

# Beyond Price Taker: Optimizing Integrated Energy Systems Considering Market/Grid Interactions

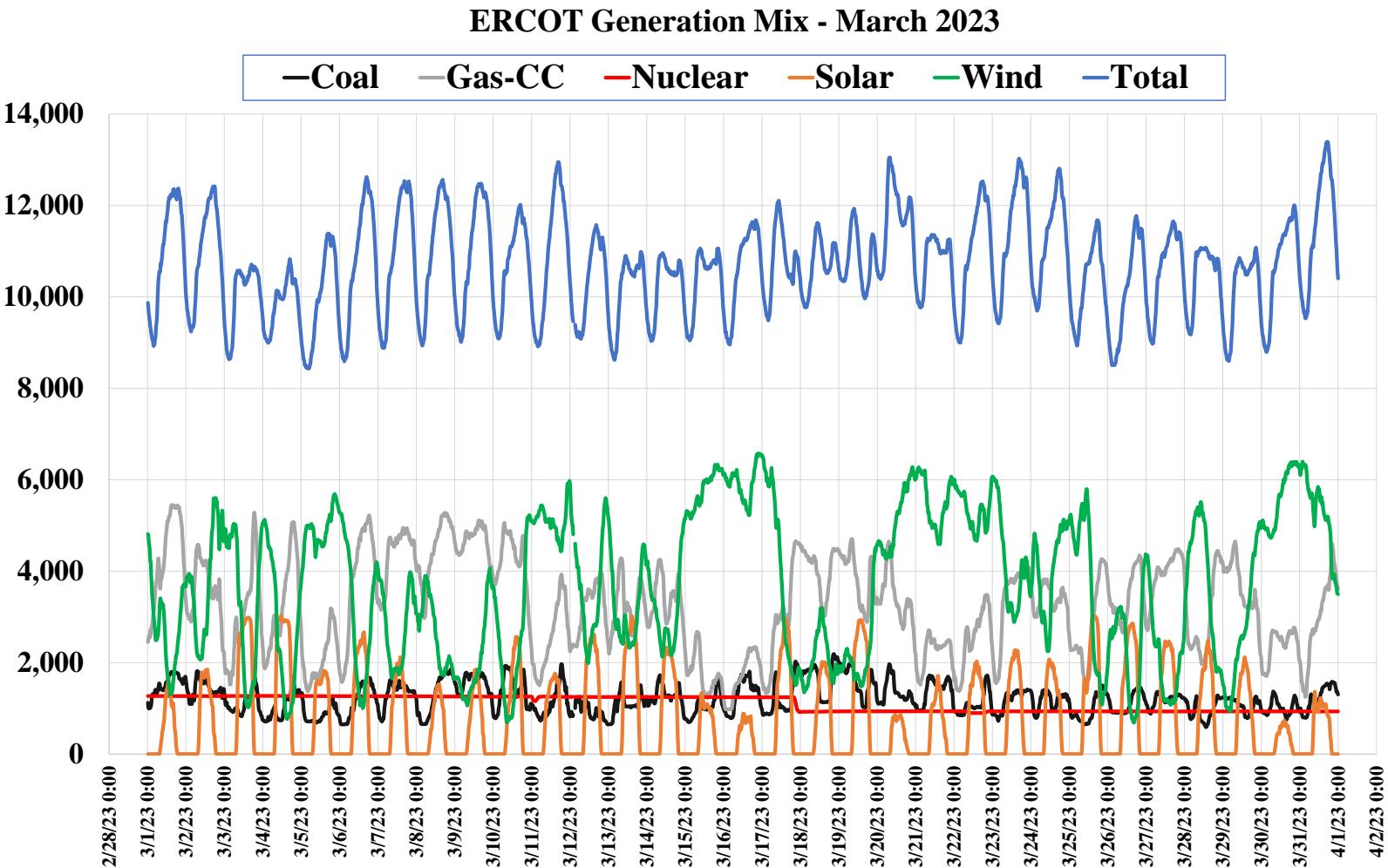
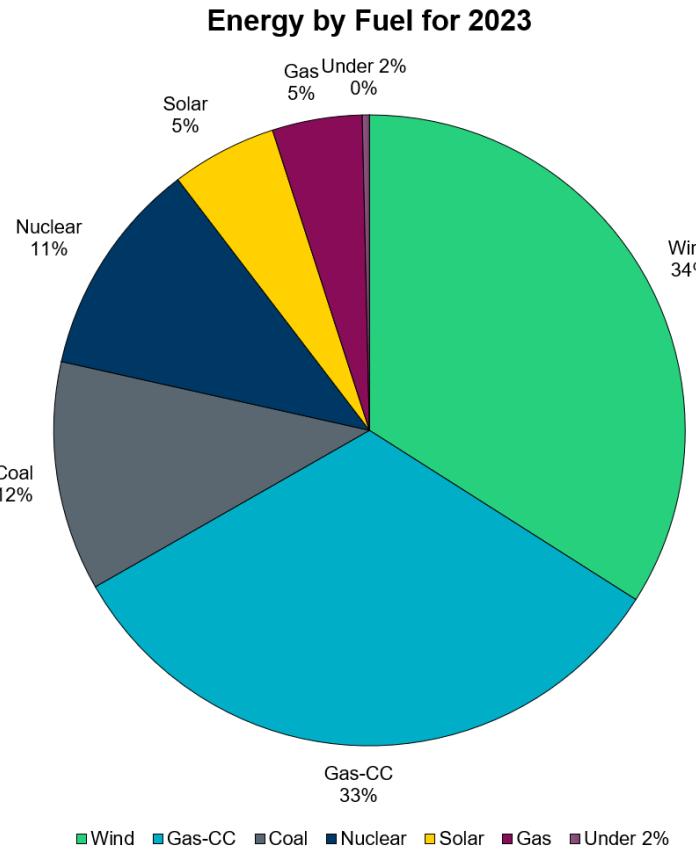
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With contributions from: Xinhe Chen (UND), Daniel Laky (UND), Radhakrishna Gooty (NETL), Tony Burgard (NETL), John Siirola (SNL), J. Kyle Skolfield (SNL), Darice Guittet (NREL), Bernard Knueven (NREL)

# Evolving Grid Increasingly Requires Flexibility

Data for Electric Reliability Council of Texas (ERCOT) ISO

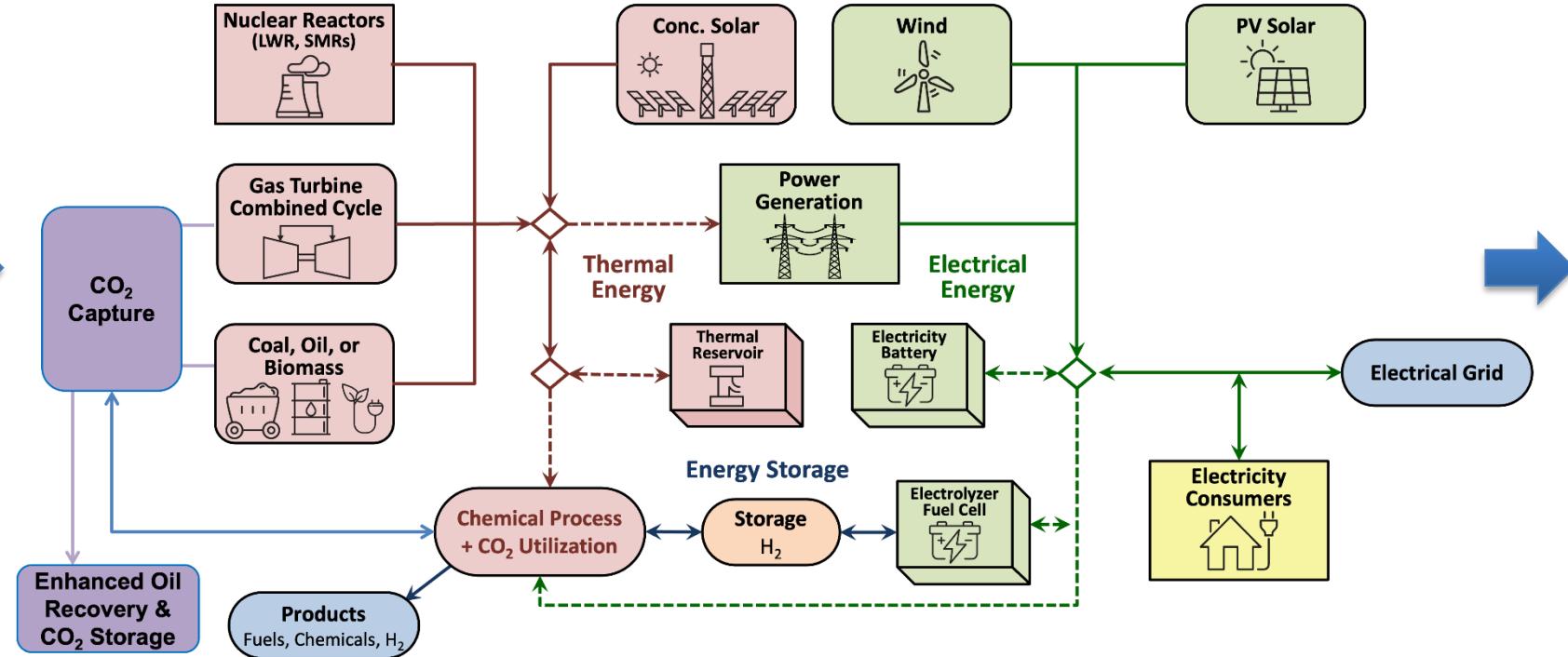


Source: <https://www.ercot.com/gridinfo/generation>

# Integrated Energy Systems (IES) Provide Dynamic Flexibility

Multiple inputs and technologies:

Nuclear  
Gas turbine  
Fossil fuels  
(w/ carbon capture)  
Solar  
Wind  
Batteries  
PEM electrolyzer



Multiple outputs and markets:

Electricity  
Energy Storage  
Ancillary Services  
Heating/Cooling  
Chemicals

## Advantages:

- Provide operation flexibility
- Facilitate integration of multiple energy sources
- Reduce grid operation costs
- Increases grid reliability and resiliency

## Challenge:

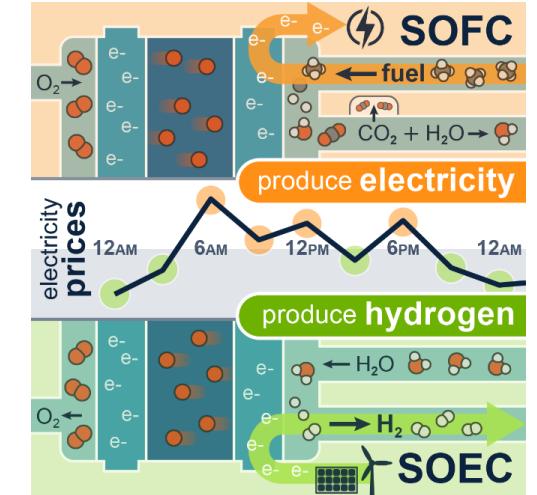
How to **co-optimize** IES design and operation considering **dynamic market interactions**?

# Presentation Outline

How to **co-optimize** IES design and operation considering **dynamic markets**

## Price Taker

Solid oxide fuel cell IESs that co-produce H<sub>2</sub> and electricity

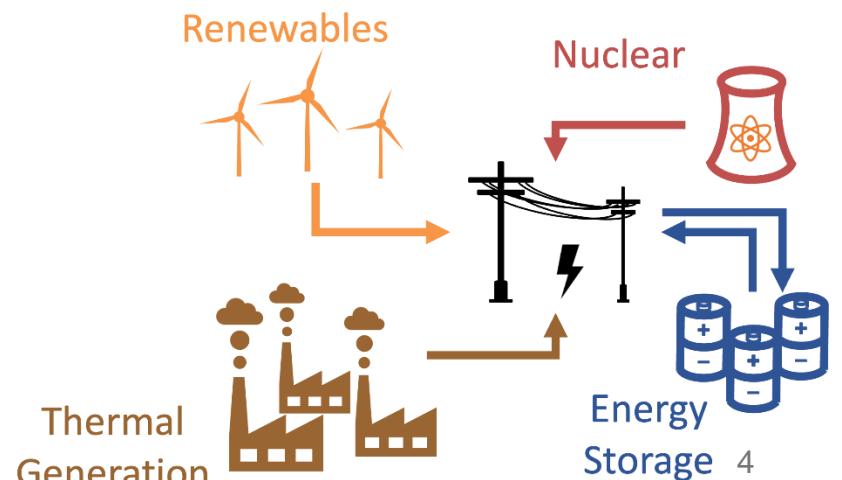


## Beyond Price Taker

Nuclear and electrolyzer IESs that co-produce H<sub>2</sub> and electricity

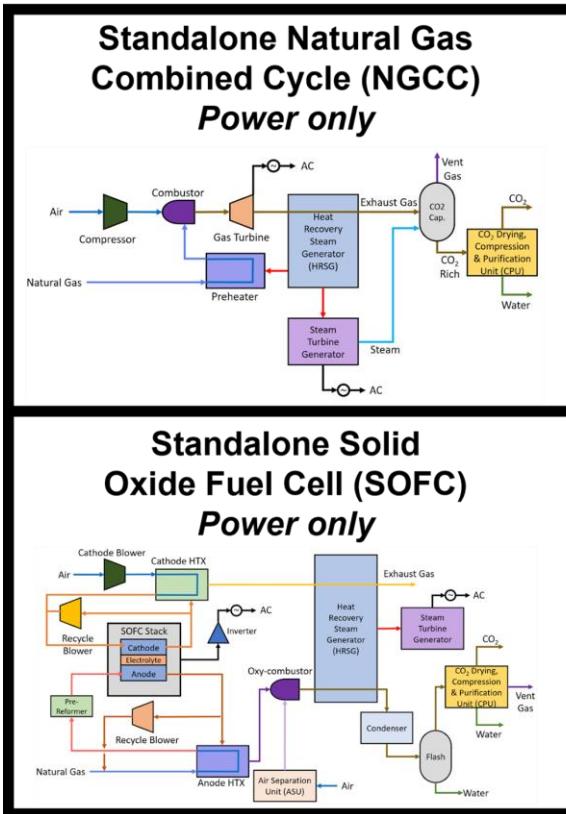
Wind and electrolyzer IESs that co-produce H<sub>2</sub> and electricity

Wind and battery IESs



# Compare Solid Oxide Cells (Emerging Technology) with Legacy Technology (NGCC)

- Analyze the viability of SOFCs against legacy technology (NGCCs)

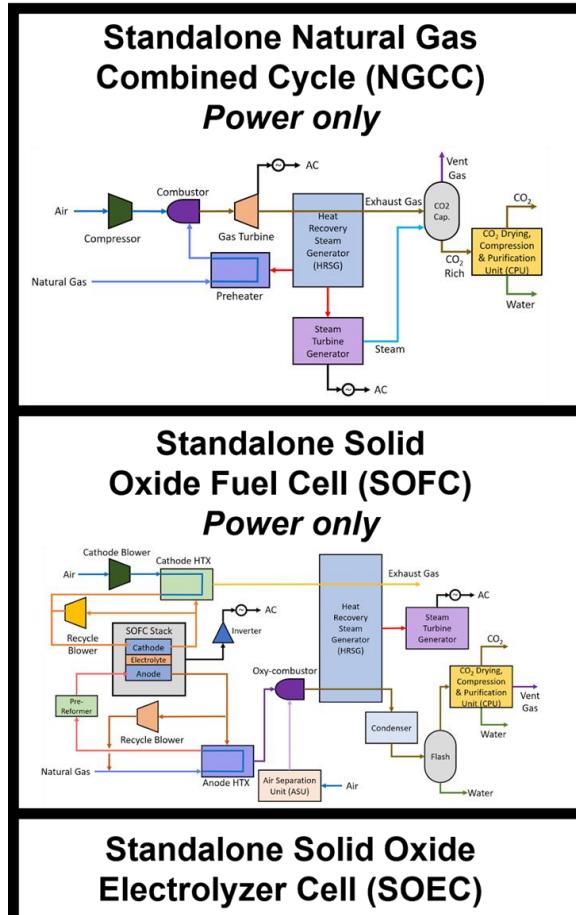


Which generators/technologies should be retired?

Which emerging technologies are worth research/scale-up investment?

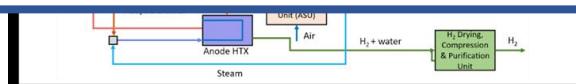
# Evaluate Production of Alternative Fuels

- Analyze the viability of SOFCs against legacy technology (NGCCs)
- Evaluate the viability of alternative fuel production (e.g., Hydrogen from SOEC)



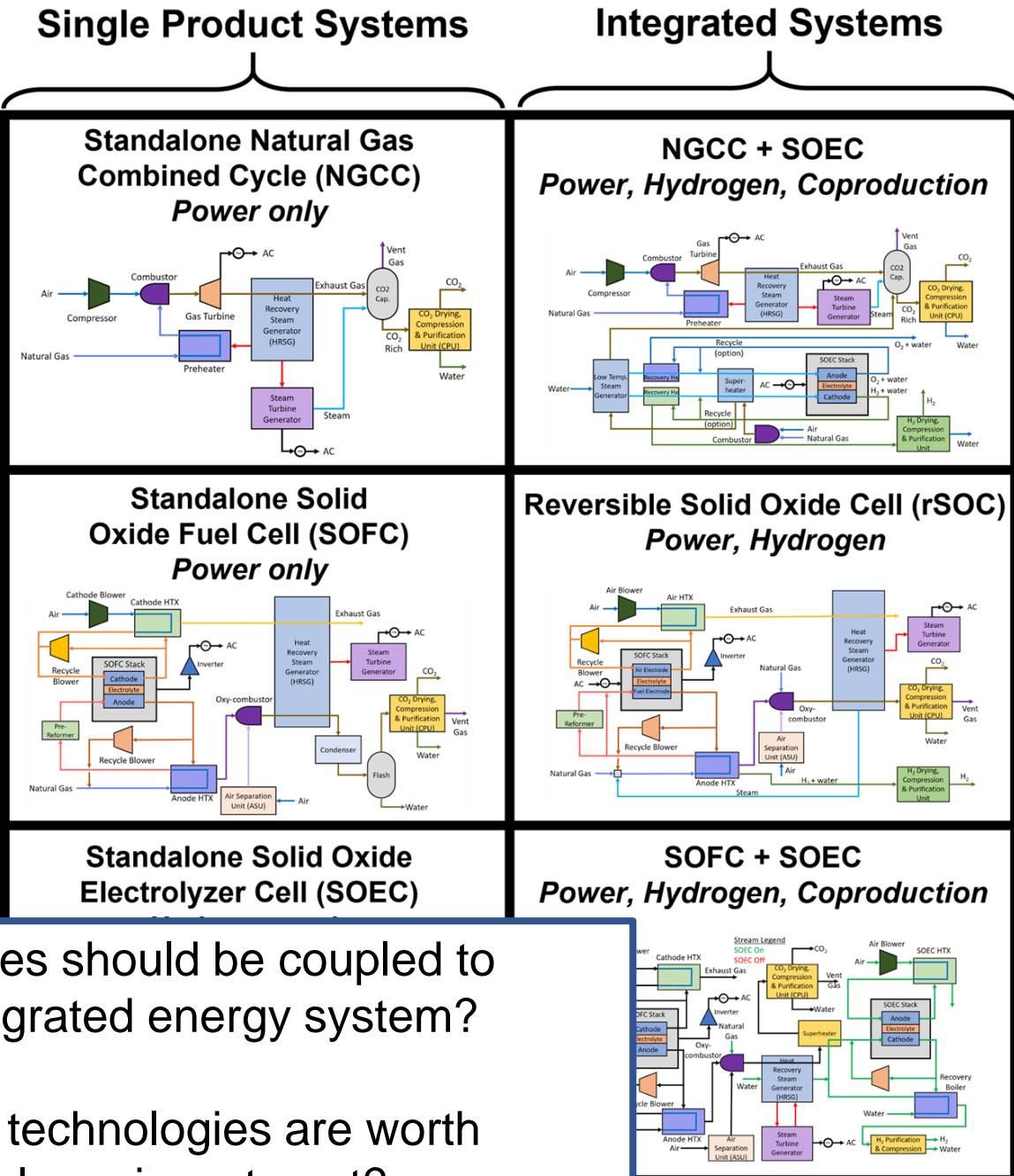
Which technologies should produce hydrogen?

What price of hydrogen is economical?



# Evaluate Coproduction

- Analyze the viability of SOFCs against legacy technology (NGCCs)
  - Evaluate the viability of alternative fuel production (e.g., hydrogen from SOEC)
  - Evaluate integrated energy systems (IESs)
    - Coproduction:
      - Power (NGCC)
      - Hydrogen (SOEC)
      - Reversible systems



Which technologies should be coupled to comprise an integrated energy system?

## Which emerging technologies are worth research/scale-up investment?

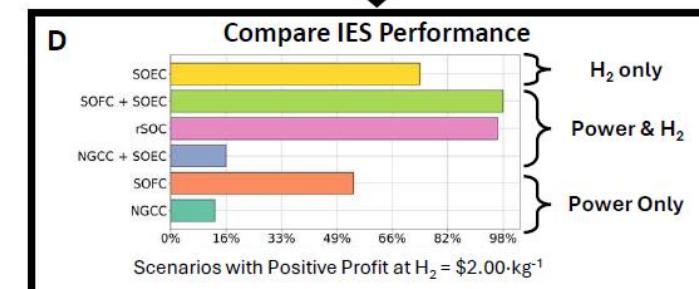
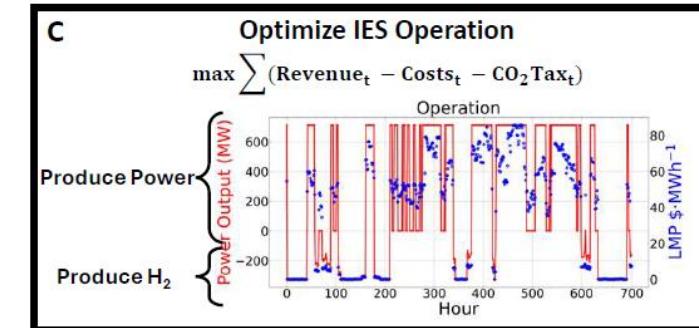
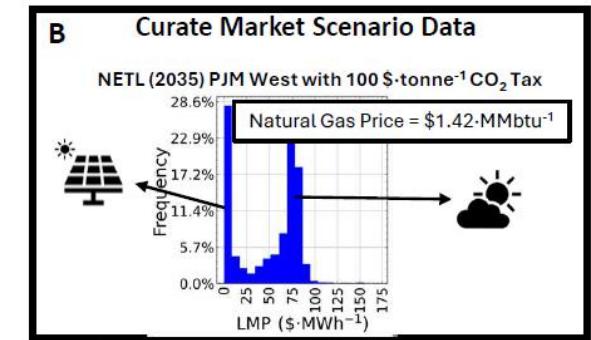
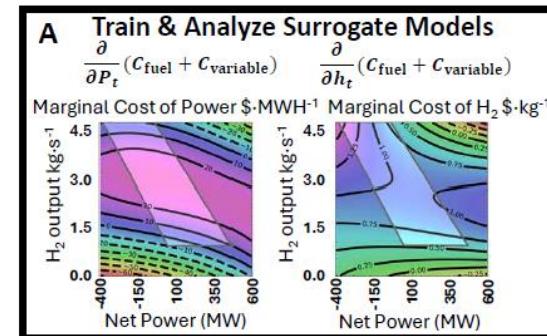
# Grid-Wide Decisions for Locational Markets Require a Streamlined Evaluation Framework

Which technologies should produce hydrogen?

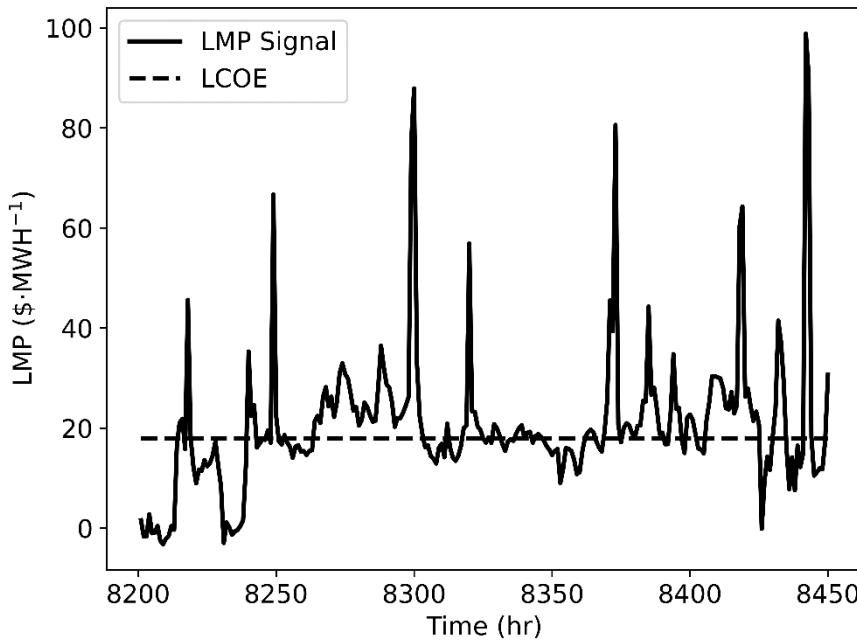
Which technologies should be coupled to comprise an integrated energy system?

Which generators/technologies should be retired?

Which emerging technologies are worth research/scale-up investment?



# Price Taker Model Considers Dynamic Prices



Locational marginal price (LMP) changes dynamically, where traditional low-fidelity modeling only uses a static leveled cost of electricity (LCOE)

**Objective options:** NPV, Annualized NPV, Net Profit

**Profit expression at each time period (e.g., hour)**

$$f_t^{\text{profit}} = \pi_t^e p_t - \frac{\pi^g}{\pi^g} f^{\text{fuel}}(p_t) - f^{\text{var}}(p_t) - \pi^c f^{\text{carbon}}(p_t) - f_t^{\text{fixed}}(P^{\max}) \quad \forall t \in \mathcal{T}$$

**Capacity Constraints**

$$P^{\min} y_t \leq P_t \leq P^{\max} y_t \quad \forall t \in \mathcal{T}$$

**Startup and Shutdown Constraints**

$$y_t \leq z_{\text{build}} \quad \forall t \in \mathcal{T}$$
$$\sum_{t-\tau^u+1}^t v_j = y_t \quad \{t \mid t > \tau^u\}$$
$$\sum_{t-\tau^d+1}^t w_j = (1 - y_t) \quad \{t \mid t > \tau^d\}$$
$$y_t - y_{t-1} = v_t - w_t \quad \{t \mid t > 1\}$$

**Ramping Constraints**

$$\frac{(P_t - P_{t-1})}{P^{\max}} \leq (r_{\text{su}} - r_{\text{op,u}}) v_t + r_{\text{op,u}} y_t \quad \forall t \in \mathcal{T}$$

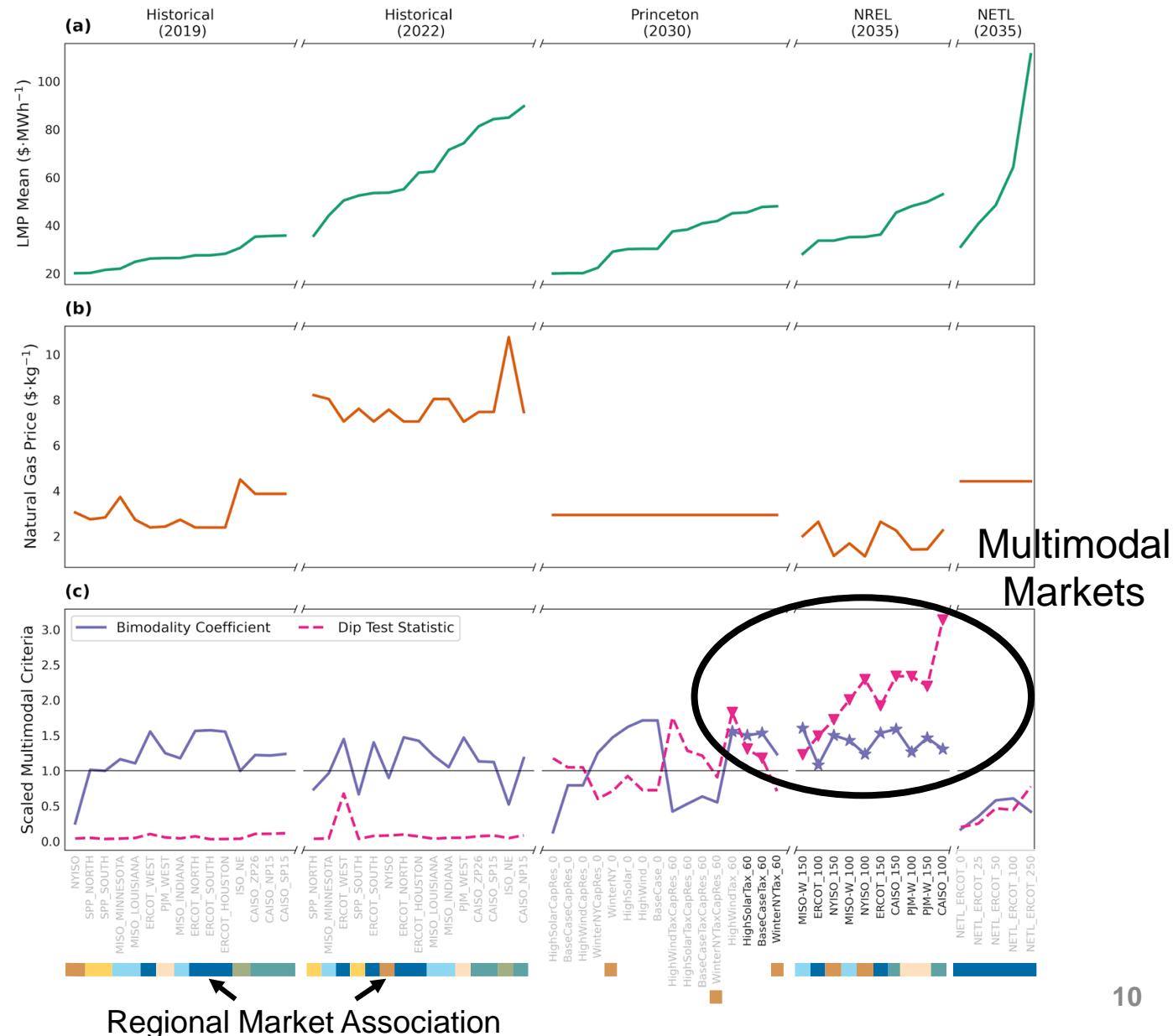
$$\frac{(P_{t-1} - P_t)}{P^{\max}} \leq r_{\text{sd}} w_t + r_{\text{op,d}} y_t \quad \forall t \in \mathcal{T}$$

# 61 Markets Used to Evaluate Emerging Technologies



Figure from FERC (<https://www.ferc.gov/electric-power-markets>)

- 15 historical markets (2019)
- 15 “current” markets (2022)
- 16 forecasted scenarios (2030)
  - “Princeton”
- 10 forecasted scenarios (2035)
  - “NREL”
- 5 forecasted scenarios (2035)
  - “NETL”



# Emerging Coproduction Technologies Make a Profit in Most Scenarios

Percentage of scenarios that make profit at each **hydrogen selling price** ( $\$1.00 \text{ kg}^{-1}$  to  $\$3.00 \text{ kg}^{-1}$ )

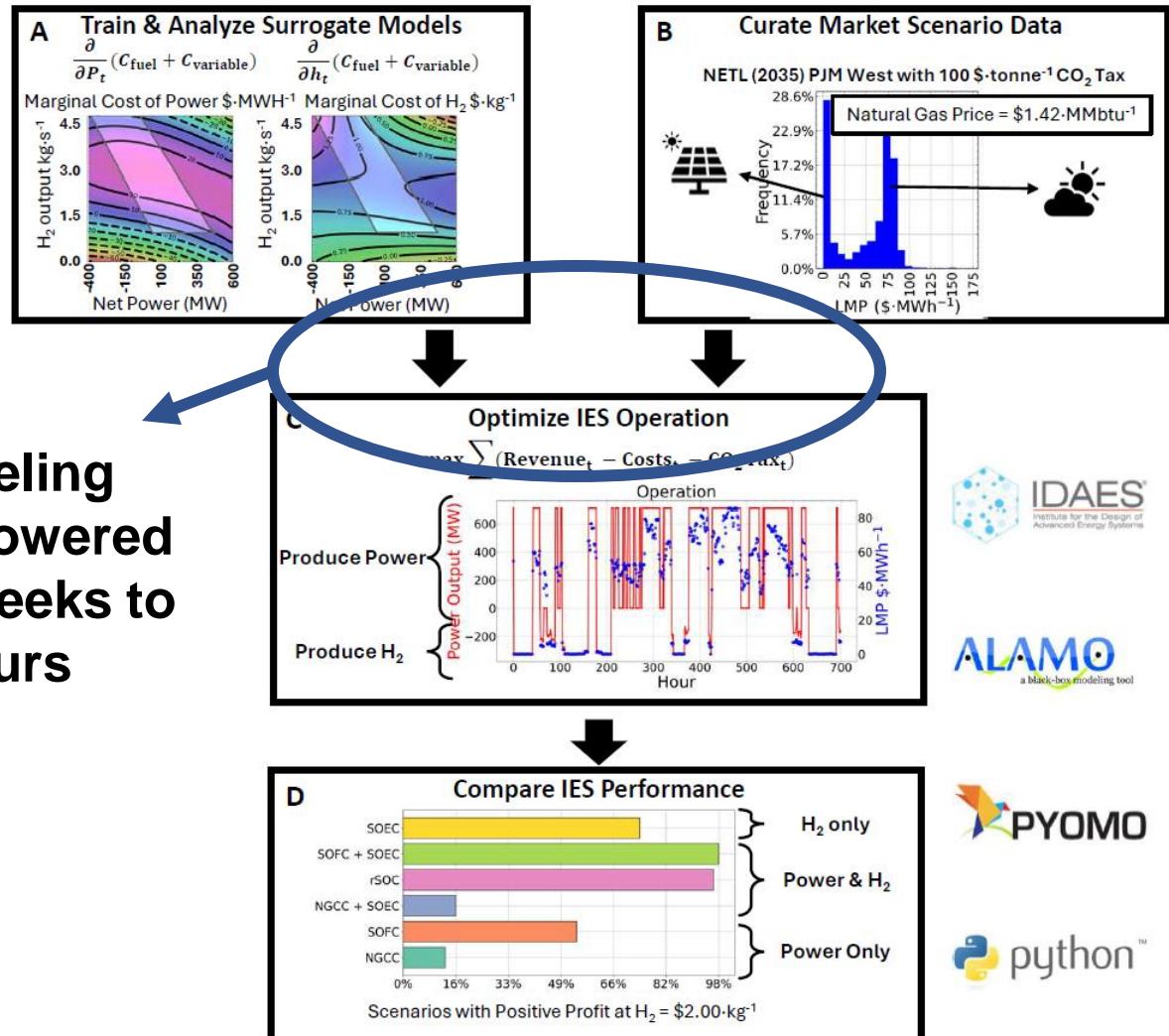
Process Concept	$1.00 \text{ \$}\cdot\text{kg}^{-1}$	$1.50 \text{ \$}\cdot\text{kg}^{-1}$	$2.00 \text{ \$}\cdot\text{kg}^{-1}$	$2.50 \text{ \$}\cdot\text{kg}^{-1}$	$3.00 \text{ \$}\cdot\text{kg}^{-1}$
NGCC	13%	13%	13%	13%	13%
SOFC	54%	54%	54%	54%	54%
NGCC + SOEC	8%	11%	16%	62%	80%
rSOC	54%	77%	97%	100%	100%
SOFC + SOEC	46%	79%	98%	100%	100%
SOEC	10%	49%	74%	87%	98%

**Takeaway:** At sufficient hydrogen price ( $\$2.50+$ ), even the existing thermal generation technology with co-production (NGCC +SOEC) sees profit in over half of the market scenarios.

# Price Taker Class Streamlines Optimal Operation Scheduling

- Automatically populates LMP (market data) in model
- Only need to specify costing equations and choose operational constraints for a representative time period
- Easily automated/scriptable using the IDAES ecosystem (Python, open-source)

**Modeling effort lowered from weeks to hours**



IDAES Documentation:

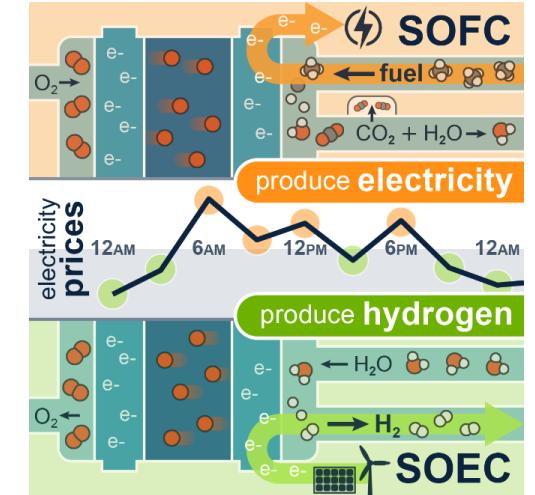
[https://idaes-pse.readthedocs.io/en/main/reference\\_guides/apps/grid\\_integration/index.html](https://idaes-pse.readthedocs.io/en/main/reference_guides/apps/grid_integration/index.html)

# Presentation Outline

How to **co-optimize** IES design and operation considering **dynamic markets**.

## Price Taker

Solid oxide fuel cell IESs that co-produce H<sub>2</sub> and electricity

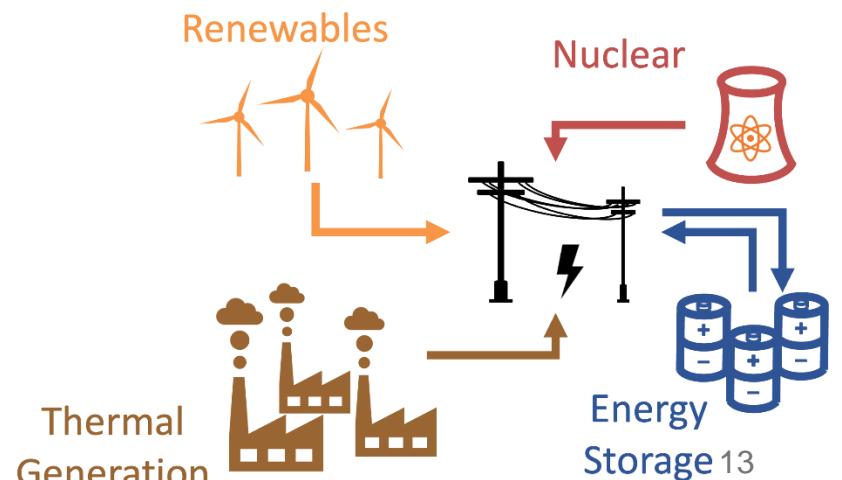


## Beyond Price Taker

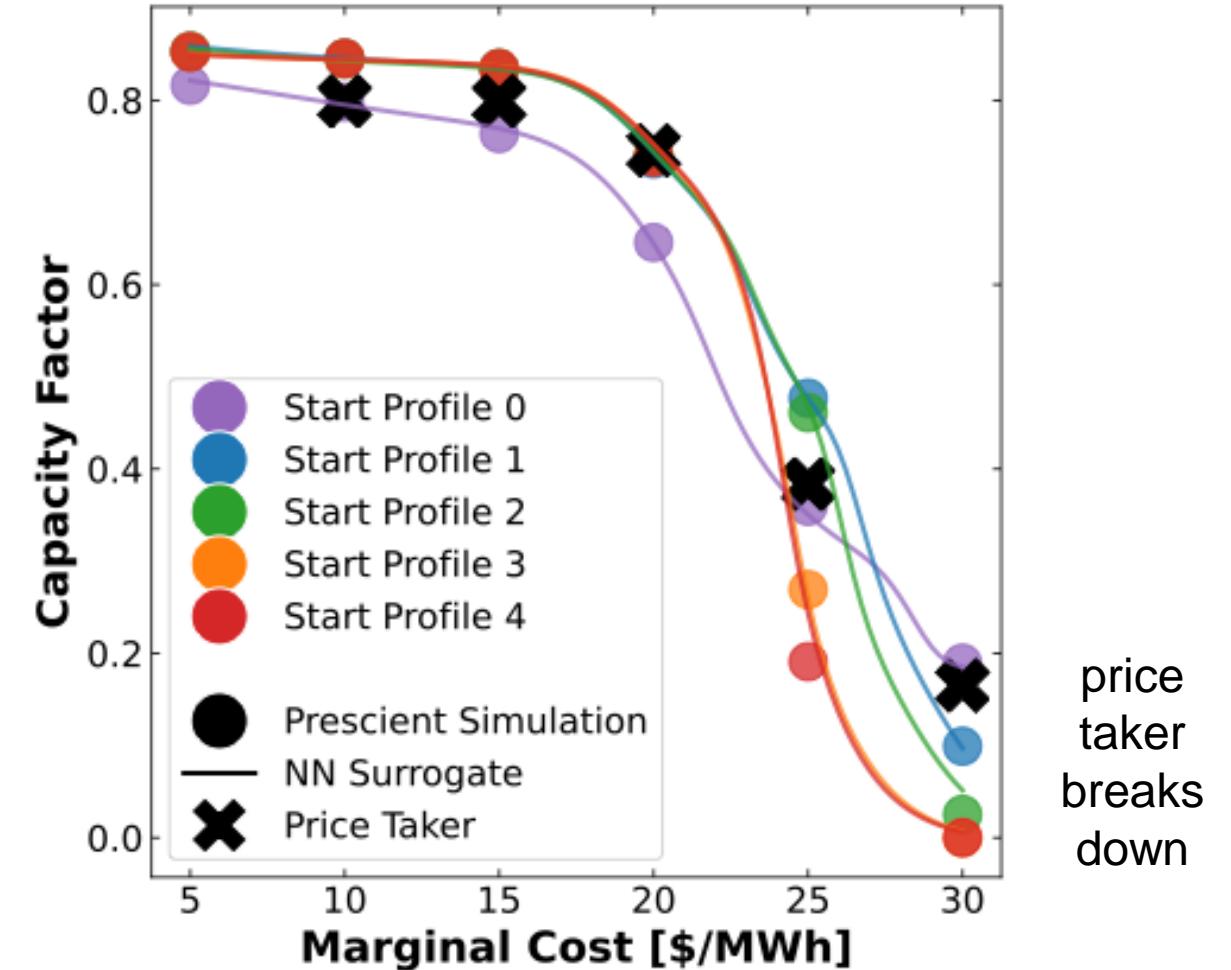
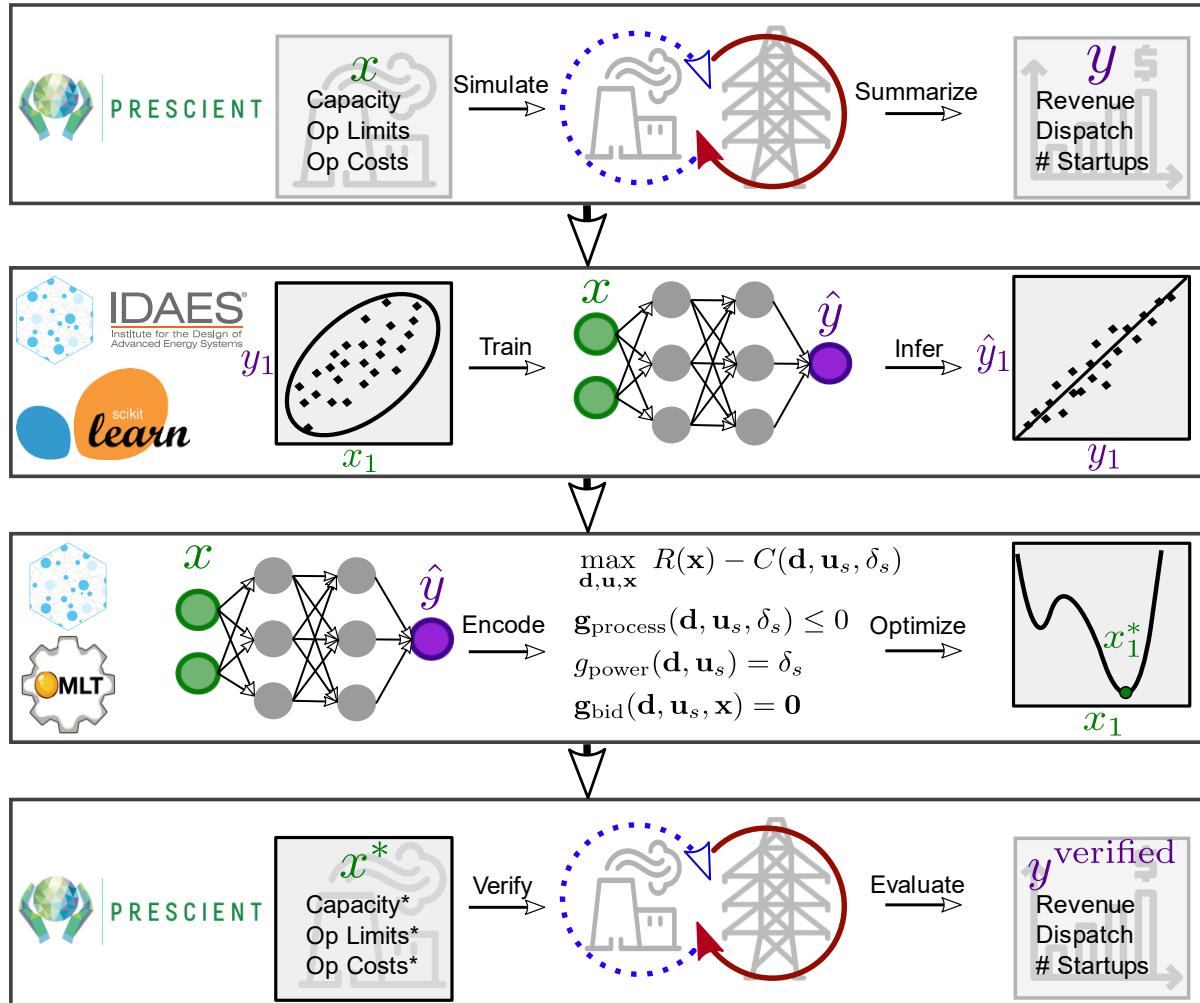
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Wind and electrolyzer IESs that co-produce H<sub>2</sub> and electricity

Wind and battery IESs



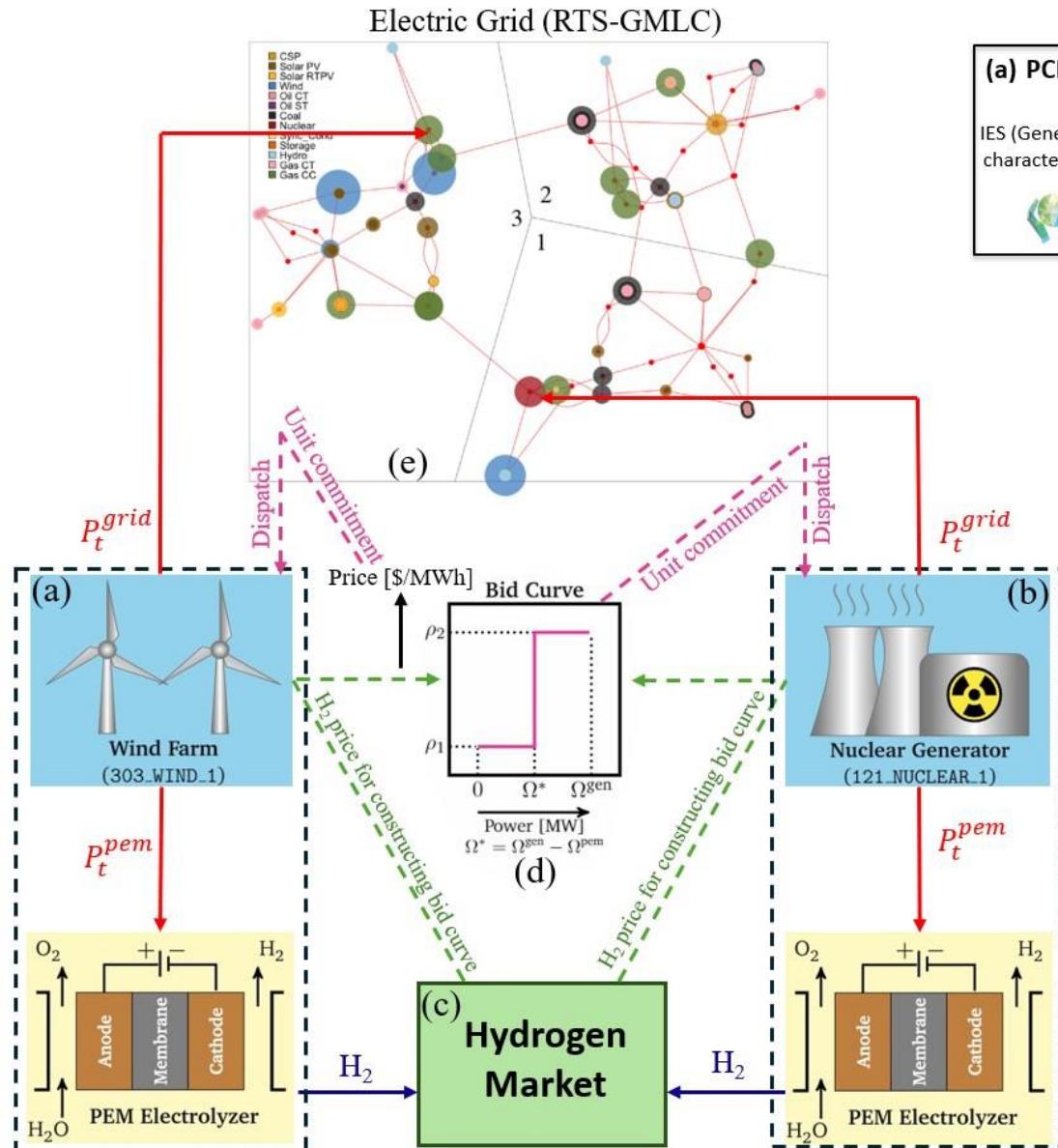
# Moving Beyond Price Taker



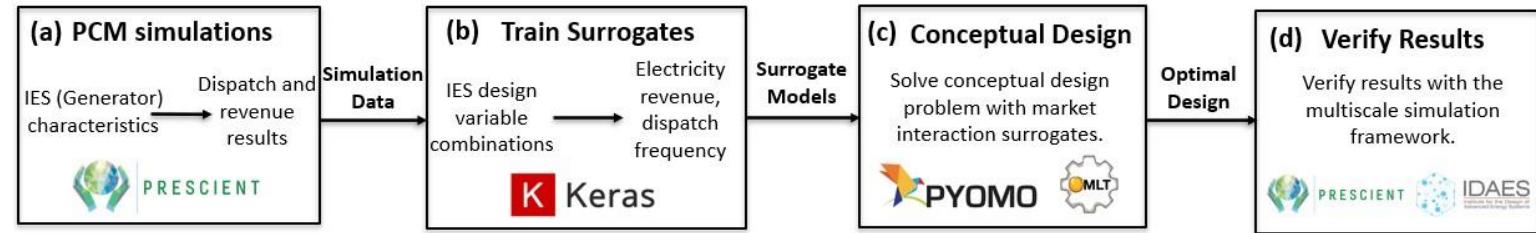
Jalving et al, *Applied Energy* (2023)

# Beyond Price Taker: Co-Production of Electricity and H<sub>2</sub>

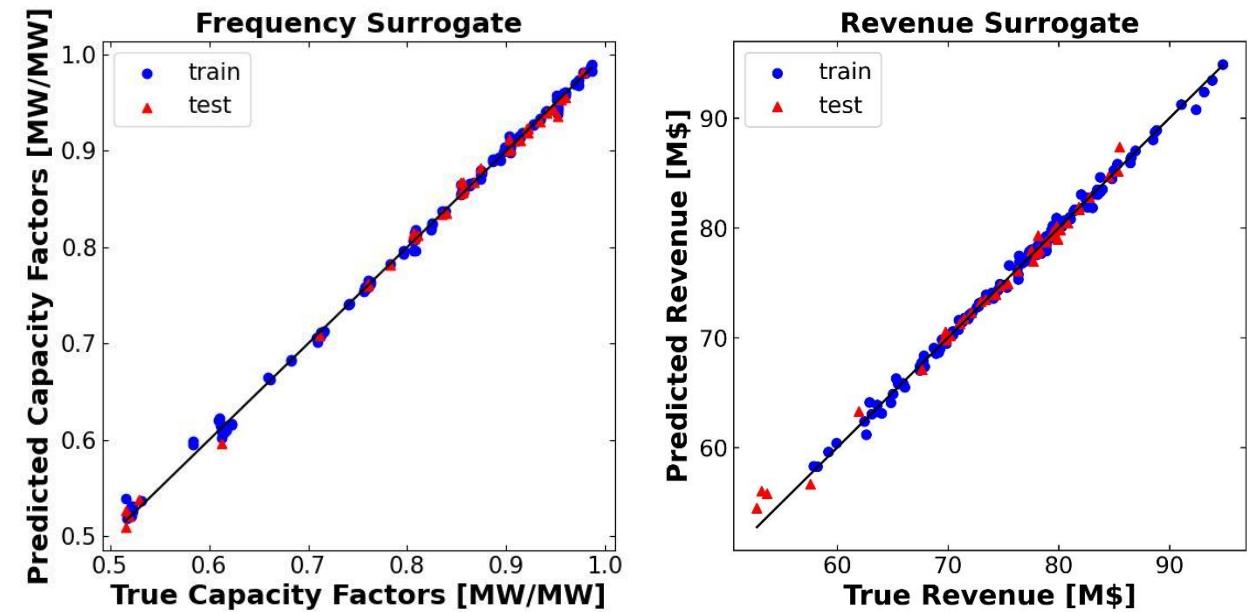
## Problem Statement



## Overall Approach



## Example Surrogates (Nuclear + PEM)

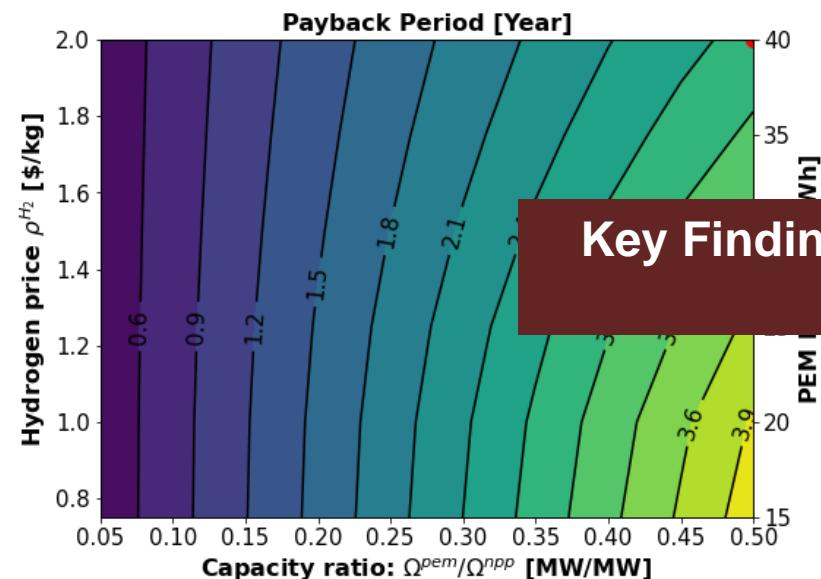
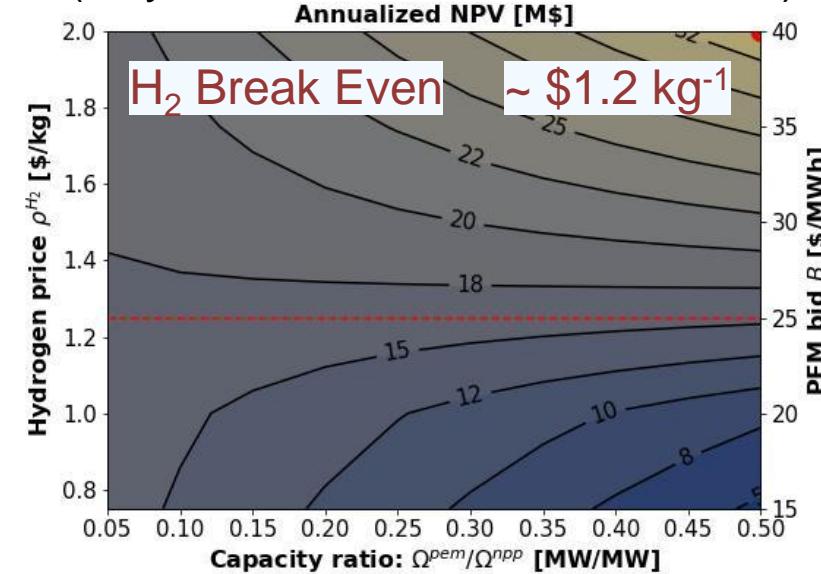


Chen et al, (2025) *in preparation*

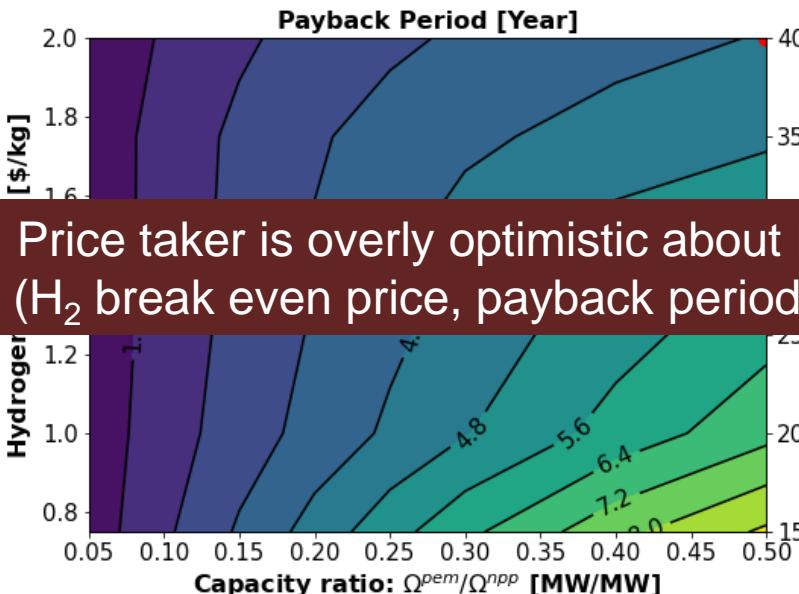
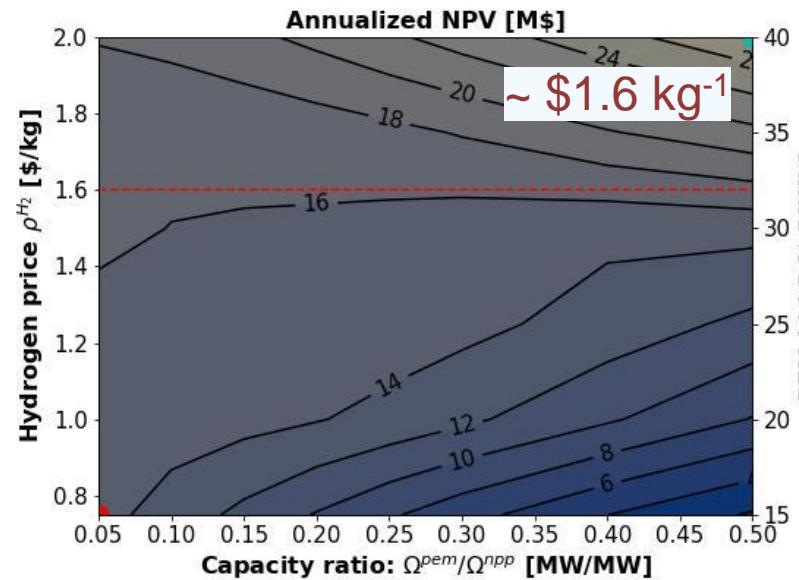
# Nuclear + PEM Case Study

## Price Taker

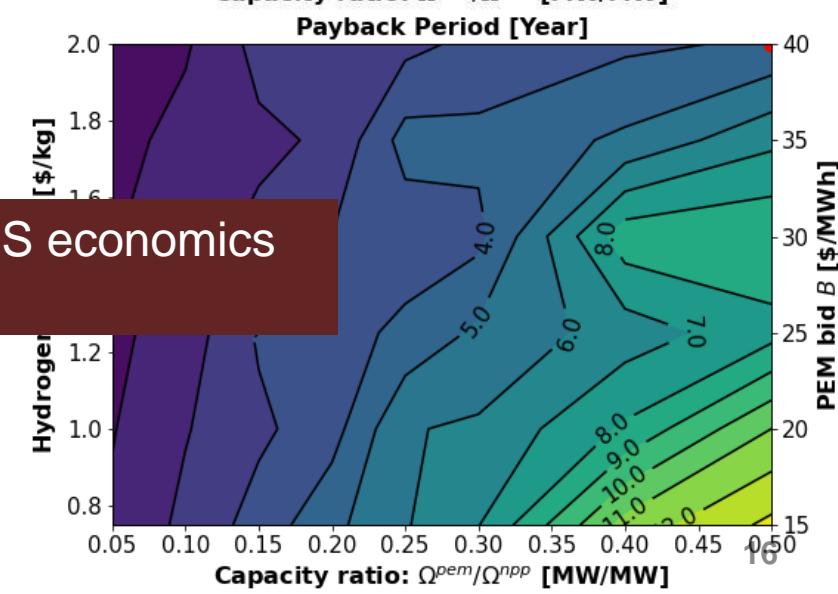
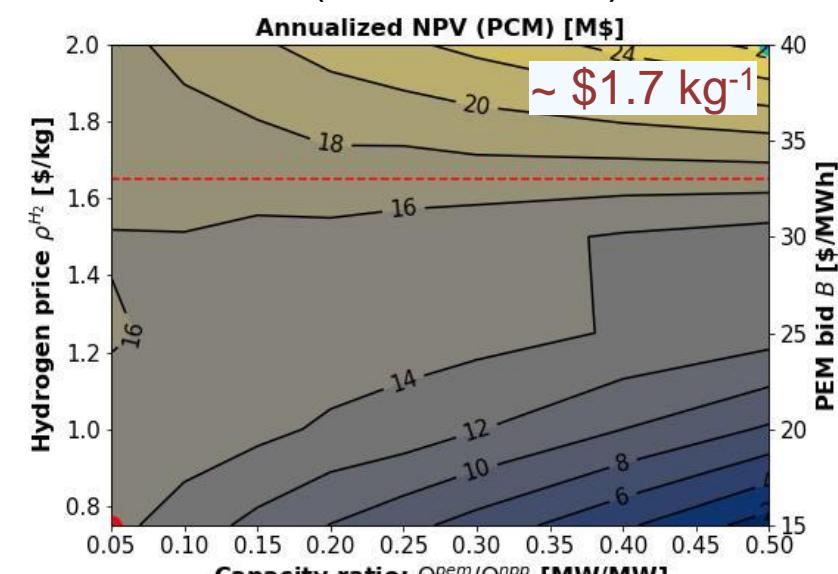
(Day-Ahead + Real-Time Markets)



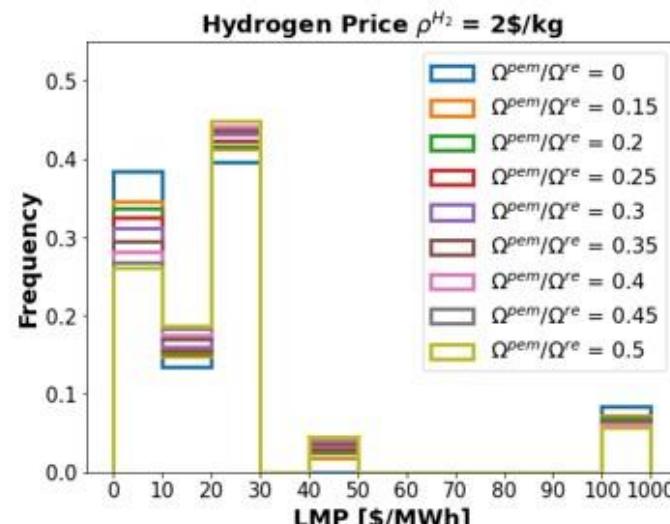
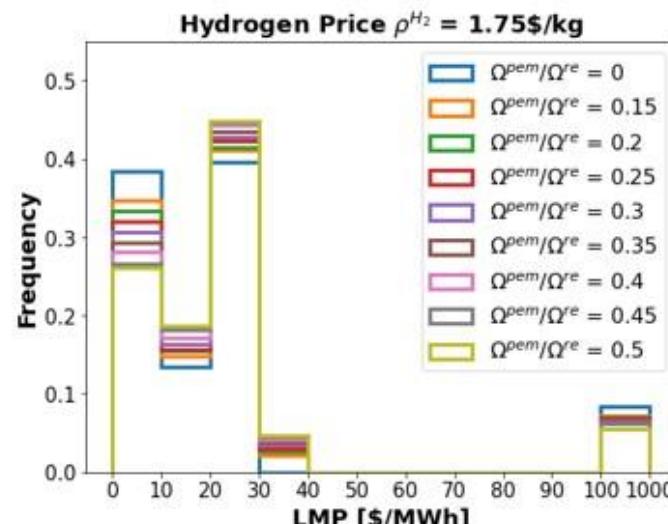
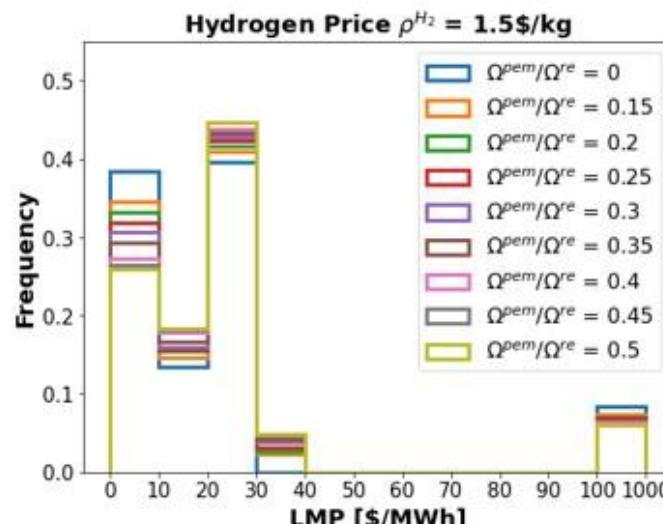
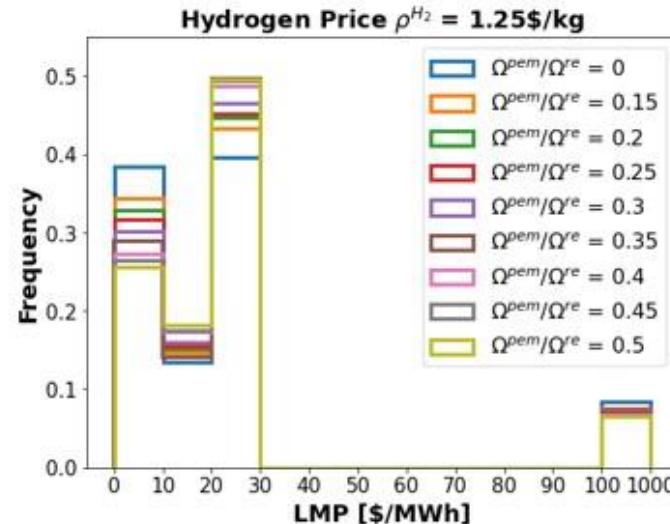
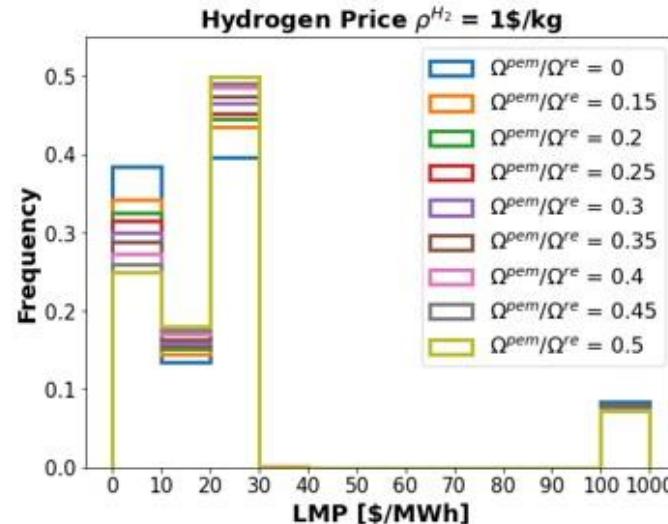
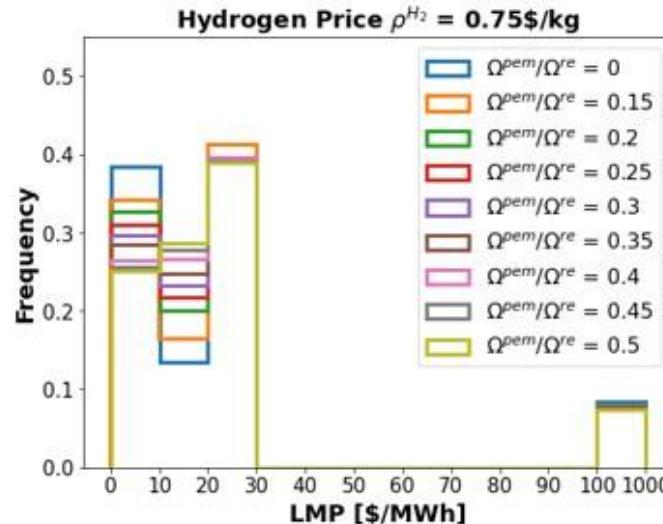
## Surrogates



## Production Cost Model (Ground Truth)



# Renewables + PEM Case Study: Key Finding

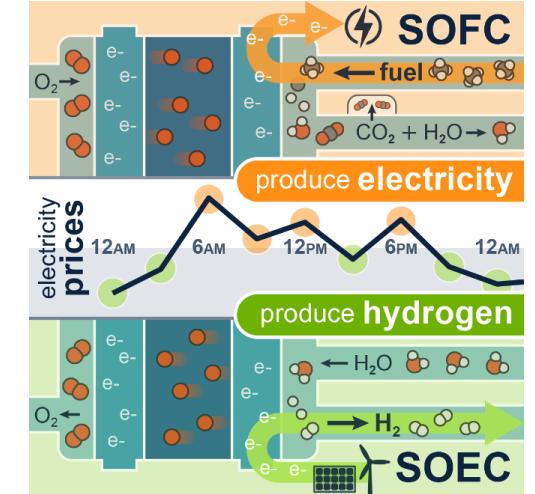


# Presentation Outline

## How to **co-optimize** IES design and operation considering **dynamic markets**

### Price Taker

Solid oxide fuel cell IESs that co-produce H<sub>2</sub> and electricity

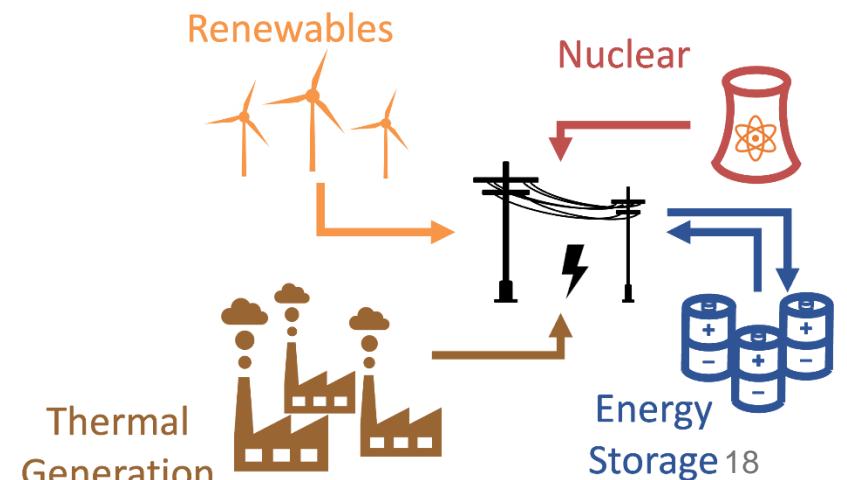


### Beyond Price Taker

Nuclear and electrolyzer IESs that co-produce H<sub>2</sub> and electricity

Wind and electrolyzer IESs that co-produce H<sub>2</sub> and electricity

Wind and battery IESs



# Multiperiod Optimization (MO) of the Wind-Battery IES

The market outcomes (LMP and dispatch schedule) are sent to the IES

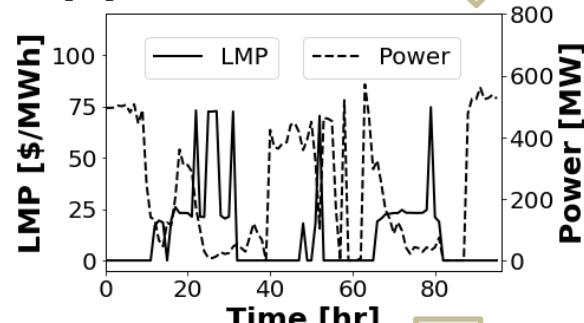
(c) MO(PCM)



(e) Electric Grid

MO (PCM, product cost model) clears the market

(d) Market Outcomes



Price Signal,  $\hat{\pi}_t$   
Dispatch Schedule,  $\hat{p}_t$

IES follows the dispatch commitment and gets paid

$p_{t,i}$

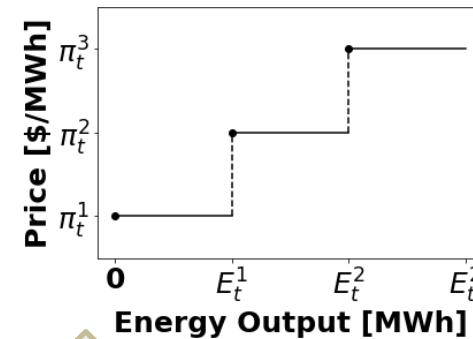
$p_{t,i}^s$

$p_{t,i}^d$



(a) Wind-Battery IES

(b) Bids,  $(E_{t,i}, \pi_{t,i})$



Solve the stochastic bidding problem to generate time-variant bids for the IES

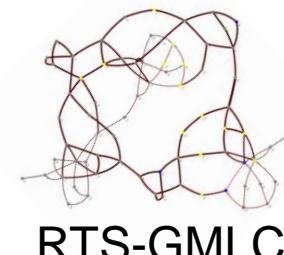


# Price-taker (PT) with Perfect Information and Uncertainty

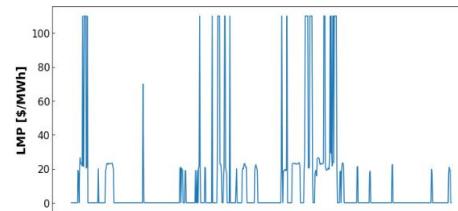
Choose wind farm '303\_WIND\_1' in the RTS-GMLC dataset



Product Cost Model (PCM)



Obtain the real-time LMP price signals



Solve the price-taker optimization

**Max** Net Present Values of IES Investments

*s. t.* Wind farm and battery operation constraints

## Perfect Information Mode:

LMP signals are deterministic

$$R_{t,i} = (\hat{\pi}_{t,i} + \varepsilon) \cdot p_{t,i} \cdot \Delta t$$

Where  $I = \{0\}, T = \{0, 1, \dots, 8783\}$

$R_{t,i}$ : Total revenue at time  $t$ , scenario  $i$ .

$\hat{\pi}_{t,i}$ : LMP at time  $t$ , perfect information.

$p_{t,i}$ : IES power output at time  $t$ , scenario  $i$ .

$\varepsilon$ : Small incentive (0.001 \$/MWh) to avoid degeneracy.

$\Delta t$ : Time step, hour.

## Uncertainty Mode:

Rolling horizon stochastic optimization and use historical prices as scenarios.

$$R_{t,i} = (\pi_{t,i} + \varepsilon) \cdot p_{t,i} \cdot \Delta t$$

Nonanticipativity constraints

$$p_{t,i} = p_{t,i'} \quad \forall t \in T'_1, \forall i' \in I \setminus i$$

Where  $I = \{0, \dots, 9\}, T = \{T'_1 \cup T'_2\}$

$\pi_{t,i}$ : LMP at time  $t$  and scenario  $i$ .

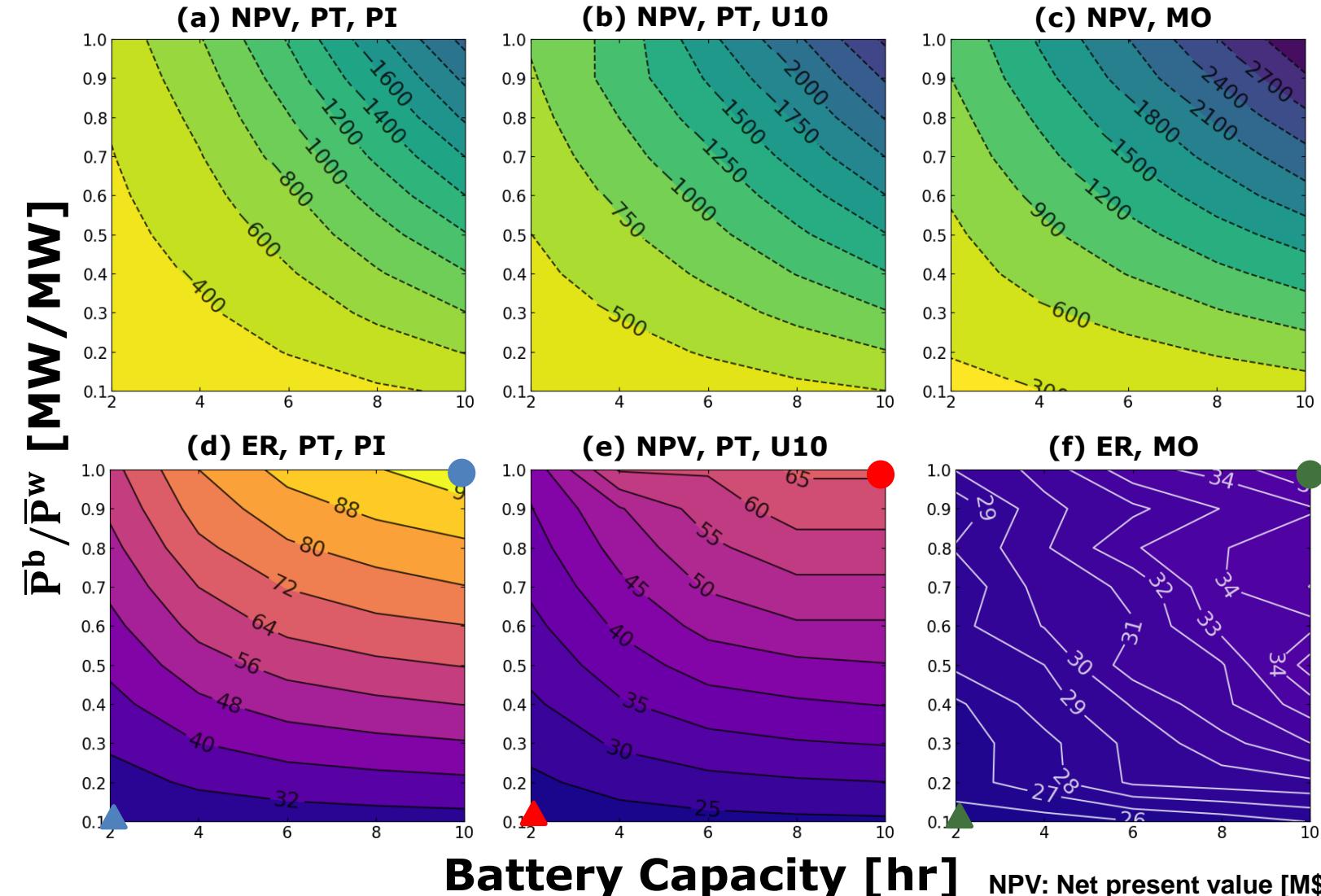
$T'_1$ : Stage 1 time set,  $\{0, \dots, 23\}$ .

$T'_2$ : Stage 2 time set,  $\{24, \dots, 71\}$ .

After optimization is solved:

$$\hat{R}_d = \sum_{t \in T'_1} \hat{\pi}_t \cdot p_{t,0} \cdot \Delta t$$

# PT is Overly Optimistic on IES Economic Values



**NPV:** Net present value [M\$]  
**ER:** Annual electricity revenue [M\$]  
**PI:** Perfect information  
**U10:** Uncertainty with 10 scenarios

- All NPV values are negative in both PT and MO (overbuilt grid).
- Electricity revenue (ER), [M\$]
  - ▲ Case 1 (PT, PI, smallest battery): 24.2
  - Case 2 (PT, PI, largest battery): 100.4
  - ▲ Case 3 (PT, U10, smallest battery): 21.2
  - Case 4 (PT, U10, largest battery): 65.9
  - ▲ Case 5 (MO, smallest battery): 25.5
  - Case 6 (MO, largest battery): 36.0
- PT overestimates the NPV and ER.
- NPV and ER are more sensitive to the maximum battery power  $\bar{P}^b$  ( $\bar{P}^w$ : maximum wind power, parameter)

# Take Away Messages

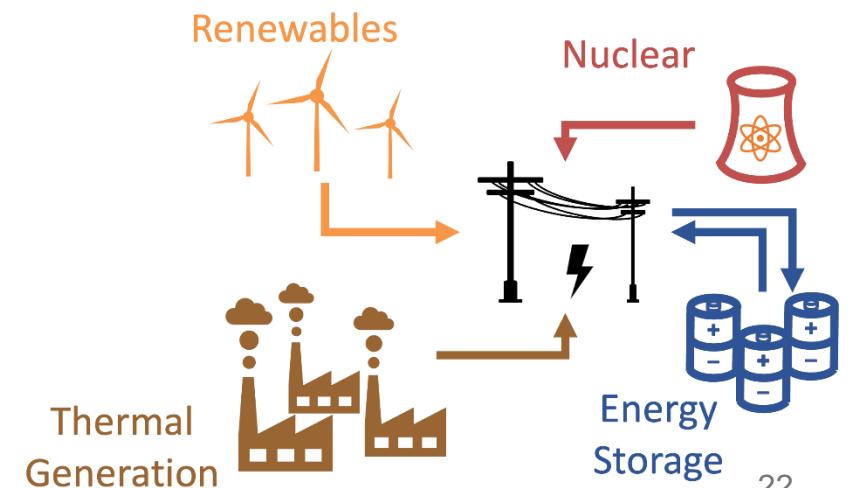
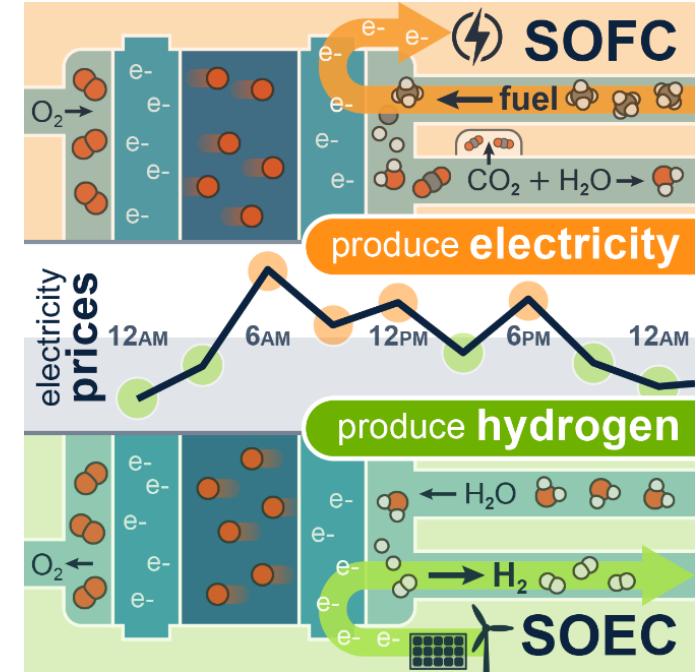
Optimization is a powerful tool to analyze integrated energy systems (IESs) in dynamic energy markets.

Price taker assumes IES decisions do not impact market prices.

- Surrogates and PriceTaker class in IDAES makes this analysis fast and easy.

Need to go beyond price taker (with IDEAS)!

- Price taker is often overly optimistic.
- IES decisions shift market prices.



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**Georgia Tech:** Nick Sahinidis, Yijiang Li, Selin Bayramoglu



**2025 Joint IDAES/CCSI<sub>2</sub>/PrOMMiS/WaterTAP Technical Team Meeting**  
**University of Notre Dame**

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

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