

IDAES[®]

Institute for the Design of Advanced Energy Systems

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Objective of Core IDAES Program

 IDAES enables the design and optimization of the increasingly integrated and dynamic energy and process systems of the future with an emphasis on facilitating deep decarbonization of the energy and industrial sectors.

- Major Focus Areas
 - 1. Continue to build out advanced capabilities
 - 2. Grow the user base in strategic areas
 - 3. Ensure that existing projects leveraging IDAES are successful !!!



Foundational Modeling and Optimization Partnerships Utilizing IDAES

Multi-lab Initiatives to Address Major National and DOE Priorities



IDAES-Core Now Supported by FECM's Hydrogen with Carbon Management Program

- **Objective:** Develop clean hydrogen as a cost-competitive alternative base fuel for power generation, energy storage and industrial heat.
- Reduce H₂ costs of \$1/kg within one decade (1-1-1) with life cycle GHG emissions reductions (including from methane) of 90% vs current levels.
- Current application areas:
 - Point source capture from gasification and reforming
 - Modular co-gasification of waste plastics (or MSW), biomass, and waste coal
 - Reversible solid oxide fuel cells
 - Hydrogen turbines
 - Clean hydrogen hubs



IDAES New Capability Development

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



Integrated Energy System for Low Carbon Power and H₂



The IDAES platform is being applied to explore whether tightly coupled integrated energy systems that have the flexibility to produce both power and hydrogen should play a role in DOE's goals of decarbonizing the power sector by 2035 and broader economy by 2050.



Analysis of Integrated Energy System Concepts



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



Process Concept Evaluation Strategy

Develop process and costing models using IDAES that are capable of optimization and offdesign performance prediction



Calculate standard metrics like

- \$/MWh
- \$/kg H₂
- kg CO2_{eq}/MWh
- kg CO2_{eq}/kg H₂



Use surrogate models in **multi-period process/market optimization model** to calculate optimal **capacity factors** and **net profit** under several scenarios.



Conventional Process-Centric Analysis was Rigorous but Limited





- Lowest cost system highly dependent on many factors (NG, H₂, electricity prices, CO₂ incentives or taxes)
- A different analysis approach is required to more fully understand the value proposition of such systems.



Eslick, Noring, Susarla, Okoli, Allan, Wang, Ma, Zamarripa, Iyengar, Burgard, Technoeconomic Evaluation of Solid Oxide Fuel Cell Hydrogen-Electricity Co-generation Concepts (<u>DOE/NETL-2023/4322</u>).

Multi-Period Optimization, Price-Taker Assumption*



Disjunctions at every time step to choose optimal operating mode:

- Buying electricity from grid
- Ramping constraints
- Start up shutdown costs

$$\begin{bmatrix} C_{var}(p_t, h_t) = 0 \\ p_t = 0 \\ h_t = 0 \end{bmatrix} \underbrace{\bigvee} \begin{bmatrix} C_{var}(p_t, h_t) = f_1(p_t) \\ p_t \ge P_{min} \\ h_t = 0 \\ p_t^h = 0 \end{bmatrix} \underbrace{\bigvee} \begin{bmatrix} C_{var}(p_t, h_t) = f_2(h_t) \\ h_t \ge H_{min} \\ p_t^h = f_4(h_t) \end{bmatrix} \underbrace{\bigvee} \begin{bmatrix} C_{var}(p_t, h_t) = f_3(p_t, h_t) \\ p_t^h = f_5(h_t) \\ p_t \ge P_{min} \\ h_t \ge H_{min} \end{bmatrix}$$
Plant is off Power only Hydrogen only Hydrogen only Hydrogen



More advanced formulations: Presentation (this afternoon):

Interactions (DISPATCHES)

Advances in Modeling Power Generation Grid and Market

Alex Dowling, John Siirola

Poster:

Multi-scale Optimization of Integrated Energy Systems that Co-**Produce Electricity and Hydrogen Using Market Surrogates** Xinhe Chen

Many Electricity Market Scenarios Considered

- 61 total data sets (every hour for a year)
- 2019 & 2022 data from 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

Data sets cover very broad range of potential scenarios



System: SOFC + SOEC Scenario: MiNg_\$100_MISO-W_2035 (only first 700 hours of year shown)



Compiled Results from Integrated Process/Market Optimization



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

NGCC (power only)	13%
SOFC (power only)	52%
SOEC (H2 only)	74%
NGCC + SOEC (power and/or H2)	16%
Reversible SOC (power or H2)	97%
SOFC + SOEC (power and/or H2)	98%

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



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



Take Home Messages

- The IDAES platform enabled rigorous comparisons of processes across diverse market scenarios leading to insights beyond conventional TEA.
- This is perhaps the first study to quantitatively make the business case for why DOE is investing in reversible SOFC technology.
- Emphasis in 2023 on developing publicly available, configurable, workflow for process/market optimization that reduces analysis time from months to weeks.
 - Flexible carbon capture
 - Hybrid energy systems (e.g., nuclear, solar, fossil + capture)
 - Integrated DAC systems



Integrated **Dynamic** H₂ and Power Systems

Research Challenge

- SOC-based systems need to operate flexibly with fluctuations in electricity prices.
- How can one best operate and control SOC-based systems for mode-switching (H₂/power), while minimizing degradation over long-term operation?

Key Findings

- Nonlinear model predictive control (NMPC) can track H₂ and power production setpoints, while mitigating SOC temperature gradients and mixed partial derivatives during mode-switching.
- Long-term performance/degradation optimizations (20K hours) show that choice of optimal operational scenario depends on tradeoff between energy costs and SOC replacement costs.



SOC system for $\rm H_2$ and power production

See also:

Oct 12, General Session, AM Making Models Dynamic and Controllable Doug Allan

Posters

NMPC for Mode-Switching Operation of Reversible Solid Oxide Cell Systems

Doug Allan, Michael Li

Optimal Long-Term Operation of Solid Oxide Electrolyzers considering Physical and Chemical Degradation Nishant Giridhar



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Product Family and Platform Design



https://global.toyota/en/mobility/tnga/powertrain2018/feature/ https://global.toyota/pages/global_toyota/ir/financial-results/2019_1q_competitiveness_en.pdf

Background

Number of Plant Installations

← Total Plant Capacity



Climate change goals require **rapid**, **broad** deployment of new technologies and process variants for different applications

- Reduce time to deployment through decreased engineering design effort
 - Avoid unique and independent designs for each installation
- Improve manufacturing timelines and costs
 - Exploit economies of numbers
 - Reduce manufacturing complexity
- Simultaneous platform and process design
 - Assemble processes from a smaller subset of subcomponents (platform)



Mapping to PSE: <u>Process</u> Family Design

Variations could be from:





Mapping to PSE: <u>Process</u> Family Design





Process Family

Optimization Formulation

min.
$$\sum_{v \in V} w_v p_v$$

s.t.

$$p_{v} = f_{v}^{p}(\mathbf{r}_{v}, \mathbf{d}_{v,1}, \dots, \mathbf{d}_{v,m}, \mathbf{o}_{v}) \qquad \forall v \in V$$

$$\mathbf{i}_{v} = f_{v}^{i}(\mathbf{r}_{v}, \mathbf{d}_{v,1}, \dots, \mathbf{d}_{v,m}, \mathbf{o}_{v}) \qquad \forall v \in V$$

$$0 = h(\mathbf{r}_{v}, \mathbf{d}_{v,1}, \dots, \mathbf{d}_{v,m}, \mathbf{o}_{v}) \qquad \forall v \in V$$

$$\underbrace{\bigvee}_{l \in L_{c}} \begin{bmatrix} Y_{v,c,l} \\ \mathbf{d}_{v,c} = \hat{\mathbf{d}}_{c,l} \end{bmatrix} \qquad \forall v \in V, c \in C$$

$$\hat{\mathbf{d}}_{c}^{\text{LB}} \leq \hat{\mathbf{d}}_{c,l} \leq \hat{\mathbf{d}}_{c}^{\text{UB}}$$

$$\mathbf{o}_{v}^{\text{LB}} \leq \mathbf{o}_{v} \leq \mathbf{o}_{v}^{\text{UB}}$$

$$\mathbf{i}_{v}^{\text{LB}} \leq \mathbf{i}_{v} \leq \mathbf{i}_{v}^{\text{UB}}$$

 $Y_{v,c,l} \in \{\text{True, False}\}$

$$v \in V$$
set of process variants W_v parameter weight of each process variant v p_v variable cost of each process variant v $m \in M$ set of unit module types \mathbf{r}_v parameter vector of design requirements for variant v $\mathbf{d}_{v,m}$ variable vector unit module design of unit module type m for variant v \mathbf{o}_v variable vector of operating variables for all $m \in M$ for variant v \mathbf{i}_v variable vector of performance indicators for process variant v $c \in C$ set of common unit module types ($C \subseteq M$) $l \in L_c$ set labels for all designs of common unit module design for unit module c $Y_{v,c,l}$ decision variable; selection of common unit module designs

Several different formulations based on this foundation

- Discretization → MILP
- Use of ML surrogates \rightarrow MILP
- Direct solution of MINLP

 $\forall v \in V, c \in C , l \in L_c$

 $\forall c \in C, l \in L_c$

 $\forall v \in V$

 $\forall v \in V$

Computational Framework for MEA Process Family Design







Discretization Formulation Case Study 2: MEA Carbon Capture





Conclusions and Current Work

- Process family design: alternative to build-to-order & pure modularity
- Reduced costs and time to deployment
 - Modular concepts at unit level \rightarrow economies of numbers
 - Customization to the design range \rightarrow economies of scale
 - Reduced engineering design time/effort
 - Reduced manufacturing time/costs
- Multiple scalable optimization formulations
- Estimated capital cost reductions of 8-14% (using literature parameters)

Current Work

- Incorporate economies of numbers within optimization formulation
- Decomposition strategies for larger-scale problems: Alg. \rightarrow HPC
- Extensions to other climate change processes





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Infrastructure Planning of Reliable & Carbon-Neutral Power Systems

Objective

 To determine long-term (yearly) investment decisions for future carbon-neutral power systems 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.





Infrastructure Planning of Reliable & Carbon-Neutral Power Systems

San Diego County Case Study

California Policy and Regulatory Environment	Scenario #1	Scenario #2	Scenario #3
CO ₂ emission limits (30% reduction by Y10)	X	0	0
Renewable generation (60% of the total generation by Y10)	X	X	0



See also:

Presentation (this afternoon) Advancing the State of the Art in Expansion Planning

for the California Grid in Partnership with IDAES Seolhee Cho, Chris McLean, Ben Omell



Posters

Optimization for Infrastructure Planning of Reliable and Carbonneutral Power Systems: Application to San Diego County Seolhee Cho Flexible Modular Formulations for Grid Infrastructure Planning Kyle Skolfield

ML-Guided Optimization of Energy Systems Nick Sahinidis

Start up cost

Fuel cost

Variable operating cost

Line investment cost

Renewable expansion cost

Shut down cost

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 advanced capabilities.
 - Examining the design, market potential, dynamics, and controllability of integrated power and H_2 systems.
 - Explicitly integrating manufacturing considerations into process design to reduce both deployment times and manufacturing costs.
 - Better integrating short-term operational realities into long term expansion planning of reliable, decarbonized electricity grids.
- Emphasis in 2023 on developing diagnostics and enhanced visualization features a direct result on stakeholder feedback.



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2023 Joint CCSI₂/IDAES Technical Team Meeting Lawrence Berkeley National Lab

https://idaes.org/about/contact-us/



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Diagnostics and Visualization

Research Challenge

- Solving EO models is extremely challenging, and often takes significantly more time than initial model development.
- Despite decades of experience, there are no published workflows for debugging models

Objectives

- Develop tools and workflows for model diagnostics to assist users with developing and troubleshooting models.
- Make diagnostic information visually accessible to model developers.





Estimated U.S. Energy Consumption in 2021: 97.3 Quads





Source: LLNL March, 2022. Data is based on DOE/EIA MER (2021). If this information or a reproduction of it is used, credit must be given to the Lawrence Livermore National Laboratory and the Department of Energy, under whose auspices the work was performed. Distributed electricity represents only retail electricity sales and does not include self-generation. EIA reports consumption of renewable resources (i.e., hydro, wind, geothermal and solar) for electricity in BTU-equivalent values by assuming a typical focsil fuel plant heat rate. The efficiency of electricity production is calculated as the total retail electricity delivered divided by the primary energy input into electricity generation. End use efficiency is estimated as 65% for the residential sector, 21% for the transportation sector and 49% for the industrial sector, which was updated in 2017 to reflect DOE's analysis of manufacturing. Totals may not equal sum of components due to independent rounding. LLNL-MI-410527

Evolving Grid Increasingly Requires Flexibility

-Coal

Data for Electric Reliability Council of Texas (ERCOT) ISO

-Gas-CC

3/11/23 0:00 3/12/23 0:00 3/13/23 0:00 3/14/23 0:00

3/9/23 0:00 3/10/23 0:00



ERCOT Generation Mix - March 2023

3/16/23 0:00 3/17/23 0:00 3/18/23 0:00 3/19/23 0:00 3/20/23 0:00 3/21/23 0:00 3/22/23 0:00 3/23/23 0:00 3/24/23 0:00 3/25/23 0:00 3/26/23 0:00 3/27/23 0:00 3/28/23 0:00 3/29/23 0:00 3/30/23 0:00 3/31/23 0:00

3/15/23 0:00

-Solar

_

-Wind

-Total

-Nuclear



3/3/23 0:00

3/4/23 0:00 3/5/23 0:00 3/6/23 0:00 3/7/23 0:00 3/8/23 0:00

3/1/23 0:00 3/2/23 0:00 4/1/23 0:00

4/2/23 0:00

DOE's Office of Fossil Energy & Carbon Management (FECM) Strategic Directions and Priorities

- Advancing Justice, Labor, and Engagement
 - Justice
 - Labor
- Advancing Carbon Management Approaches toward Deep Decarbonization
 - Point-Source Carbon Capture
 - Carbon Dioxide Conversion
 - Carbon Dioxide Removal
 - Reliable Carbon Storage and Transport
- Advancing Technologies that Lead to Sustainable Energy Resources
 - Hydrogen with Carbon Management (now funds Sim-based Engineering & IDAES-Core)
 - Domestic Critical Minerals Production
 - Methane Mitigation



Next-generation multi-scale modeling & optimization framework



IDAES is connecting cutting edge research with practice

- The IDAES team is developing a comprehensive, integrated set of PSE tools
 - Core unit modeling framework
 - Customized property packages
 - Initialization schemes
 - Diagnostics Toolbox
 - Custom system models
 - PC, NGSC, NGCC-based power generation, SOFC/SOEC, SMR, integrated power/hydrogen systems, hybrid energy systems, solvent-based carbon capture, direct air capture, etc.
 - Dynamic modeling
 - Dynamic unit model library
 - Model reduction techniques
 - Nonlinear state estimation and control

- Data-driven modeling
 - ALAMO machine learning framework
 - Helmholtz energy equations of state fitting (HELMET)
 - General surrogate generation (PySMO)
- Conceptual design
 - GDP-based superstructure design (Pyosyn)
- Integrated process/market optimization
- Process family design
- Capacity expansion planning w/ reliability
 - Capacity expansion planning
 - Market modeling and simulation (Prescient)
- Systems integration & materials design

IDAES provides both a vehicle for rapid dissemination of cutting-edge research results and an ecosystem for the maturation of those results into industrially-applicable capabilities.





Why IDAES?

- Hierarchical structure supports familiar modular assembly of flowsheets
- Integrated Ecosystem all the tools you need in one place
 dynamics, conceptual design, diagnostics, UQ, AI/ML, UI built
- Optimization focused many commercial tools are designs for simulation
- Flexibility object oriented programing allows more control over models
- Cost open-source codebase, free of charge



Open-Source Platform

Website: https://idaes.org/

GitHub repo: https://github.com/IDAES/idaes-pse

Support: idaes-support@idaes.org

Ask questions, subscribe to our user and/or stakeholder email lists

Documentation: https://idaes-pse.readthedocs.io

Getting started, install, tutorials & examples

Overview Video

https://youtu.be/28qjcHb4JfQ

Tutorial 1: IDAES 101: Python and Pyomo Basics

https://youtu.be/_E1H4C-hy14

Tutorial 2: IDAES Flash Unit Model and Parameter Estimation (NRTL)

https://youtu.be/H698yy3yu6E

Tutorial 3: IDAES Flowsheet Simulation and Optimization; Visualization Demo

https://youtu.be/v9HyCiP0LHg



IDAES Contributions



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





IDAES Projects Span Multiple Time-Scales

 Technoeconomic and market analysis of SOEC/SOFC-based hydrogen and electricity co-production systems (hours → years)

 Dynamic & health modeling, control, and optimization of SOEC/SOFC-based systems (seconds (dynamic operation) → years (health))

 Integrating short-term operational realities (e.g., unit commitment and dispatch) into long-term expansion planning models (minutes → decades)



Solid Oxide Cell (SOC)-based Integrated Energy Systems (IES)

Key Challenge

- How can we best operate and control SOC-based IES for mode-switching (H₂/power), while minimizing degradation over long-term flexible operation?
 - SOCs operate at much higher temperatures than other fuel cell/ electrolysis technologies
 - While high-temperature operation offers higher current density and efficiency, it also poses significant challenges:
 - Additional heat exchange equipment
 - Accelerated degradation
 - Tight controls for optimizing performance and health during setpoint transitions and mode-switching operation



Operating principles for H₂ fuel in SOFC mode and steam electrolysis in SOEC mode.



Optimization of SOC-based IES Flexible Operations *Dynamics, Control, and Health Modeling*

Technical Approach

- Dynamic Modeling
 - Develop first-principles dynamic model of SOC-based IES using IDAES software
- Process Control
 - Develop classical and advanced process controls for effective thermal management and mode-switching operation
- Health/Degradation Modeling
 - Develop first-principles sub-models for physical and chemical degradation, as well as their synergistic effects, to quantify impact on cell health
- Optimization
 - Optimize performance and health of SOC-based IES for long-term flexible operation



Dynamic Model of H₂-fueled SOC-based IES for Mode-Switching

- **IDAES** open-source, equation-oriented modeling and optimization framework (Lee et al., 2021)
- SOC dynamic model (Bhattacharyya et al., 2007)
 - First-principles, non-isothermal, planar
 - 1D channel; 2D electrodes, electrolyte, and interconnect
 - H₂ fueled in power mode
- Equipment models for thermal management
 - 1D multipass crossflow recuperative heat exchangers
 - 1D crossflow trim heaters
- System performance constraints
 - Maximum H₂O outlet concentration to ensure good conversion
 - Minimum O₂ in sweep outlet to prevent oxidation
 - Max cell thermal gradient to avoid degradation



- 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).



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

Process Control for SOC-based IES Mode-Switching Operation

- Classical Control: Proportional-Integral-Derivative (PID)
- Nonlinear Model Predictive Control (NMPC)



• Allan, D.A., et al., In Proc. FOCAPO/CPC (2023).

• Dabadghao, V., Ph.D. Thesis, CMU (2023).

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

NMPC for SOC-based IES Mode-Switching Operation

- NMPC is well suited to highly interactive manipulated variables and constraint handling
- NMPC objective function

$f_{\rm obj} = \sum_{i=1}^{N}$	$\sum_{i=0}^{N} \rho_{\mathrm{H}_{2}} \left(y_{i} - y_{i}^{R} \right)^{2} + \sum_{i=0}^{N} \left($	$\sum_{k=0}^{N} \sum_{j \in J} \rho_j \left(u_{ij} - u_{ij}^R \right)^2 + \sum_{i=0}^{N} \sum_{k \in K} \rho'_k \left(x_{ik} - x_{ik}^R \right)^2$	$+\sum_{i=1}^{N} \rho' \left(\nu_{i} - \nu_{i-1}\right)^{2}$	$+\rho_s \sum_{i=0}^N \sum_{z=1}^{z_L} (p_{iz} + n_{iz})$
−	rajectory	Deviations of manipulated variables (u_{ij}) and controlled variables (x_{ik}) from reference values	Rate of change	ℓ ₁ -penalties for
T	racking of		penalties on	temperature
tr	H ₂ /power		trim heater	gradient
F	production rate		duties	constraints

- To prevent thermal degradation over time, the temperature gradient along the cell length (z-direction) is constrained to be below dT/dz_{ub} K/m
- An l_1 -penalty relaxation treats them as soft constraints with non-negative slack variables p and n penalized in the objective

$$dT/dz - dT/dz_{ub} \le p$$
 and $- dT/dz - dT/dz_{ub} \le n$



SOC-based IES Mode-Switching Operation

Mode-Switching

- Maximum H₂ (2.0 kg/s) to maximum power (-0.92 kg/s) and back to maximum H₂
- Ramps performed over 30 min, followed by 2 hours of settling time

IDAES Solution Approaches

- Classical control: PETSc variablestep implicit Euler dynamic integrator
- NMPC: Full-discretization NLP with IPOPT optimizer





NMPC Results for SOC-based IES Mode-Switching Operation



Hydrogen production tracking has no overshoot, and is correlated to cell voltage and total power usage



NMPC Results for SOC-based IES Mode-Switching Operation

Performance constraints are satisfied

- Maximum H_2O in outlet to ensure good conversion in SOEC mode
- O_2 in sweep outlet $\leq 35\%$ (mole basis) to prevent oxidation
- Conversion of steam to $H_2 \ge 75\%$ to avoid steam starvation
- Maximum cell thermal gradient \leq 1000 K/m to avoid stress





SOC Health/Degradation Modeling

Physical Degradation

- High spatial and temporal temperature gradients
- Thermo-mechanical stresses
- Creep and fatigue damage Strain continuity at layer interfaces $T = T_{ref} + \Delta T$ Fuel electrode (Ni/YSZ) Oxygen electrode (Ni/YSZ) Compressive stress Tensile stress

- Chemical Degradation (H₂ fuel)
 - Oxygen electrode
 - Chromium oxide scale growth
 - Increased local ohmic resistances
 - Lanthanum zirconate scale growth
 - LSM-YSZ coarsening
 - Fuel electrode
 - Ni agglomeration and volatilization
 - Electrolyte
 - YSZ electrolyte delamination

- Synergistic Effects
 - Chemical degradation negatively impacts physical degradation by:
 - increasing local Ohmic resistance and cell temperature
 - affecting thermo-physical properties of the ceramic materials, which result in variation in the cell thermal profile
 - affecting mechanical properties of cell components such as Young's modulus and Poisson's ratio



Case Study: SOEC Health Optimization over Long-Term Operation

- 20,000 hrs of operation
- Electrolysis mode
 - High H₂ production rate: 1.5 kg/s
- Chemical degradation (O₂ electrode)
- Health Optimization Case
 - Minimize final ohmic resistance min R_{ohmic,tf}
 - Decision variables at every time point
 - Fuel and oxygen trim heater duties
 - Fuel and oxygen inlet flowrate
 - Fuel and oxygen recycle ratio
 - Quasi-steady optimization
 - Dynamic degradation model
 - Steady-state SOEC system model



- Base Case
 - No optimization for health/degradation
 - Constant inlet temperatures over operating horizon from steady-state optimization at t=0 hrs to maximize efficiency



Case Study: SOEC Health Optimization over Long-Term Operation

High H ₂ production rate : 1.5 kg/s					
Objective Function	$\left. \frac{dT}{dz} \right _{max}$ (K/m)	Т _{core} (К)	$oldsymbol{\eta}_{ ext{average}}$	R_{ohmic} (mΩ/ khr)	P _{specific} (MWh/kg H ₂)
Base Case	1020	1033	0.872	0.34	38.05
Degradation Optimization Case: Minimize final resistance	980	1020	0.875	0.26	38.15

- About **25% reduction in resistance** growth rates (*R_{ohmic}*)
- System efficiency ($\eta_{average}$) and power requirement ($P_{specific}$) remain unchanged
 - Resistive heating in trim heaters instead of inside the cell
- Minimizing resistance can keep absolute cell temperatures (T_{core}) in control
- Thermal gradients constraints $\left(\frac{dT}{dz}\right|_{max}$ < 1000 K/m) remain feasible after 20,000 hrs of optimized performance



Please stop by poster for more details/results on SOC health modeling and optimization.

Summary

- **IDAES** offers an open-source modeling framework for **optimization** of the operation, control, and health of **flexible SOC-based IES**.
- NMPC provides accurate H₂/power production setpoint tracking during mode-switching operation.
- Results for SOEC health optimization over long-term operation show that:
 - ohmic resistance growth and cell temperature are reduced,
 - H₂ production rate and efficiency are maintained, and
 - thermal gradients are kept under control.



Future Work

- Enhance NMPC to maximize SOC system performance for "faster" mode-switching operation, while reducing temperature gradients to benefit cell health
- Analyze synergistic effects of physical and chemical degradation for mode-switching operation
- Optimize SOC system performance over operational lifetime
 using measure of health on economics
- Develop prototype of multiple timescale computational approach in IDAES for solving coupled dynamic simulations of long-term flexible operation and degradation



IDAES Projects Span Multiple Time-Scales

 Technoeconomic and market analysis of SOEC/SOFC-based hydrogen and electricity co-production systems (hours → years)

 Dynamic & health modeling, control, and optimization of SOEC/SOFC-based systems (seconds (dynamic operation) → years (health))

 Integrating short-term operational realities (e.g., unit commitment and dispatch) into long-term expansion planning models (minutes → decades)



Expansion Planning Modeling: Will Technology be Deployed?





Expansion Planning Problems Are "Huge"

- At the core, an expansion planning model considers
 - Systems with $>10^2$ generators, $>10^3$ transmission lines,
 - Balancing loads over each of 10^6 time periods,
 - With numerous opportunities to install, extend, and retire assets,
 - And significant uncertainty in all parameters (generator costs, available technology, load growth and patterns, renewable resources),
- Too large to "directly solve"
- Numerous simplifications and approximations to develop "tractable" models
 - ACOFP \rightarrow DCOPF \rightarrow Transshipment
 - Full network \rightarrow "skeletonized" network \rightarrow "copper plate"
 - Individual generators \rightarrow generator clusters
 - Full time horizon \rightarrow representative days \rightarrow representative loads
 - Discrete decisions \rightarrow continuous relaxations
- Simplifications for tractability will impact accuracy



Why is IDAES Developing Expansion Planning Models?

- Integrated Energy Systems must be designed for the system
 - Designing in isolation (e.g., "max efficiency") does not guarantee participation / revenue from the market
- Existing expansion planning models focus primarily on *capacity*
 - Operability (e.g., the role of dynamics, flexibility, and uncertainty) is not explicitly included, leading to results that overvalue LCOE and undervalue dispatchability and flexibility
- Extending expansion planning models is more than just adding features
 - Scaling up the model requires exploring new algorithmic approaches to solving the model. Model is open, allowing for customization for the problem you are interested in addressing



Current IDAES Expansion Planning Activities

- Develop reliability models and algorithms (Carnegie Mellon University, Seolhee Cho and Ignacio E. Grossmann)
 - Improve valuation of flexibility
 - Incorporate resilience with reliability
 - Expand to new case studies (partnering with California Energy Commission)
- Model maturation (Sandia National Laboratory)
 - Generalizing / standardizing the models, leveraging standardizing modeling components from EGRET
 - Generalizing / standardizing algorithms (remove explicit ties to case studies)



Quantifying the Impact of Flexibility

- Expansion planning with SPP case study (hourly load balance with seasonal representational days) ٠
 - Results indicated significant reduction of installed flexible generation with higher carbon tax
 - Gas turbine, internal combustion turbine units •
 - Lower efficiency, higher relative emissions
 - Counter-intuitive result
- Root cause: "representative" days did not capture •
 - High ramp rates (volatility)

0.9

0.8

0.7 0.6

0.5 0.4

0.3

0.2

🗕 wind

-3

Jan-29-2020

3 16 19 22

-load

0.8

0.6

0.4

0.2

0

Low non-dispatchable generation (intermittency)

Mar-05-2020

🗕 solar



Accounting for Intermittency and Volatility

- "Non-representative" capacity and ramp scenarios critical in understanding dispatchable unit requirements
- Modified algorithm provides insights into low renewable capacity and/or rapid dispatchable ramp scenarios
 - Lazy capacity constraints
 - Extreme ramp events





- "Representative Days Only" underestimates total required capacity
- More dispatchable capacity required with additional capacity constraints and ramp events

How to Improve Reliability - Redundancy

- Power systems reliability can be enhanced by improving availability of power plants.
- *Redundancy* Adding units in parallel enables a power plant to be highly available.





Including The Cost of Not Meeting Demand – Optimizing Considering Reliability

Illustrative example (2 regions, 3 types of power plants (Coal, natural gas (NG), and biomass (Bio))

Cost results

(a) Model A (w/ reliability), (b) Model B (w/o reliability)



LOLE (Loss Of Load Expectation) - time of not satisfying the load demand

LOEE (Loss of Energy Expectation) - The amount of demand that the system cannot satisfy



Model A requires higher CAPEX and OPEX due to having more parallel generators.

- However, **lower reliability penalties are occurred in Model A** as the model considers slack capacity to reallocate the load demand when the generators fail.
- Model B has lower CAPEX and OPEX than Model A but incurs in higher reliability penalties due to its insufficient capacity.
- The more reliable design obtained by Model A enables the power generation systems to have a better economic performance than Model B.

CEC Case Study: Planning of Reliable Power Generation Systems with High Renewable Penetration

Case study with new capability (results expected 3/31/2024)

• Target area: San Diego County, California

Problem description

• For 5 major existing conventional power plants and peakers (supplementary power plants),

→ determine the time to retire/decommission
(Installation of new conventional plants and peakers is prohibited)

- For renewable generations such as wind turbines and PV panels,
 → time, size, location to newly install
- By installing *batteries*, power systems reliability can be further improved.

 → determine the time, size, location to newly install/retire, and operational strategies
- Alternate cost of decarbonization with conventional plants with capture.

*Practical constraints

• Target renewable generation share, CO_2 emission limit, LOLE < 0.1*



[Simplified power plants map of San Diego County]

*: 1 day outage with an event in 10 years



Summary

- IDAES is a multi-lab initiative created to support long term DOE goals
 - Decarbonizing power by 2035, economy by 2050
 - Evolving energy ecosystem requires greater flexibility & integration
- IDAES enables unique and innovative analyses across multiple time-scales
- Significant capabilities have been built to examine the market potential and controllability SOFC/SOEC-based integrated power and hydrogen systems
- Upcoming analysis entails better integrating operational realities into long term expansion planning of reliable, decarbonized electricity grids, with a key case study in collaboration with CEC.





Useful Costing References for IES Work

- Integrated Energy Systems: Eslick, Noring, Susarla, Okoli, Allan, Wang, Ma, Zamarripa, Iyengar, Burgard, Technoeconomic Evaluation of Solid Oxide Fuel Cell Hydrogen-Electricity Cogeneration Concepts (DOE/NETL-2023/4322).
- **Costing Methodology:** Theis, Quality Guidelines for Energy System Studies Cost Estimation Methodology for NETL Assessments of Power Plant Performance (NETL-PUB-22580).
- **NGCC:** Schmitt, Leptinsky, Turner, Zoelle, White, Hughes, Homsy, Woods, Hoffman, Shultz, and James. Cost And Performance Baseline for Fossil Energy Plants Volume 1: Bituminous Coal and Natural Gas to Electricity (DOE/NETL-2023/4320).
- **SOFC:** Iyengar, Noring, Mackay, Keairns, and Hackett. Techno-economic Analysis of Natural Gas Fuel Cell Plant Configurations (DOE/NETL-2022/3259).
- **SMR & ATR:** Lewis, McNaul, Jamieson, Henriksen, Matthews, White, Walsh, Grove, Shultz, Skone and Stevens, Comparison of commercial, state-of-the-art, fossil-based hydrogen production technologies (DOE/NETL-2022/3241).



High Level Block Flow Diagrams

- Compare optimized IES to stand-alone "competitive" systems
- Evaluate dispatchability in context of real energy markets



Design and Costing Basis*

- Greenfield Plants, Midwestern US, 2018 \$'s
- Hydrogen: 6.479 MPa, < 10 ppm H_2O
- All systems designed to capture > 97% CO₂
- 100% capacity factor**

Process Concepts	Capacity (MW _{e,net})	Capacity (kg/s)
NGCC	650	-
SOFC	650	-
NGCC + SOEC	650	5
rSOC	650	5
SOFC + SOEC	710	5
SOEC	-	5

Power

Hydrogon

- SOFC: \$225/kW stack cost⁺
- SOEC: \$105/kW stack cost
- Stack degradation rate: 0.2% / 1000 hr (~7 yrs stack life)⁺

* Theis, Quality Guidelines for Energy System Studies – Cost Estimation Methodology for NETL Assessments of Power Plant Performance, February 2021, (<u>NETL-PUB-22580</u>) ** Major assumption that process-market optimization allows us to relax.

+ Iyengar, Noring, Mackay, Keairns, and Hackett. Techno-economic Analysis of Natural Gas Fuel Cell Plant Configurations (DOE/NETL-2022/3259).



Compiled Results from Integrated Process/Market Optimization



Key Conclusions

% of electricity market scenarios with positive annualized profit assuming $2/kg H_2$ selling price

NGCC (power only)	13%
SOFC (power only)	52%
SOEC (H2 only)	74%
NGCC + SOEC (power and/or H2)	16%
Reversible SOC (power or H2)	97%
SOFC + SOEC (power and/or H2)	98%

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

Bubble Size = Value of Integration:

Annual Profit from SOEC+SOFC – Max (Annual Profit from SOEC, Annual Profit from SOFC)



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

