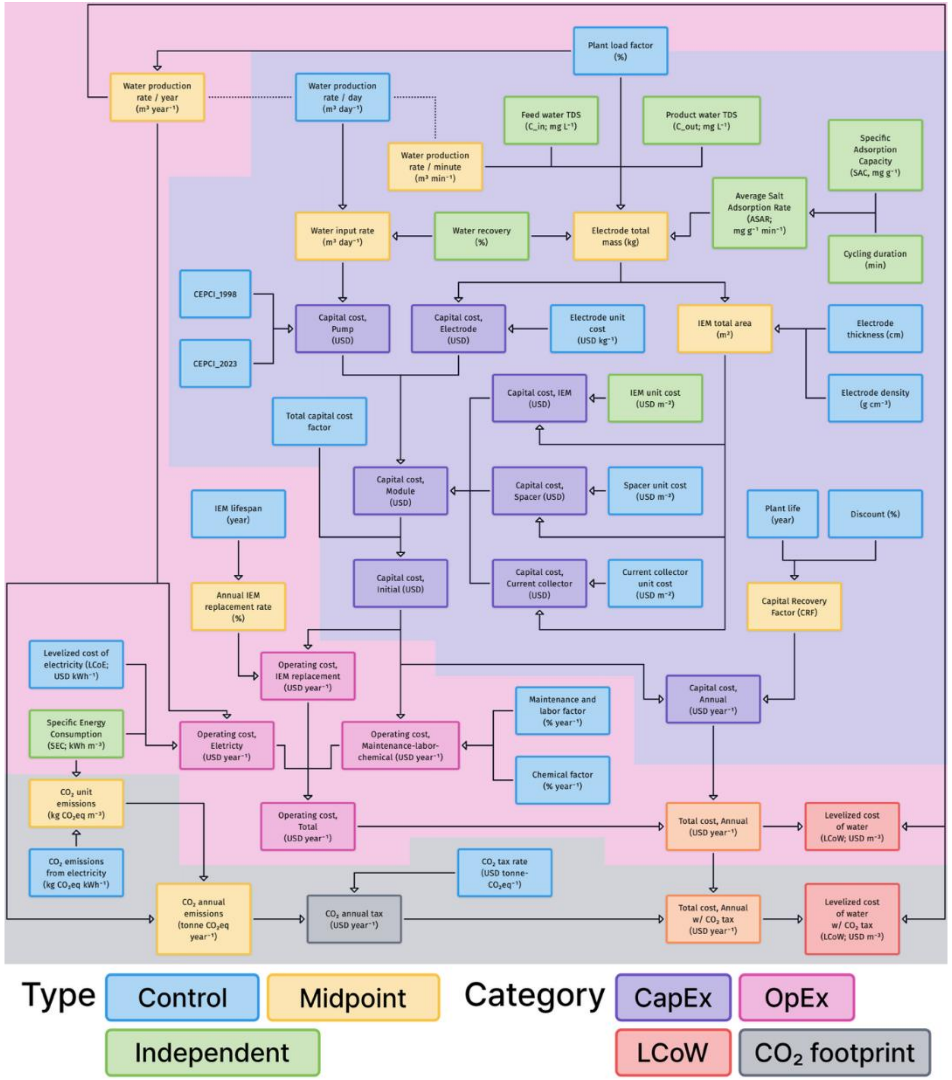
Direct Reuse of Lithium-ion-Battery

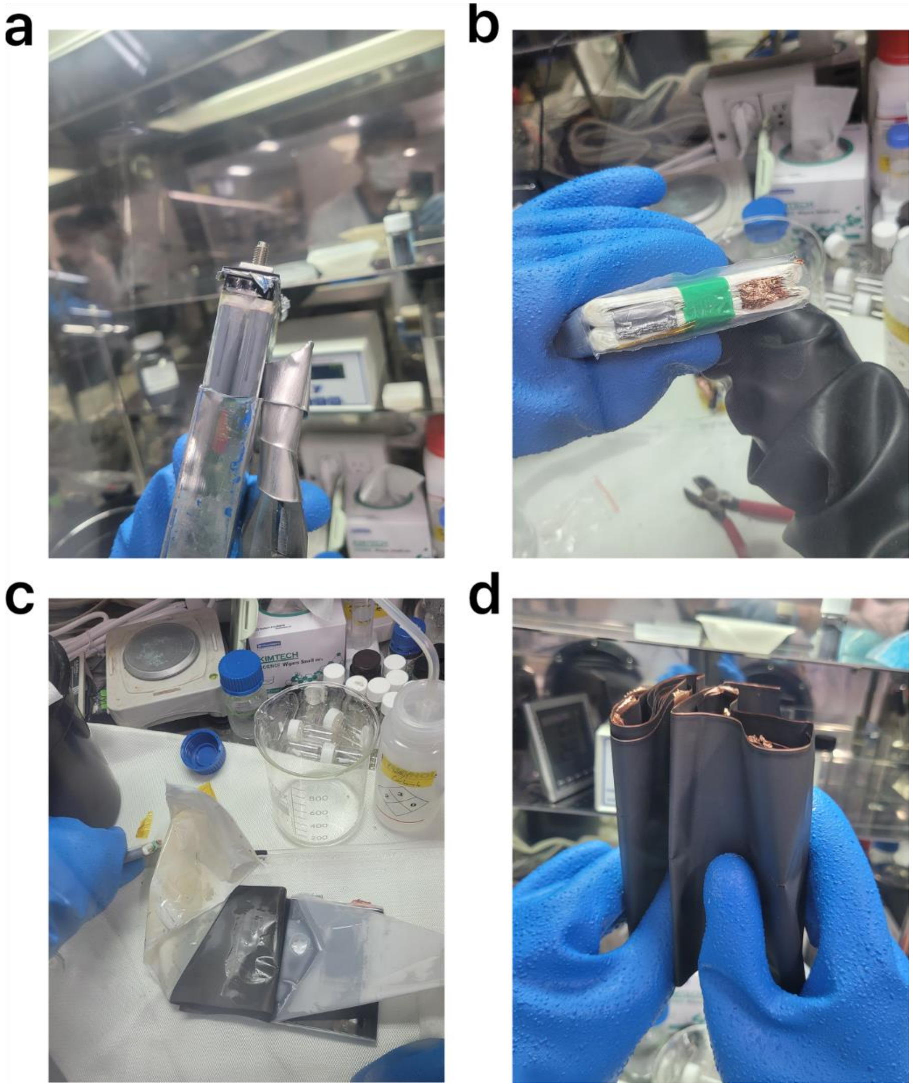




Under Review

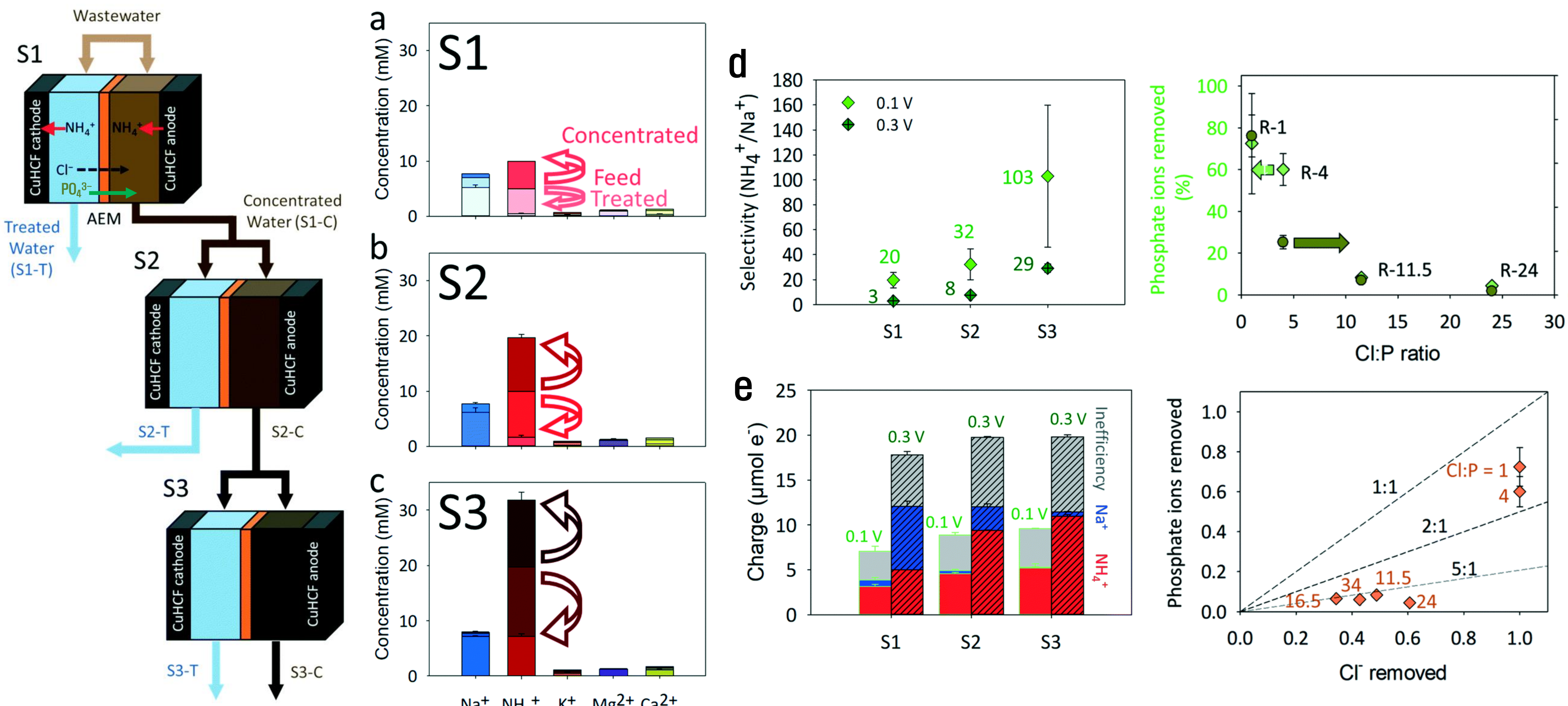
Techno-Economical Analysis (TEA)





Under Review

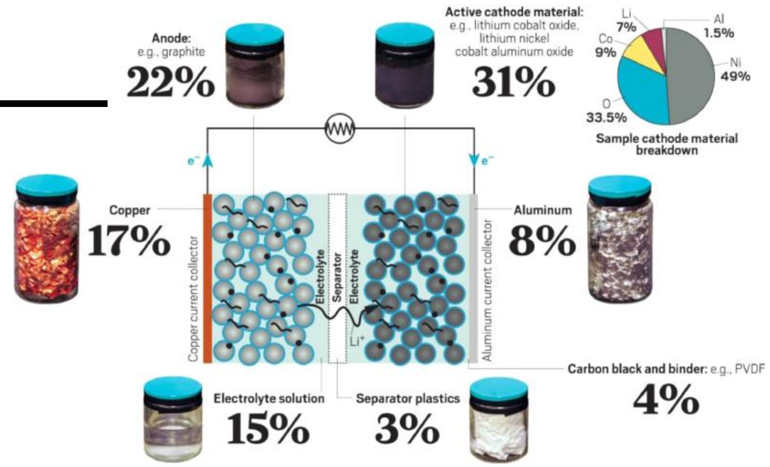
BDI for Fertilizer (NH_4^+ & PO_4^{3-})



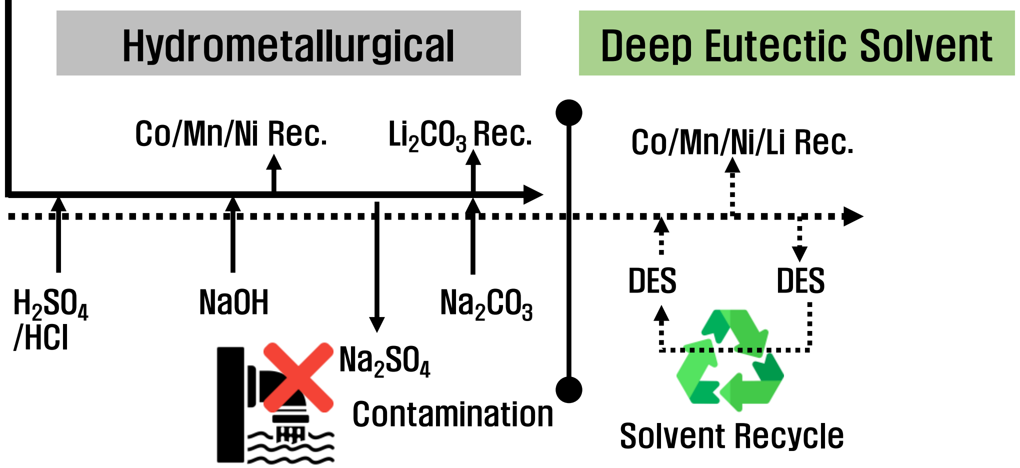
Son et al., Environ. Sci.: Water Res. Technol. Technol., 2020 (a)
Son et al., Environ. Sci.: Water Res. Technol. Technol., 2020 (b)

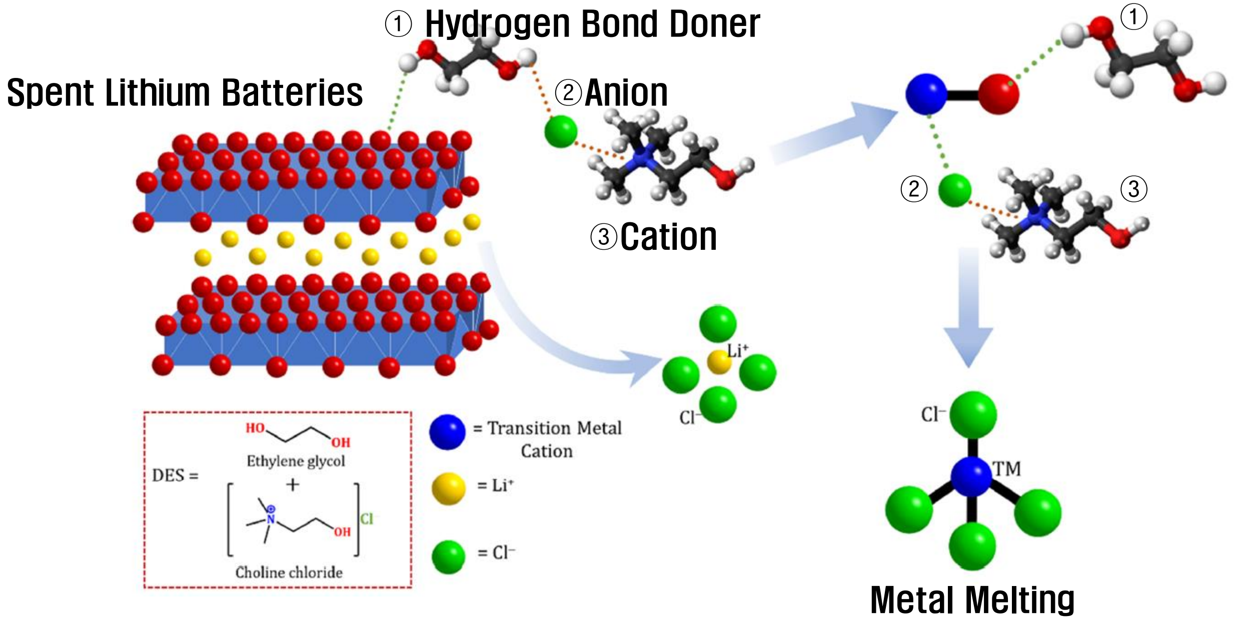
Green Solvent for Rare Metal Recovery

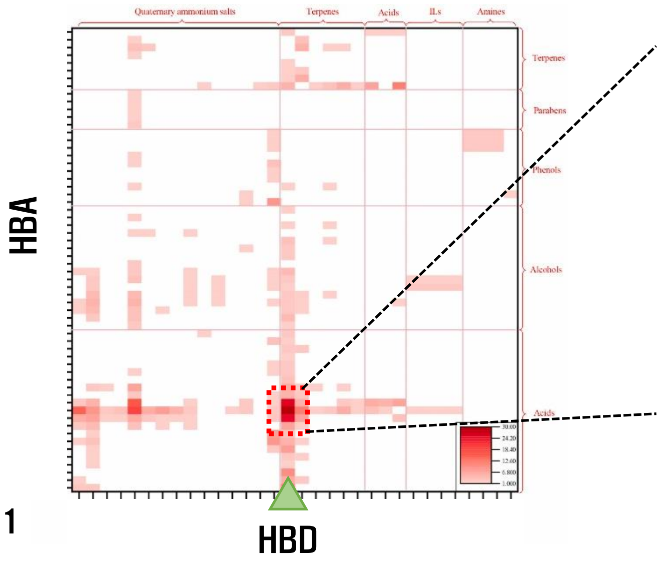
Battery Recycling Pathways

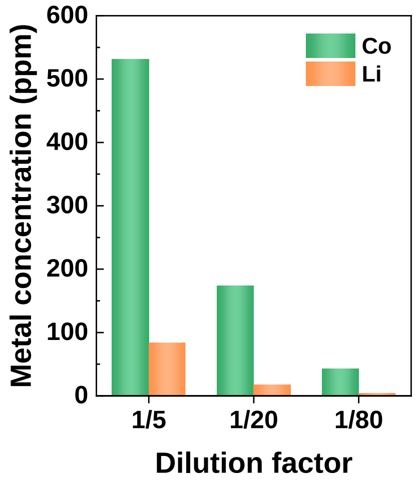


NCA cathode, Chem. Eng. News, 97 (28) (2019)









In Preparation

Artificial Intelligence for Environ. Eng.

Numerical Modeling

$$\Delta\emptyset_{sp,half} = -\frac{I(y)\cdot\delta_{sp}}{2(D_{Na}C_{Na,sp}+4D_{Ca}C_{Ca,sp}+D_{Cl}C_{Cl,sp})}$$

$$H^3 - \frac{wX}{C_{Cl,sp}}H^2 - \frac{C_{Na,sp}}{C_{Cl,sp}}H - \frac{2C_{Ca,sp}}{C_{Cl,sp}} = 0$$

$$\Delta\phi_{d,\frac{mem}{sp}} = \log(\mathrm{H})$$

$$H^3 - \frac{wX}{C_{Cl,mA}}H^2 - \frac{C_{Na,mA}}{C_{Cl,mA}}H - \frac{2C_{Ca,mA}}{C_{Cl,mA}} = 0$$

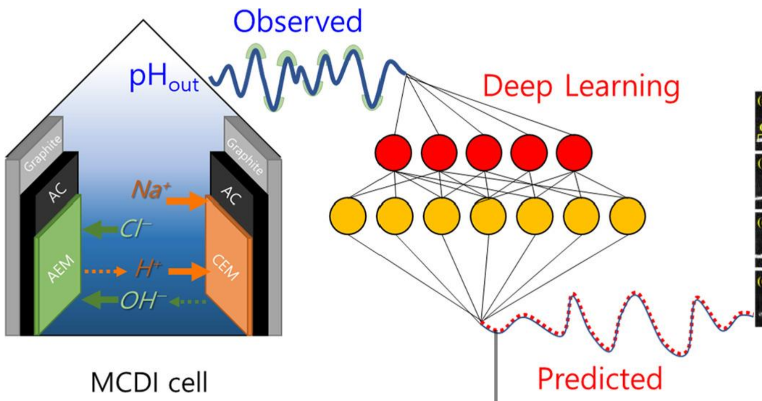
$$\Delta\phi_{d,\frac{mem}{elec}} = \log(\mathrm{H})$$

$$\Delta\phi_{mem} = -\frac{I(y)\delta_{mem}}{(D_{Na}\langle C_{Na,mem}\rangle+4D_{Ca}\langle C_{Ca,mem}\rangle+D_{Cl}\langle C_{Cl,mem}\rangle)}$$

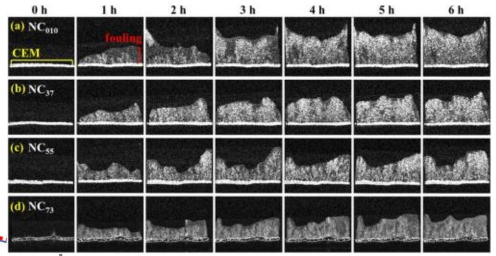
$$\Delta\phi_{elec} = -\frac{I(y)\cdot F\cdot(R_{elec}+k_f\times fouling\ thickness}{(C_{Na,mA}+2C_{Ca,mA})\cdot V_T}$$

$$\Delta\phi_{d,mi} = \frac{1}{2}\left[ln\left(\frac{C_{Ca,mA}}{C_{Ca,mi}}\right)+\mu_{att}\right]$$

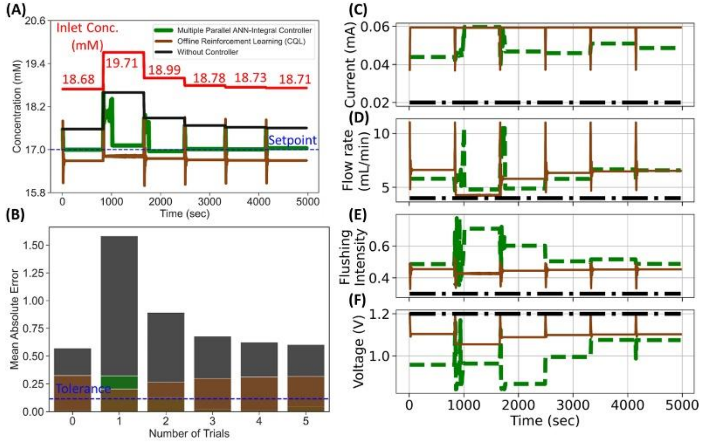
$$\Delta\phi_{st,mi} = -\frac{C_{charge,mi}\cdot F}{V_T\cdot(C_{st,vol,0}+\alpha\cdot C_{charge,mi}{}^2)}$$



First ML study
Desalination

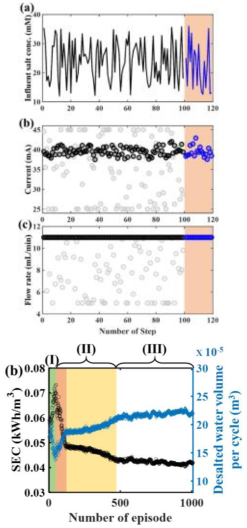


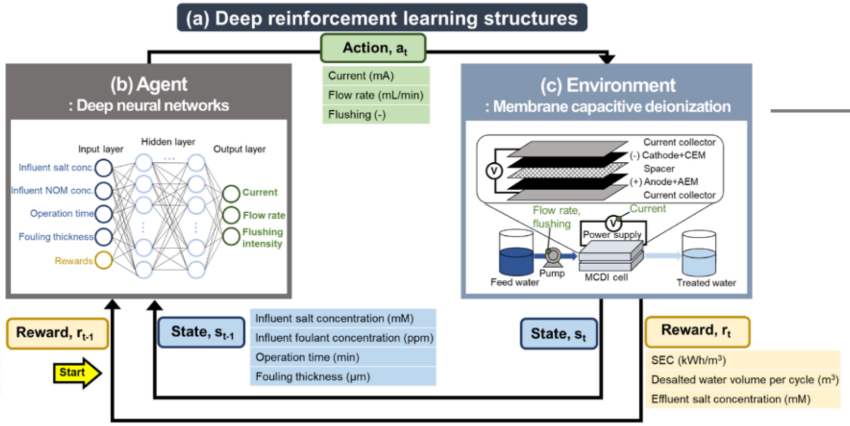
Real-time fouling monitoring
Desalination



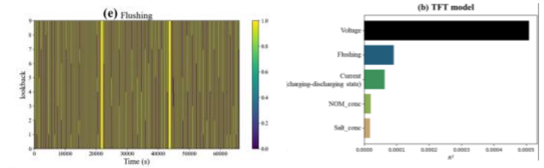
Process Automation (ML vs. RL)
Water Res.

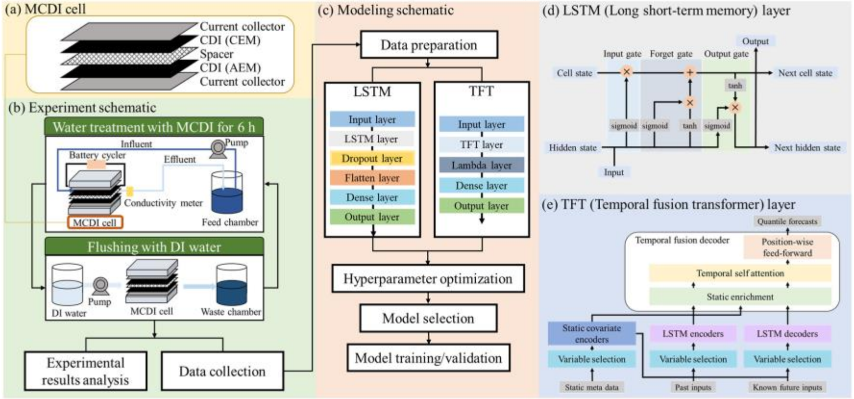
Process Automation (RL)
Water Res.





Explainable DL
Desalination





ML: Machine Leaning, RL: Reinforcement Learning, DL: Deep Learning

Autonomous Water Treatment Process

Control current or voltage for low-energy & high production

Low Energy Consumption

$$SEC\ (\mathrm{kWh\ m^{-3}}) = \frac{\sum(\mathrm{V} \times \mathrm{I})}{(\mathrm{Q} \times \mathrm{t})}$$

Specific Energy Consumption

$$TEE(\%) = \frac{\Delta g}{\mathrm{SEC}} \times 100$$

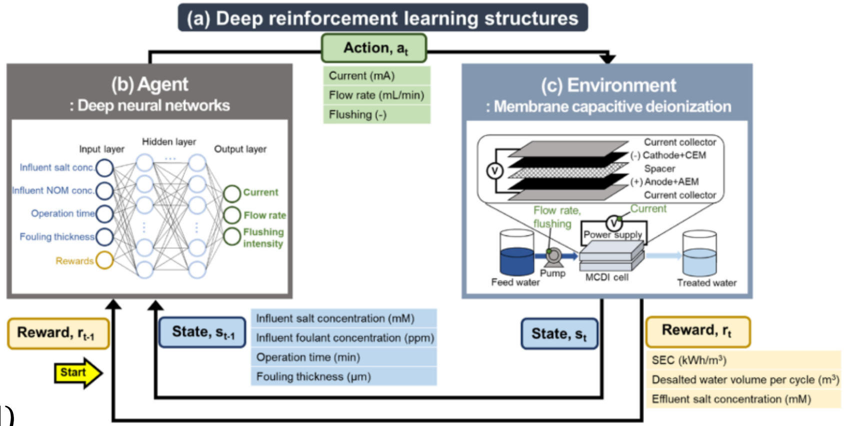
Thermodynamic Energy Efficiency

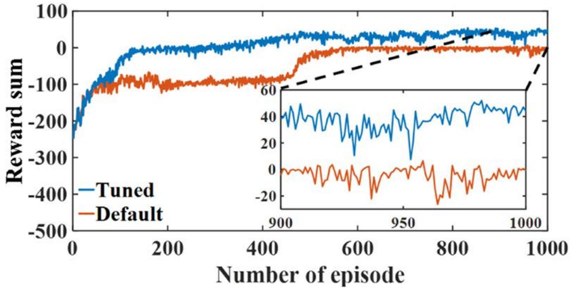
$$\Delta g = 2RT\left\{\frac{C_o}{\gamma}\ln\left[\frac{C_o - \gamma C_D}{C_o(1-\gamma)}\right] - C_D\ln\left[\frac{C_o - \gamma C_D}{C_D(1-\gamma)}\right]\right\}$$

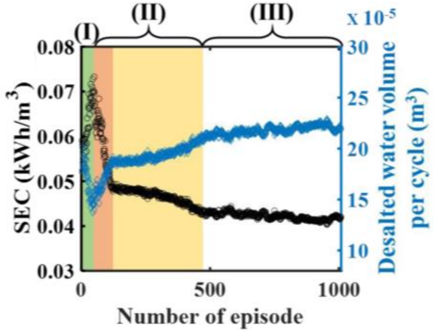
Gibbs energy of mixing

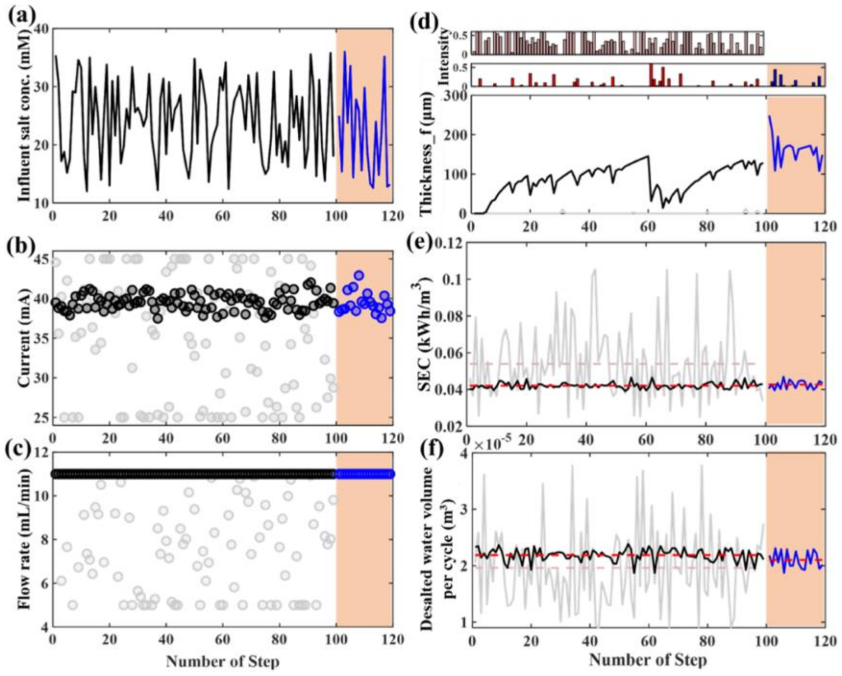
High Water Production

$$Production\ (m^3) = \emptyset * T_{ads}$$





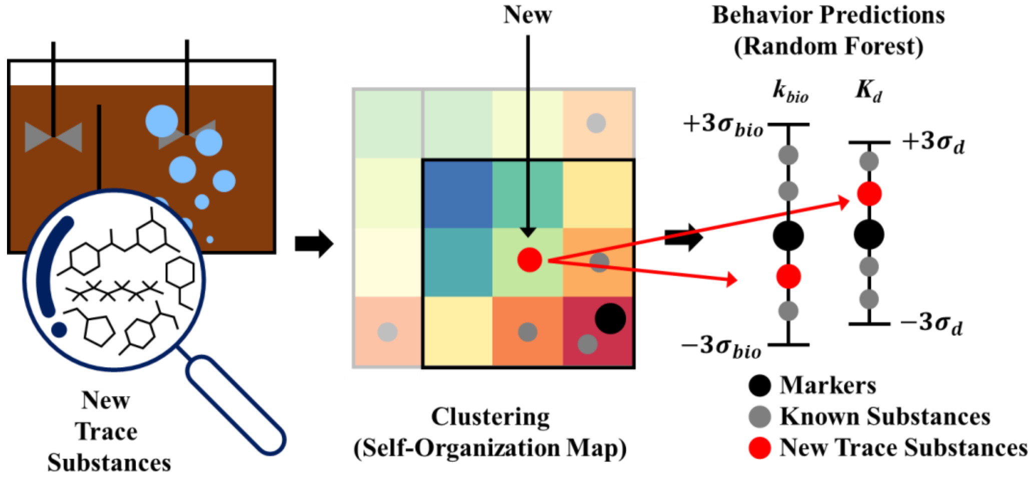


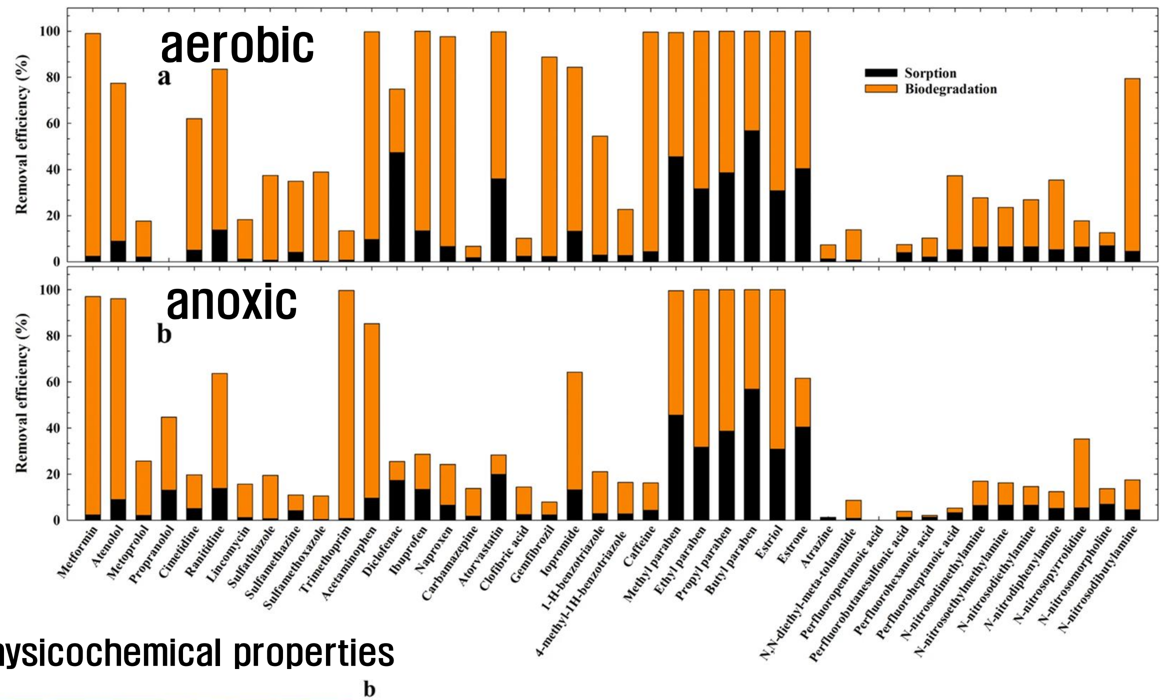


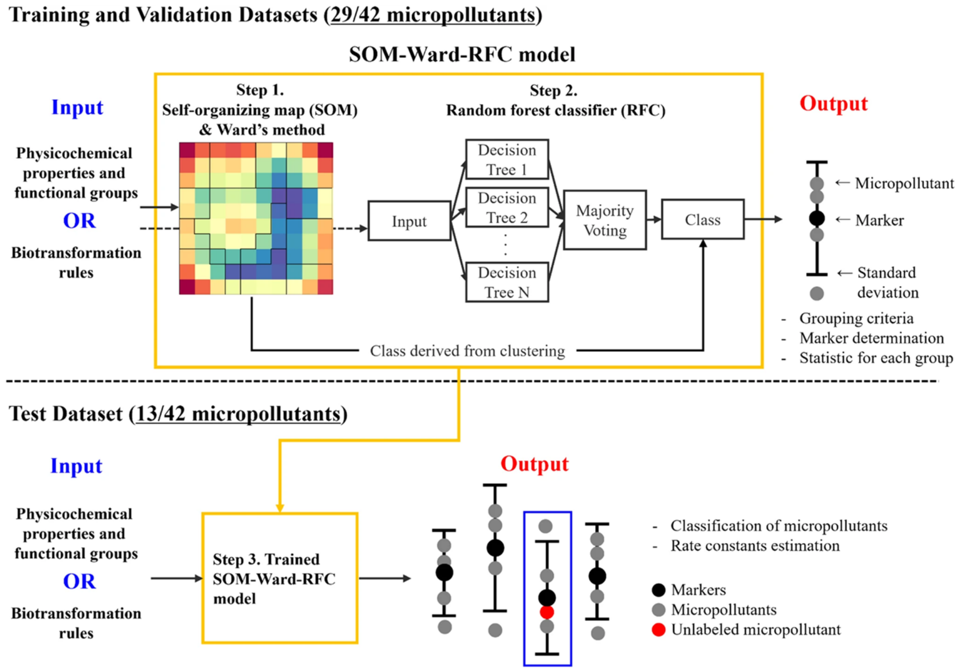
- **A 22% reduction in specific energy consumption** (from 0.054 to 0.042 kWh m^{-3})
- **A 11% increase in water desalted water volume per cycle** (from 1.96×10^{-5} to 2.19×10^{-5} m^3)
- **Achieving the desired degree of desalination**, compared to the first episode

Water Research, 2022
Water Research, 2025

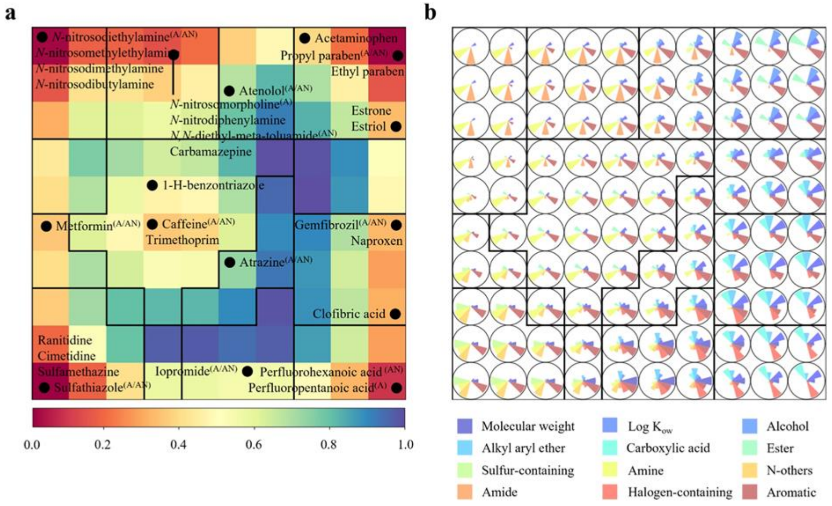
AI Sensor for Micropollutant Monitoring







Physicochemical properties



Process	Input feature	Estimation accuracy ($N = 1$)	Estimation accuracy ($N = 2$)	Estimation accuracy ($N = 3$)
Aerobic	Physicochemical properties and functional groups	0.38	0.69	0.77
	Biotransformation rule	0.10	0.20	0.40
Anoxic	Physicochemical properties and functional groups	0.46	0.70	0.77
	Biotransformation rule	0.30	0.40	0.40

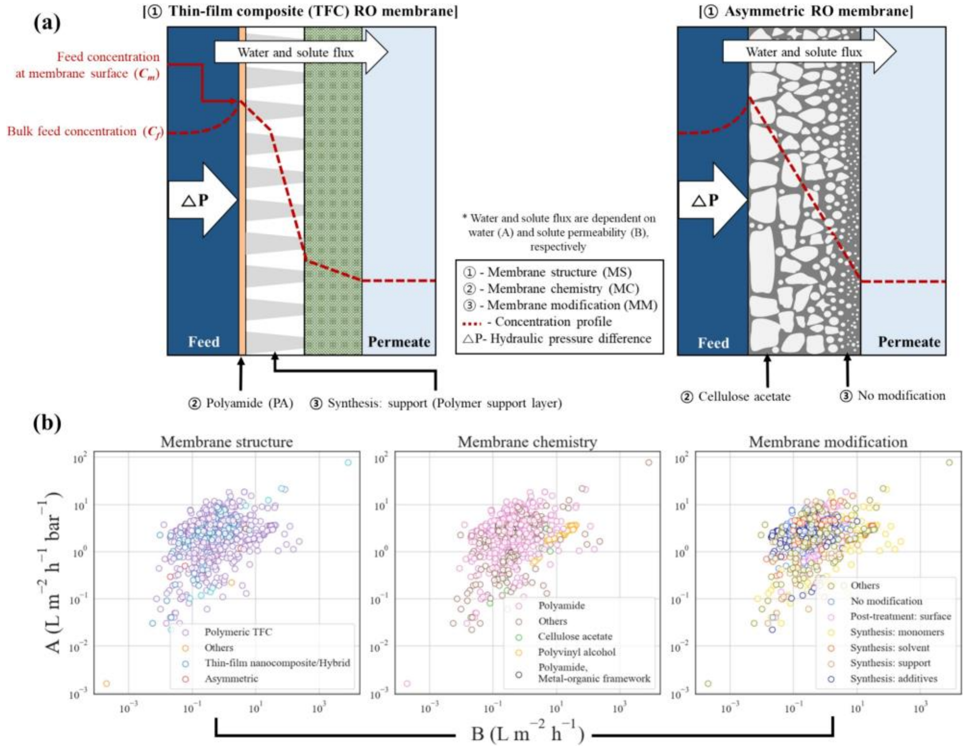
The standard deviation of classification perEstimation performance was compared with different N values, deciding the estimation range of rate const

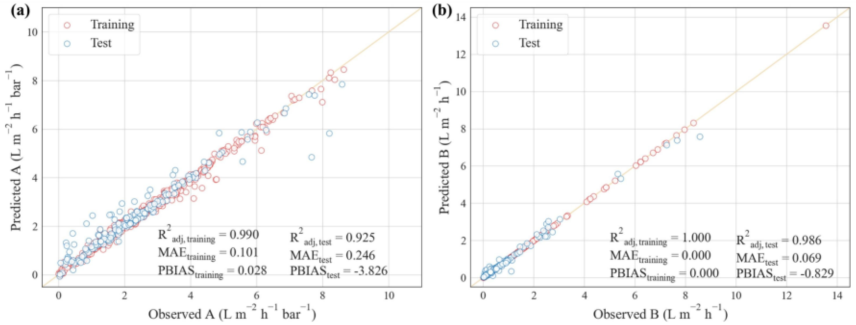
* Accuracy 0.38~0.77
* Literature: <0.38

npj Clean Water, 2023

AI for Environ. Material Sci.

Determining Membrane Performances using a Machine Learning Pipeline





J. Water Process Eng., 2024

Thank you for your attention.

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https://scholar.google.co.kr/citations?user=nPx7KdEAAAAJ&hl=en

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