

IDAES[®]
Institute for the Design of
Advanced Energy Systems

IDAES Integrated Platform for Multi-Scale Modeling and Optimization

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Carnegie Mellon



IDAES Overview

- IDAES is an open-source, equation-oriented software platform, written in Pyomo (Python-based), that enables the design and optimization of multi-scale, dynamic, interacting technologies and systems.
- Objective: Accelerate design & deployment of integrated power, H₂, and industrial processes to support broad decarbonization and emerging R&D priorities.

Also see: [Overview – IDAES](#)

More in-depth overview: [Energy Institute Lecture Series: Dr. David C. Miller – Texas A&M Energy Institute \(tamu.edu\)](#)

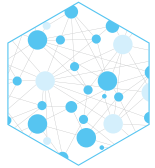
On-line documentation:

[Institute for the Design of Advanced Energy Systems \(IDAES\) — IDAES v2.4.0 \(idaes-pse.readthedocs.io\)](#)

- Major Focus Areas:

1. Growing the user base in strategic areas
2. Ensuring that existing projects leveraging IDAES are successful
3. Continuing to build out advanced capabilities

Several Modeling Collaborations Now Use IDAES

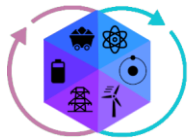


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H₂ with Capture
FECM



Post-Combustion
Carbon Capture/CDR
FECM



DISPATCHES
Design Integration and Synthesis
Platform to Advance Tightly
Coupled Hybrid Energy Systems

Hybrid Energy Systems
FECM, NE, EERE via GMLC



PROMMIS
Process Optimization and Modeling
for Minerals Sustainability

Rare Earth Element &
Critical Mineral Recovery
BIL via FECM



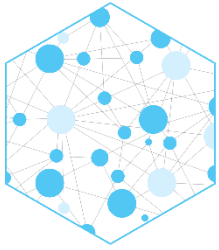
Water Desalination
EERE via NAWI & IEDO



PARETO
The Produced Water
Optimization Initiative

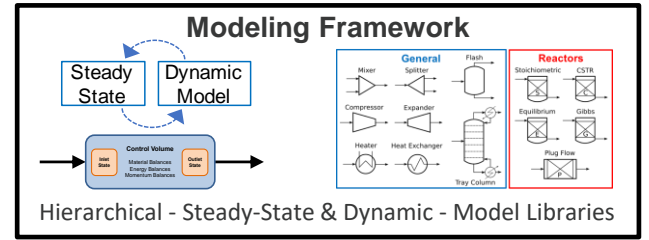
Produced Water
Management
FECM



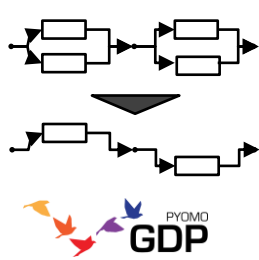


IDAES Integrated Platform

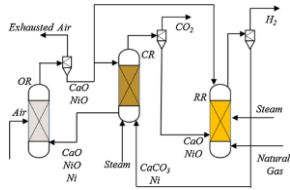
Institute for the Design of Advanced Energy Systems



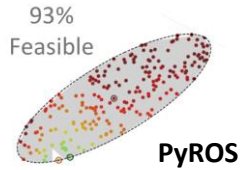
Conceptual Design



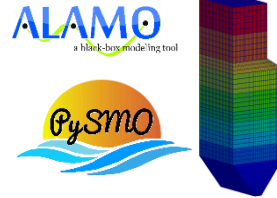
Plant Design
Process Optimization



Uncertainty Quantification
Robust Optimization



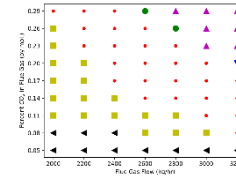
AI/ML
Surrogate Modeling



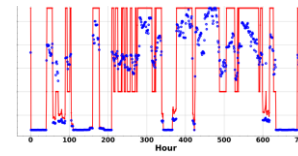
Infrastructure Planning of
Reliable Carbon Neutral
Power Systems



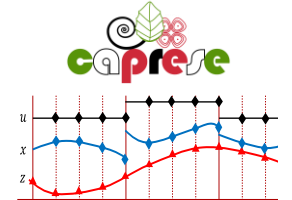
Process Family
Design



Process/Market
Co-Optimization

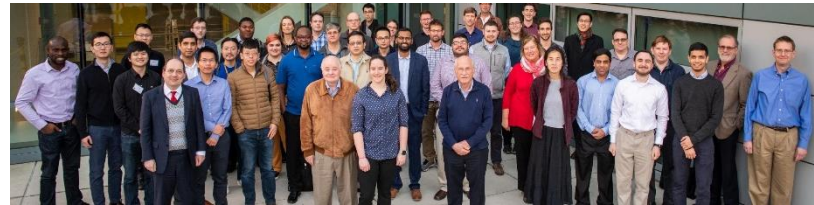


Process Operations
Dynamics & Control



Open Source: <https://github.com/IDAES/idaes-pse>

Lee, et al., *J. of Adv. Manufacturing and Processing* (2021)



Gurobi

CPLEX

Xpress

CBC

Ipopt

GAMS

NEOS

Mosek

BARON

GLPK

IDAES New Capability Development

- **Infrastructure planning of reliable and carbon-neutral power systems**
- Integrating manufacturing considerations into process design
- Integrated process market optimization of power and H₂ systems
- Dynamics, control, health modeling and optimization of power and H₂ systems

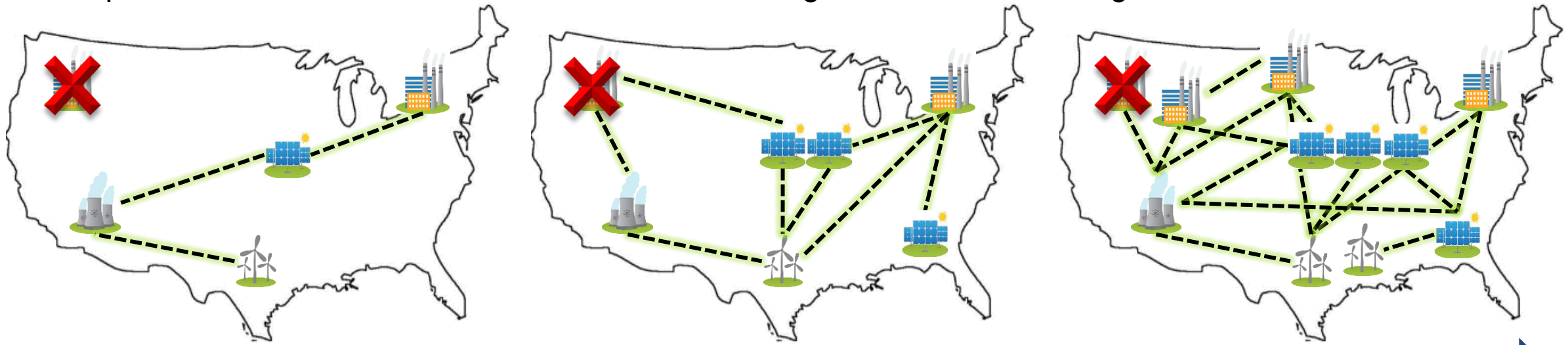
Infrastructure Planning of Reliable & Carbon-Neutral Power Systems

- **Objective**

- To determine long-term (yearly) investment decisions (time, location, number of power facilities) while considering short-term (hourly) operation decisions and explicitly valuing power system reliability.

- **Research challenge**

- How to solve these problems at a meaningful scale!
- **Simplifications** (e.g., representative days, ignoring reliability penalties, storage, and uncertainty) and **scale reductions** (e.g., short time horizons, small regions, clustering of generators) are needed to make the problems solvable but **limit their usefulness** for long-term decision making.

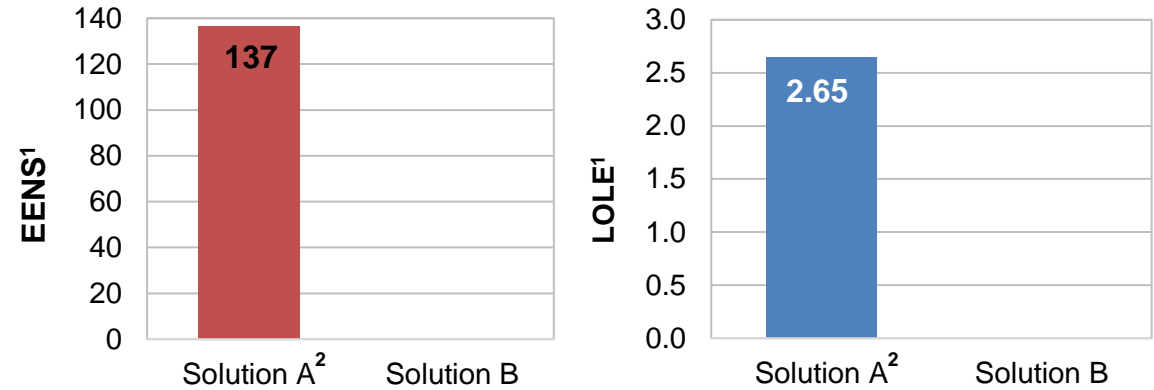
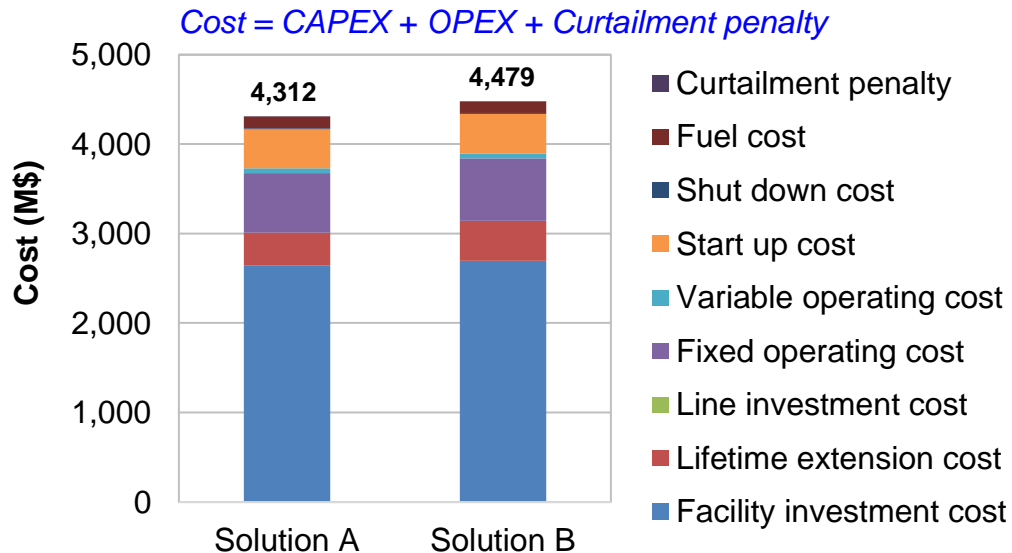


San Diego County Case Study: Why consider reliability?

California Policy and Regulatory Environment	Scenario #1	Scenario #2	Scenario #3
CO ₂ emission limits (30% reduction by Y10)	X	O	O
Renewable generation (60% of the total generation by Y10)	X	X	O

Solution A: Results of expansion planning **without** reliability consideration

Solution B: Results of expansion planning **with** reliability consideration



¹ EENS (MWh/planning period) and LOLE (hours/planning period) over 10 years are estimated.

² LOLE and EENS of solution A are analyzed after obtaining the optimal configuration.

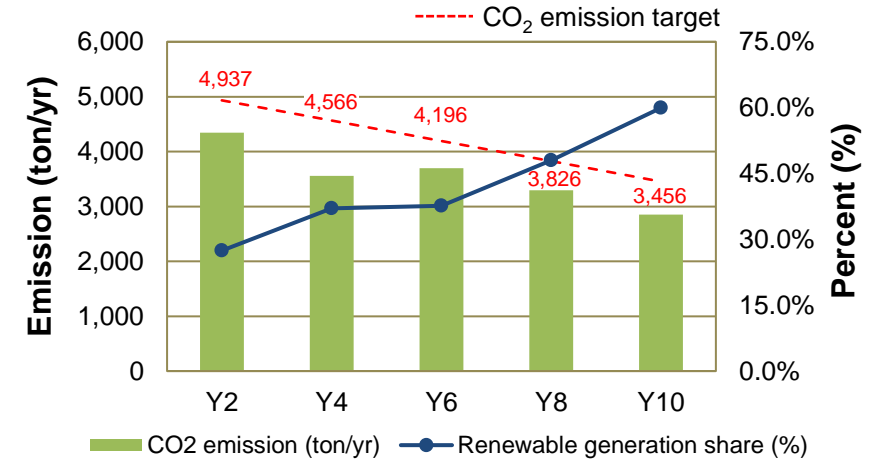
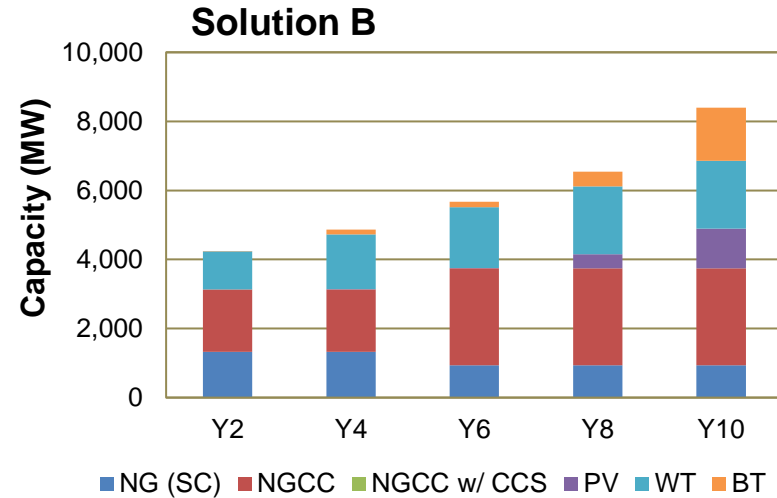
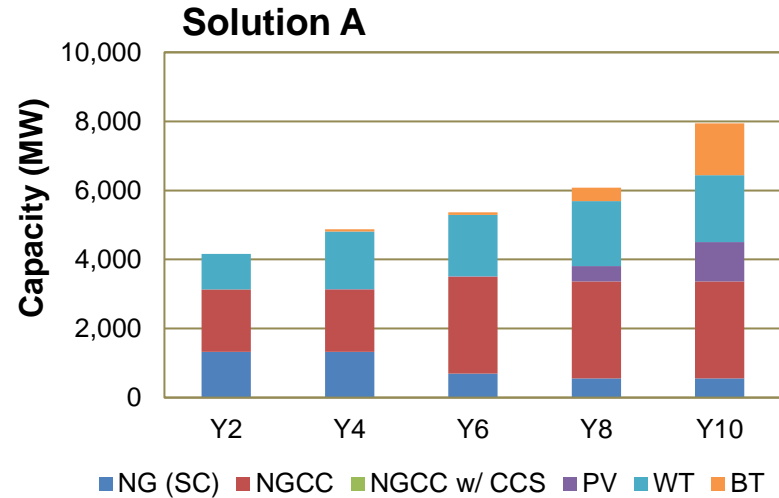
Higher EENS and LOLE indicate the power system has a relatively lower reliability level.

The framework enables users to estimate cost of designing power systems that can flexibly respond to failures.

San Diego County Case Study: What leads to reliability improvement?

Solution A: Results of expansion planning **without** reliability consideration

Solution B: Results of expansion planning **with** reliability consideration



- Primary means of improving reliability was extending lifetimes of NG simple cycle plants to serve as back-ups.
- Capacity of renewable generators, which have lower failure rates than dispatchable generators, is also increased, albeit minimally.

IDAES New Capability Development

- Infrastructure planning of reliable and carbon-neutral power systems
- **Integrating manufacturing considerations into process design**
- Integrated process market optimization of power and H₂ systems
- Dynamics, control, health modeling and optimization of power and H₂ systems

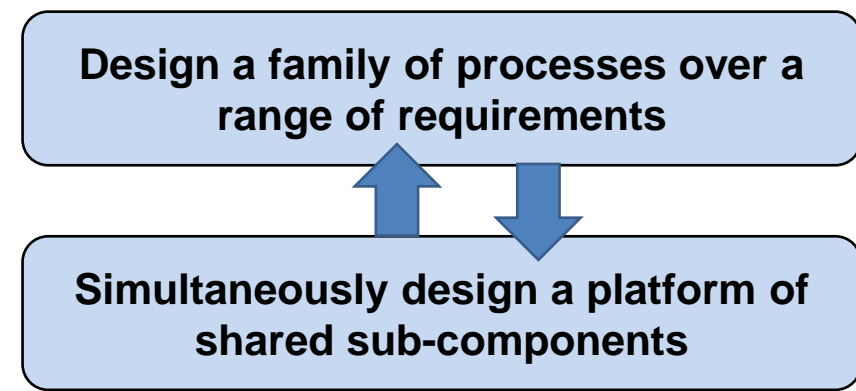
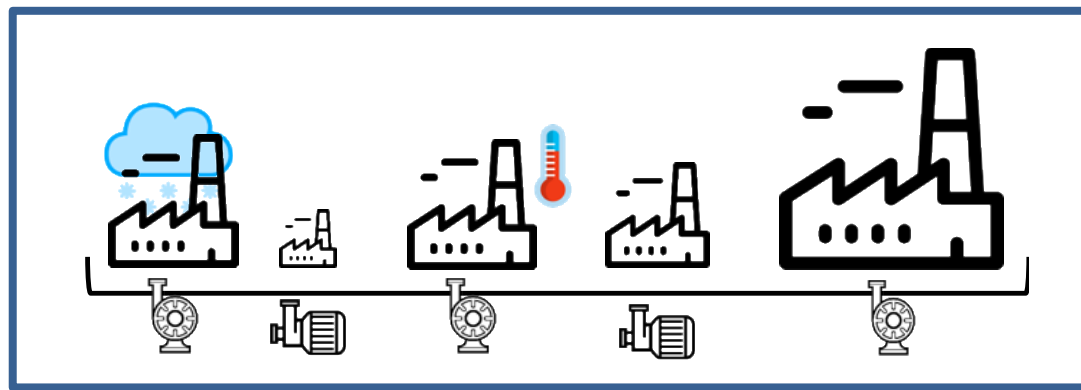
Optimization Approaches for Rapid Design and Deployment of Industrial Decarbonization Processes

- **Objective**

- Simultaneously design families of processes able to address a wide range of operating conditions and performance requirements, that maximize the use of shared sub-components/unit operations.

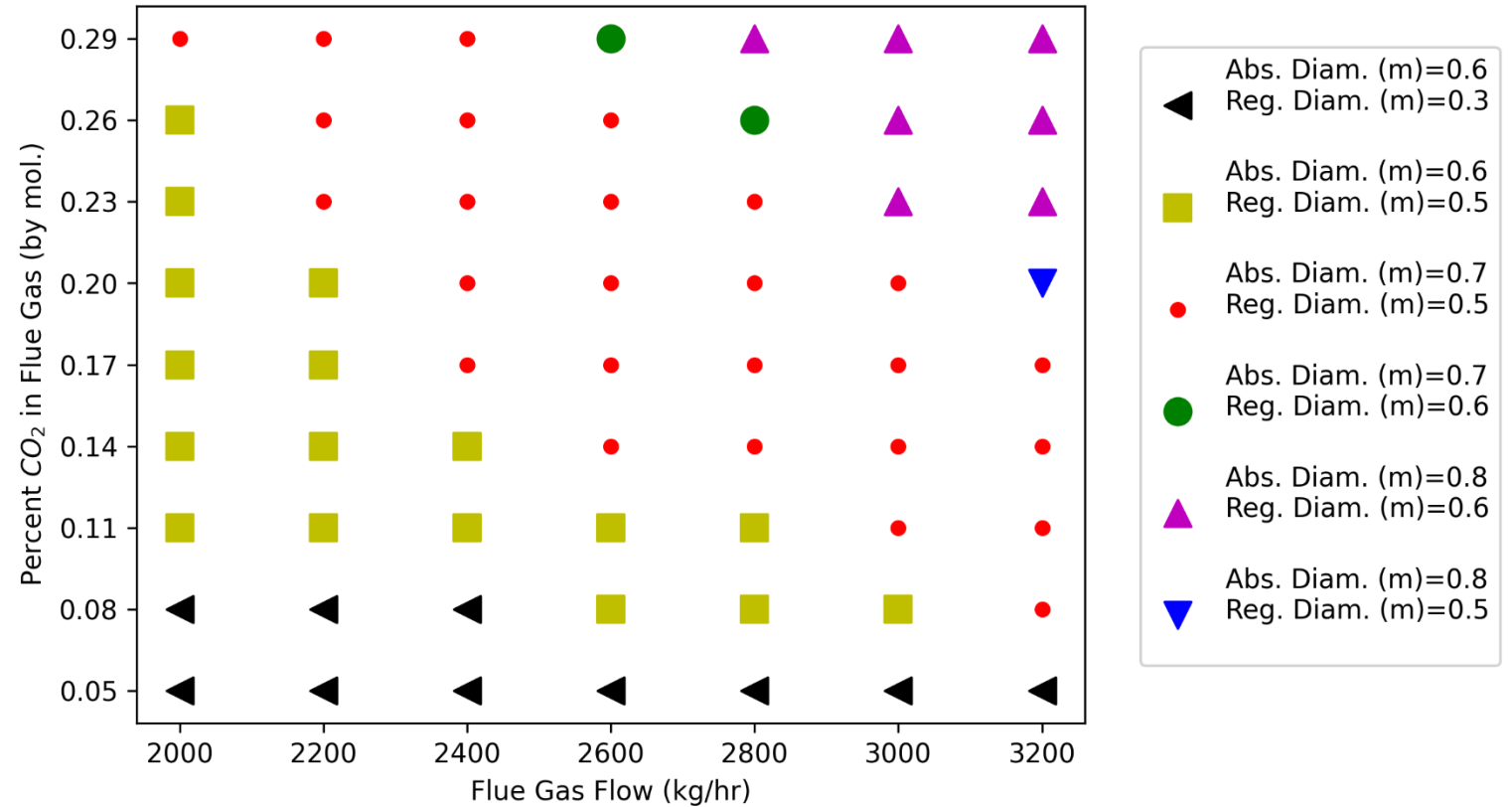
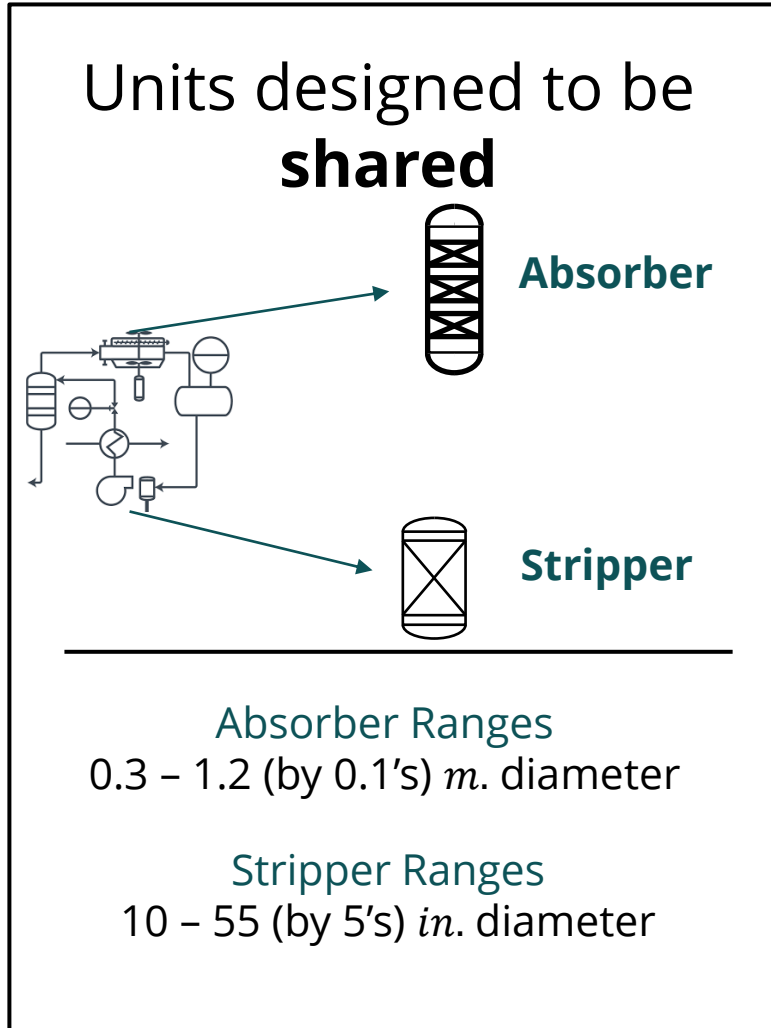
- **Why does this matter?**

- **De-risks large-scale deployments** by explicitly integrating manufacturing considerations into design
- **Reduces both deployment times** (since fewer units will require custom design & fabrication) and **manufacturing costs** (by exploiting economies of learning since we produce a larger number of each of the units)



Case Study: MEA Carbon Capture

Successfully designed 63 carbon capture systems using only 3 optimally designed absorbers & strippers



Total cost savings (economies of numbers) estimated to be **14.3%**

- Currently using literature values for economies of numbers savings
- Investigating specific parameters for CO₂ capture processes

IDAES New Capability Development

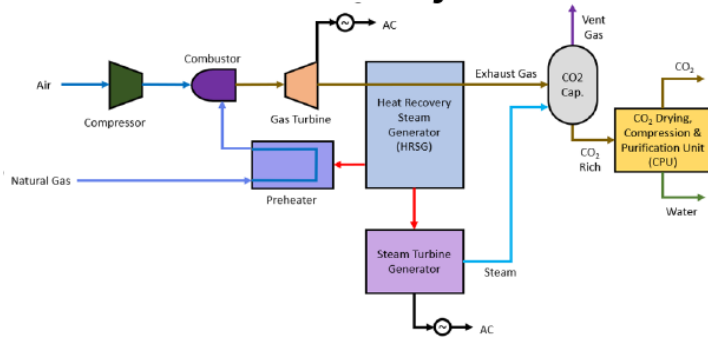
- Infrastructure planning of reliable and carbon-neutral power systems
- Integrating manufacturing considerations into process design
- **Integrated process market optimization of power and H₂ systems**
- Dynamics, control, health modeling & optimization of power and H₂ systems

Analysis of Integrated Energy System Concepts

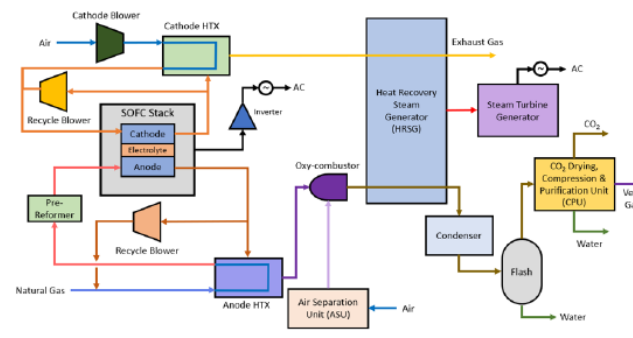
Fuel = Natural Gas
CO₂ capture > 97%

Baseline Systems
Single Product

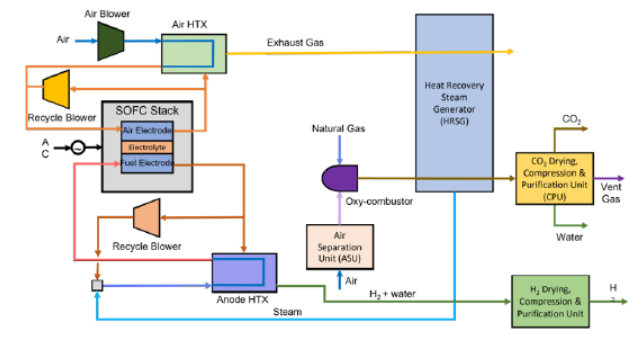
Standalone Natural Gas Combined Cycle (NGCC) Power Only



Standalone Solid Oxide Fuel Cell (SOFC) Power Only

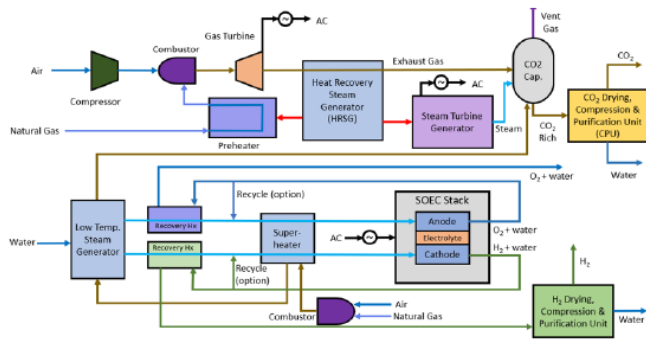


Standalone Solid Oxide Electrolyzer Cell (SOEC) Hydrogen Only

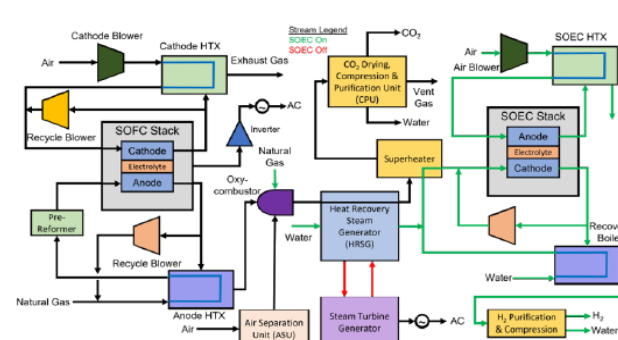


Integrated Systems
Multi-Product

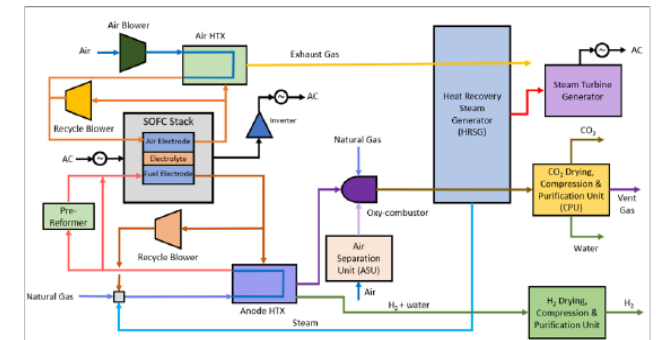
NGCC + SOEC Power, Hydrogen, Coproduction



SOFC + SOEC Power, Hydrogen, Coproduction



Reversible Solid Oxide Cell (rSOC) Power, Hydrogen



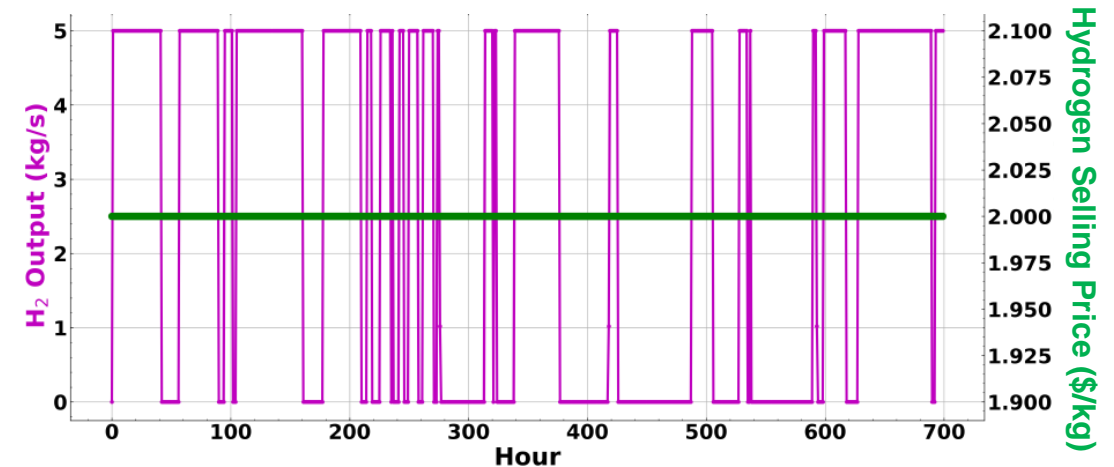
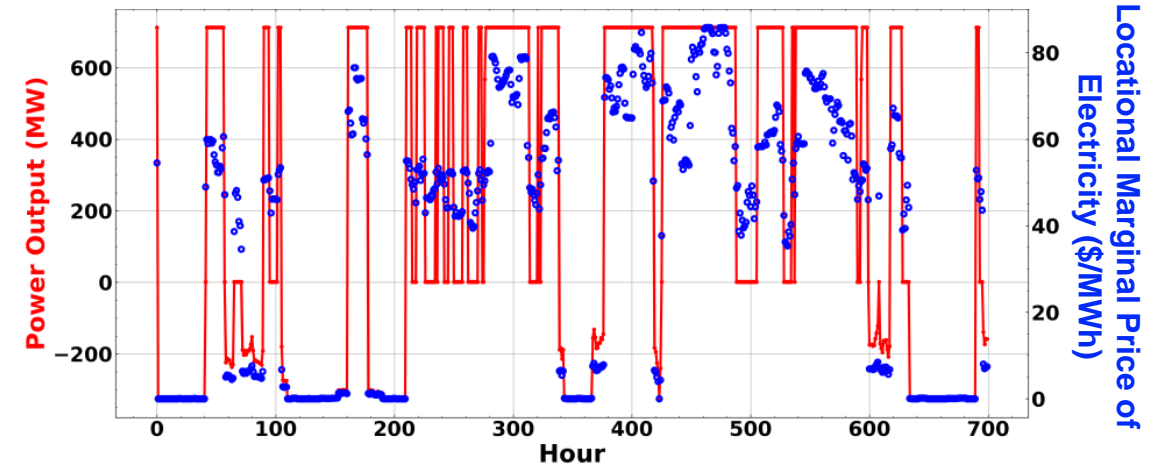
**Are there plausible electricity market scenarios where an integrated system makes sense?
If so, which system is the best?**

Analysis of Flexible Power and H₂ Systems

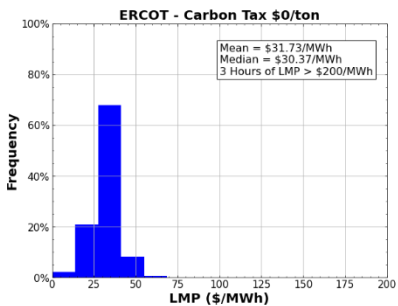
- **Systems Under Evaluation** All > 97% CO₂ Capture
 - Single Product: NGCC, SOFC, SOEC
 - Multi Product: NGCC+SOEC, SOFC+SOEC, rSOC
- **61 total data sets** (every hour for a year)
 - 2019 & 2022: ERCOT, ISO_NE, MISO, PJM, SPP, NYISO
 - Future projections from NREL and Princeton from ARPA-E FLECCS program
 - Future projections from NETL for ERCOT using PROMOD IV

Optimize IES Operation

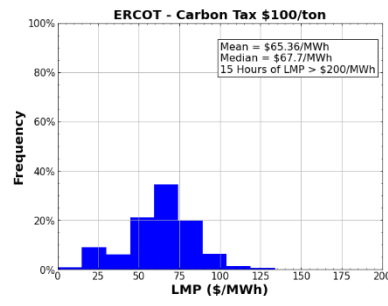
$$\max \sum (\text{Revenue}_t - \text{Costs}_t - \text{CO}_2 \text{Tax}_t)$$



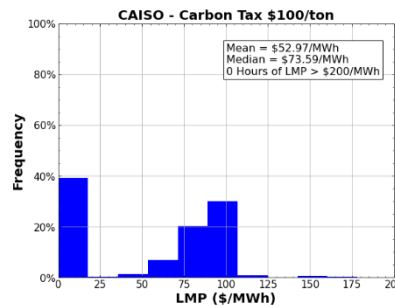
Data sets cover very broad range of potential scenarios



Low Prices



High Prices



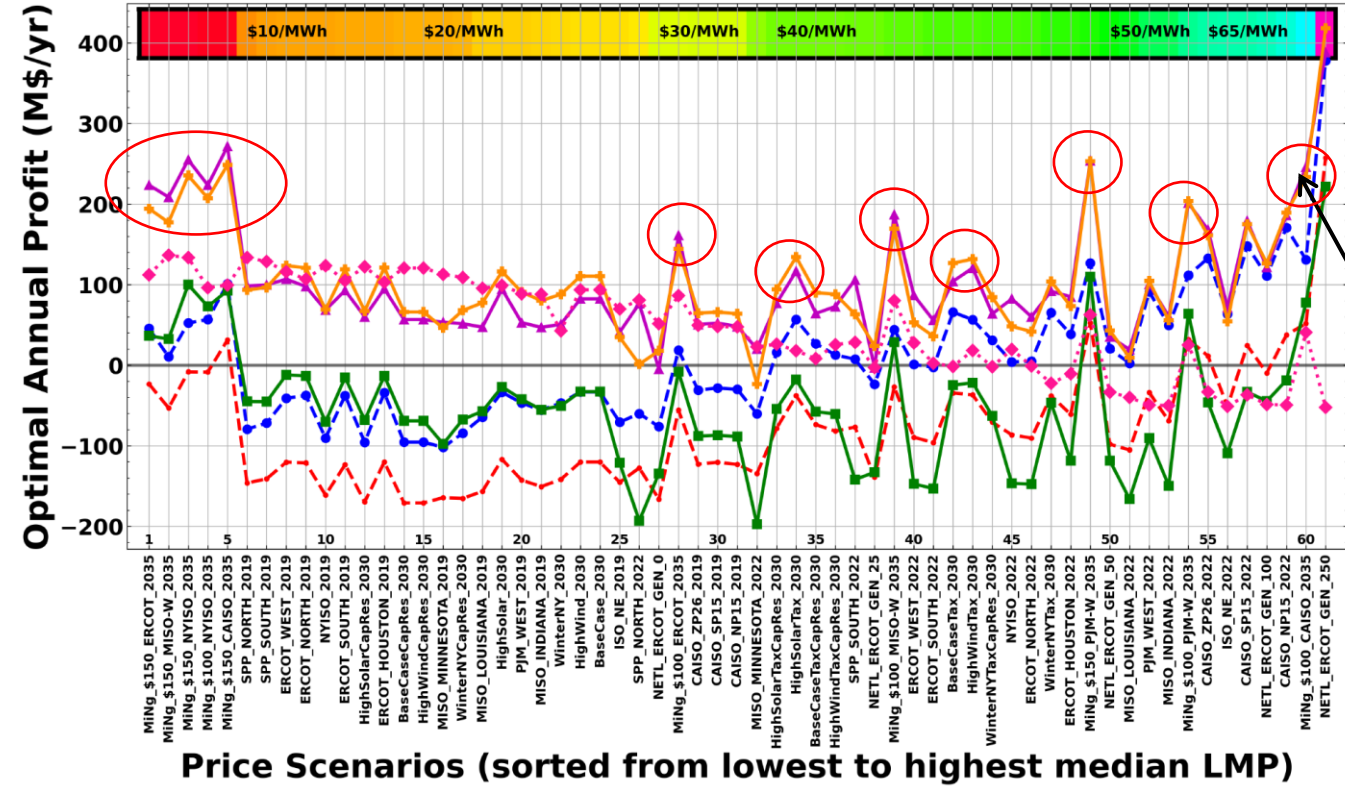
Bimodal
(e.g., high VRE)

Flexible Power/H₂ Systems Outperform Single Product Systems

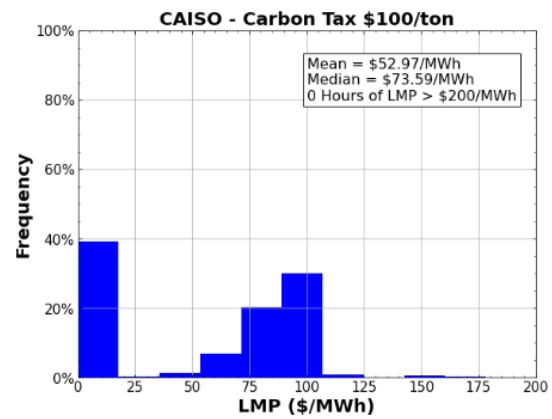
% of electricity market scenarios with positive annualized profit assuming \$2/kg H₂ selling price

NGCC (power only)	13%
SOFC (power only)	52%
SOEC (H ₂ only)	74%
NGCC + SOEC (power and/or H ₂)	16%
Reversible SOC (power or H ₂)	97%
SOFC + SOEC (power and/or H ₂)	98%

Hydrogen Price = \$2.0/kg



Integrated power and hydrogen systems are the most robust to electricity market assumptions.



How might we control these systems to switch between operating modes while minimizing degradation over long-term operation?

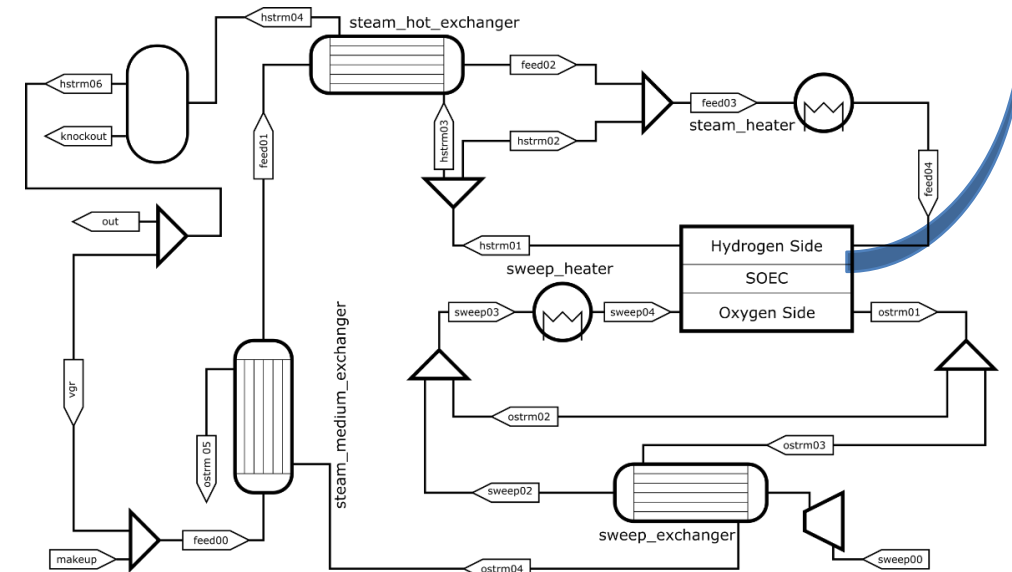
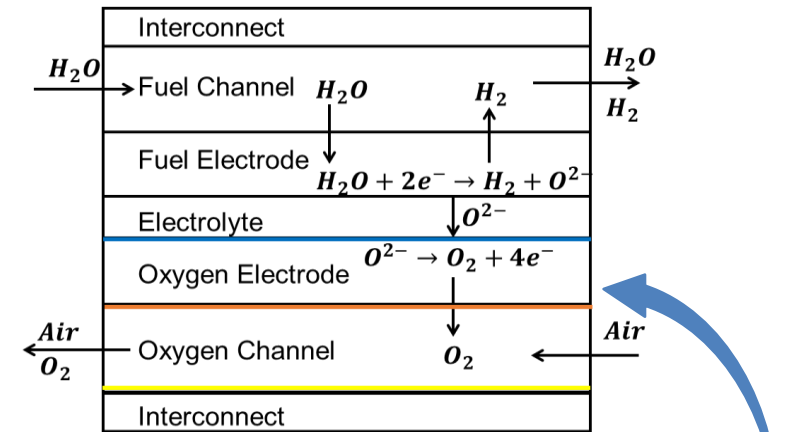
Integrated power and hydrogen systems provide greatest benefits in scenarios with bimodal electricity pricing (e.g., high VRE).

IDAES New Capability Development

- Infrastructure planning of reliable and carbon-neutral power systems
- Integrating manufacturing considerations into process design
- Integrated process market optimization of power and H₂ systems
- **Dynamics, control, health modeling & optimization of power and H₂ systems**

Dynamic Model of SOC-based System for Mode-Switching

- **SOC dynamic model** (Bhattacharyya et al., 2007)
 - First-principles, non-isothermal, planar cell
 - 2D electrodes, electrolyte, and interconnect
 - 1D fuel and oxygen channels
 - Operates in fuel cell and electrolysis modes
- **Dynamic SOC-based system model** (Allan et al., 2023)
 - Now [publicly available online](#)
 - Soon to be merged into the IDAES examples repository
 - **H₂ fueled** in fuel cell mode
 - **Vent gas recirculation** with purge
 - **Condenser** to remove water from H₂-side off-gas
 - Equipment models for **thermal management**
 - 1D multi-pass crossflow recuperative heat exchangers
 - 1D crossflow trim heaters



Block flow diagram of H₂-fueled SOC-based IES for Mode-Switching Operation

- Lee, A., et al., J Adv Manuf Process 2021, 3(3) (2021).
- Bhattacharyya et al., Chem Eng Sci, 62, 4250-4267 (2007).
- Allan, D.A., et al., In Proc. FOCAPO/CPC (2023).

SOEC Microstructure Chemical Degradation Modeling

Fuel electrode nickel (Ni) agglomeration

- Ni particles grow with time under high temperature operation
- Ni₂OH formation drives the process
- Surface-diffusion – Ostwald ripening

$$\frac{d(\overline{d_{Ni}})}{dt} = C \frac{X_{Ni}}{X_{YSZ} A_{YSZ} d_{Ni}^6} \left(\frac{Y_{H_2O}}{Y_{H_2}^{0.5}} \right) \exp\left(-\frac{E_a}{RT}\right)$$

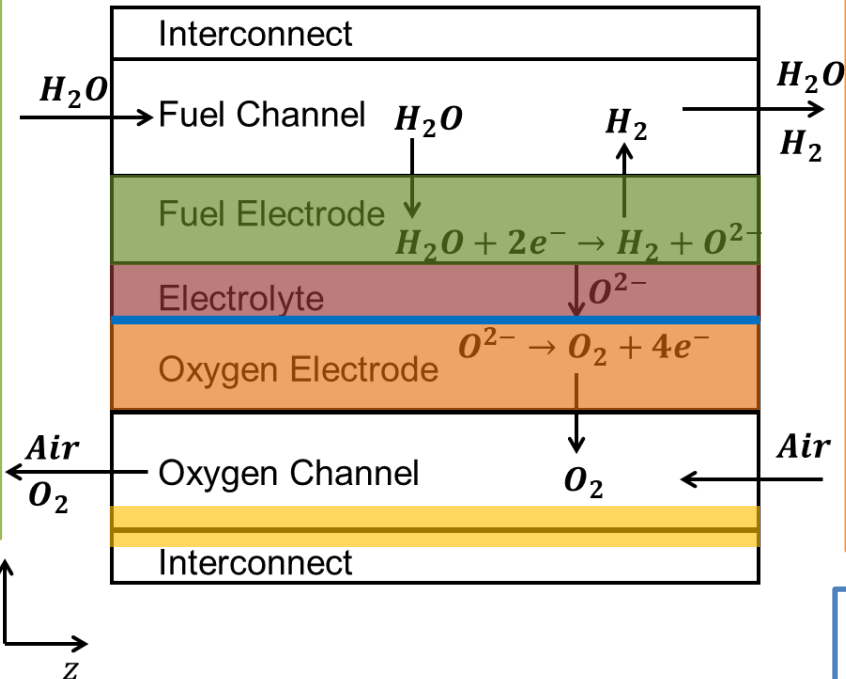
Refs: J. Sehested et al. / *Applied Catalysis A: General* 309 (2006) 237–246

YSZ electrolyte phase transformation

- Phase transformation of YSZ from cubic to tetragonal structure
- Results in decrease in electrolyte conductivity

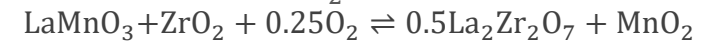
$$\sigma_{El} = \sigma_{El,0} \left[\lambda + (1 - \lambda) \exp\left(-\frac{t}{\tau}\right) \right]$$

Refs: Jiang et al. *Journal of the American Ceramic Society* 82(11):3057 - 3064



Lanthanum zirconate (LZO) scale growth

- At oxygen electrode under oxidizing conditions and high temperatures driven by high P_{O₂}



- Parabolic growth law

$$\frac{dl_{LZO}(t)}{dt} = \frac{K_{g,LZO}}{2l_{LZO}(t)X_{0,LZO}\rho_{LZO}} \exp\left(\frac{E_{LZO}}{RT}\right)$$

Refs: A. Kamkeng, and M. Wang. / *Chemical Engineering Journal* 429 (2022): 132158

Chromium oxide scale growth

- Oxidation of chromium interconnect-oxygen electrode boundary
- Parabolic growth law

$$\frac{dl_{cos}(t)}{dt} = \frac{K_{g,cos}}{2l_{cos}(t)X_{0,cos}\rho_{cos}} \exp\left(\frac{E_{cos}}{RT}\right)$$

Refs: D. Larrain et al. / *Journal of Power Sources* 161 (2006) 392–403

LSM-YSZ phase coarsening

- Driven by Mn²⁺ diffusion from LSM surface toward LSM-YSZ interface
- Results in loss of TPB length
- Model derived by assuming Fick's law diffusion of Mn²⁺

$$\frac{L_{TPB}}{L_{TPB,0}} = 1 - 2 \times \left(\frac{t \times D_{LSM}}{\pi} \right)^{1/2}$$

Refs: A. Kamkeng, and M. Wang. / *Chemical Engineering Journal* 429 (2022): 132158

Optimizing Long-Term SOEC System Operation

Case 1: Maximize Integral Efficiency

$$\max \frac{1}{t_f - t_0} \int_{t_0}^{t_f} \eta_t dt$$

st.

$$h(x) = 0$$

$$\frac{dR}{dt} = f_R(x, t)$$

$$\eta_t = \frac{HHV(\dot{m}_{H_2,t})}{P_{in,total,t}} \quad \forall t$$

Case 3: Minimize Levelized Cost of Hydrogen (LCOH)

LCOH =

$$\frac{CRF_{BOP} CC_{BOP} + \sum_{i=1}^R CRF_{stack,i} CC_{stack} + OC + EC}{m_{H_2,lifetime}}$$

Case 2: Minimize Final Degradation

$$\min \Delta V(\overline{\theta_{t_f}})$$

st.

$$h(x) = 0$$

$$\frac{dR}{dt} = f_R(x, t)$$

$$\theta_{t_f} = \theta_{t_0} + \int_{t_0}^{t_f} \dot{\theta}(x, \theta) dt$$

Decision variables at each time point:

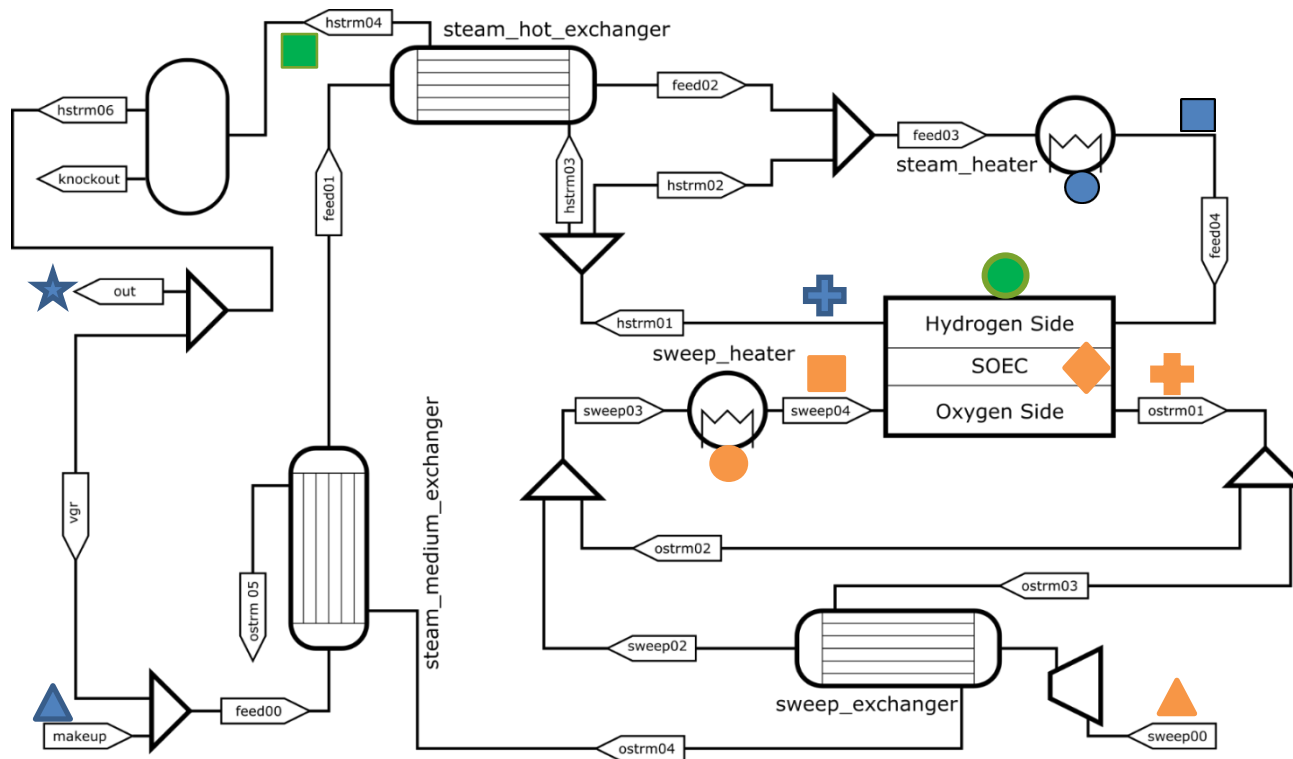
1. Feed heater duties
2. Sweep heater duties
3. Sweep blower flowrate
4. Feed exchanger flowrate
5. Feed recycle ratio
6. Sweep recycle ratio

Quasi-Steady State Optimization Results for 3 Objective Functions under Galvanostatic, Potentiostatic, and Flexible Operation for Low- and High-Price Electricity Markets

Operating Profile	Objective Function	Electricity Price = 0.03 \$/kWh		Electricity Price = 0.3 \$/kWh	
		Replacement Schedule (years)	LCOH (\$/kg H_2)	Replacement Schedule (years)	LCOH (\$/kg H_2)
Galvanostatic Operation	Minimize terminal degradation	5	2.00	5	13.00
	Maximize Integral Efficiency	2	2.29	2	11.92
	Minimize LCOH	5	1.93	2.5	11.84
Potentiostatic Operation	Minimize terminal degradation	3	2.11	3	12.51
	Maximize Integral Efficiency	2	2.30	2.0	11.93
	Minimize LCOH	3	2.05	2.0	11.91
Free Operation	Minimize terminal degradation	5	1.99	5	13.01
	Maximize Integral Efficiency	3	2.02	2.5	11.78
	Minimize LCOH	5	1.92	2.5	11.78

Process Control for SOC-based System Mode-Switching

- **Classical Control: Proportional-Integral-Derivative (PID)**
- **Nonlinear Model Predictive Control (NMPC)**
 - Well-suited to highly interactive manipulated variables and constraint handling

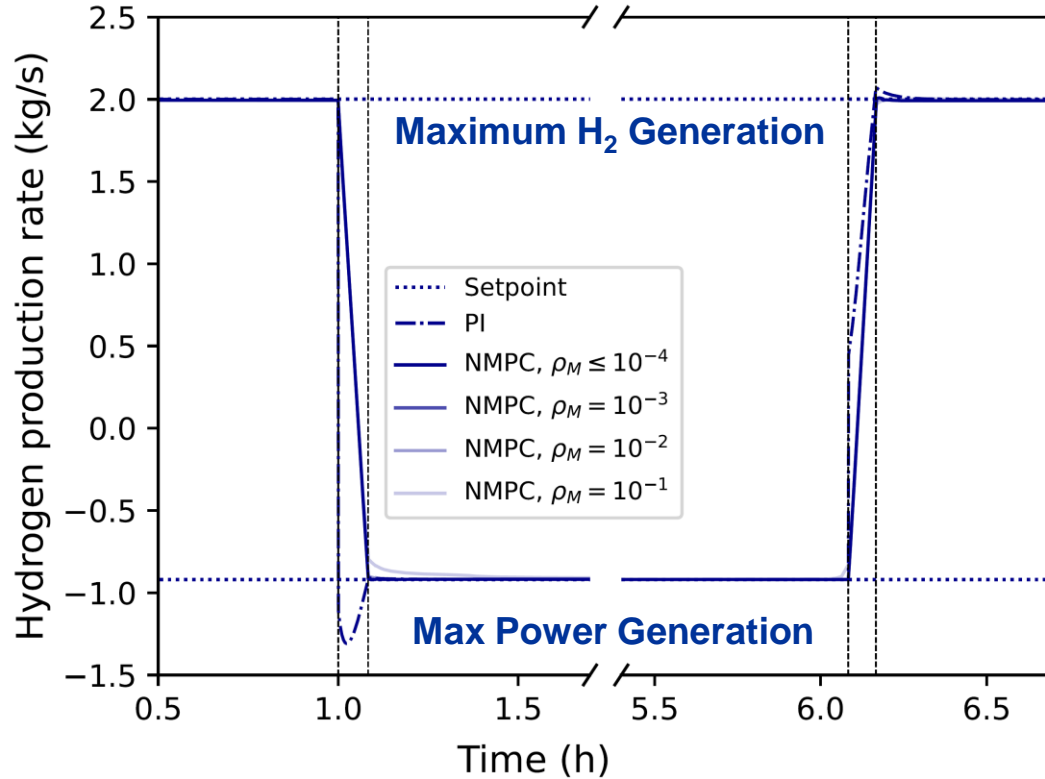


Controller	Manipulated Variables (MVs)	Controlled Variables (CVs)
PID, NMPC	Cell potential ●	Outlet Water Concentration ■
PID, NMPC	Steam/H ₂ feed rate ▲	H ₂ production rate ★
PID, NMPC	Feed heater duty ●	Feed heater outlet temperature ■
PID, NMPC	Sweep heater duty ●	Sweep heater outlet temperature ■
PID, NMPC	Steam heater outlet temperature setpoint* ■	SOC steam outlet temperature +
PID, NMPC	Sweep heater outlet temperature setpoint* ■	SOC sweep outlet temperature +
PID, NMPC	Sweep feed rate ▲	SOC temperature ◆
NMPC	Feed recycle ratio	
NMPC	Sweep recycle ratio	
NMPC	Vent gas recirculation (VGR) recycle ratio	
NMPC	H ₂ /H ₂ O ratio in make-up	

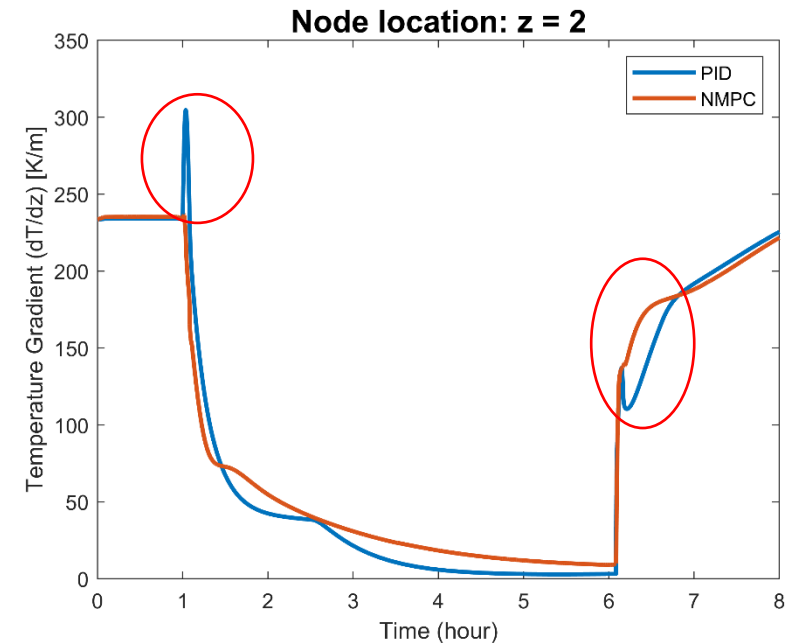
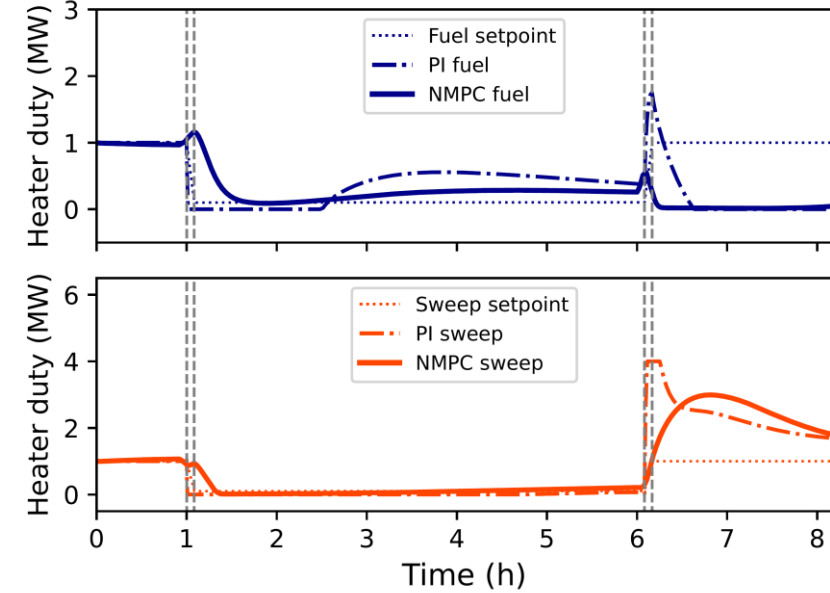
*artificial control variables

- Allan, D.A., et al., In Proc. FOCAP0/CPC (2023).
- Dabadghao, V., Ph.D. Thesis, CMU (2023).

Dynamic Simulation and Control Results for Ramping Operation



- **Classical PI control** of H₂ production rate shows **overshoot**, not exhibited by NMPC
- **NMPC** yields **smoother heater duty profiles** than PI control
- **NMPC** yields **smoother SOC temperature gradient** and lower spatial extremum magnitude than PI control



Summary

- IDAES has become a foundational modeling and optimization platform enabling us to address several major national and DOE priorities.
- The core program is focused on ensuring existing projects leveraging IDAES are successful while continuing to build out new capabilities.
 - Integrating short-term operational realities into long term expansion planning of reliable, decarbonized grids.
 - Integrating manufacturing considerations into process design to reduce both deployment times & manufacturing costs.
 - Optimizing the design, operation, and control of integrated power and H₂ systems.
- Several advanced dynamic optimization & control capabilities have been recently developed for flexible SOC systems.
 - Long-term SOEC optimization considering chemical degradation can be used to optimize stack replacement schedule and operating trajectories.
 - Nonlinear model predictive control (NMPC) can explicitly restrict temperature gradients/curvatures or other constraints compared to classical control.

Acknowledgements

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