

Multiperiod Conceptual Design of Integrated Energy Systems with Market Interaction Surrogate Models

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AIChE 2023 Annual Meeting

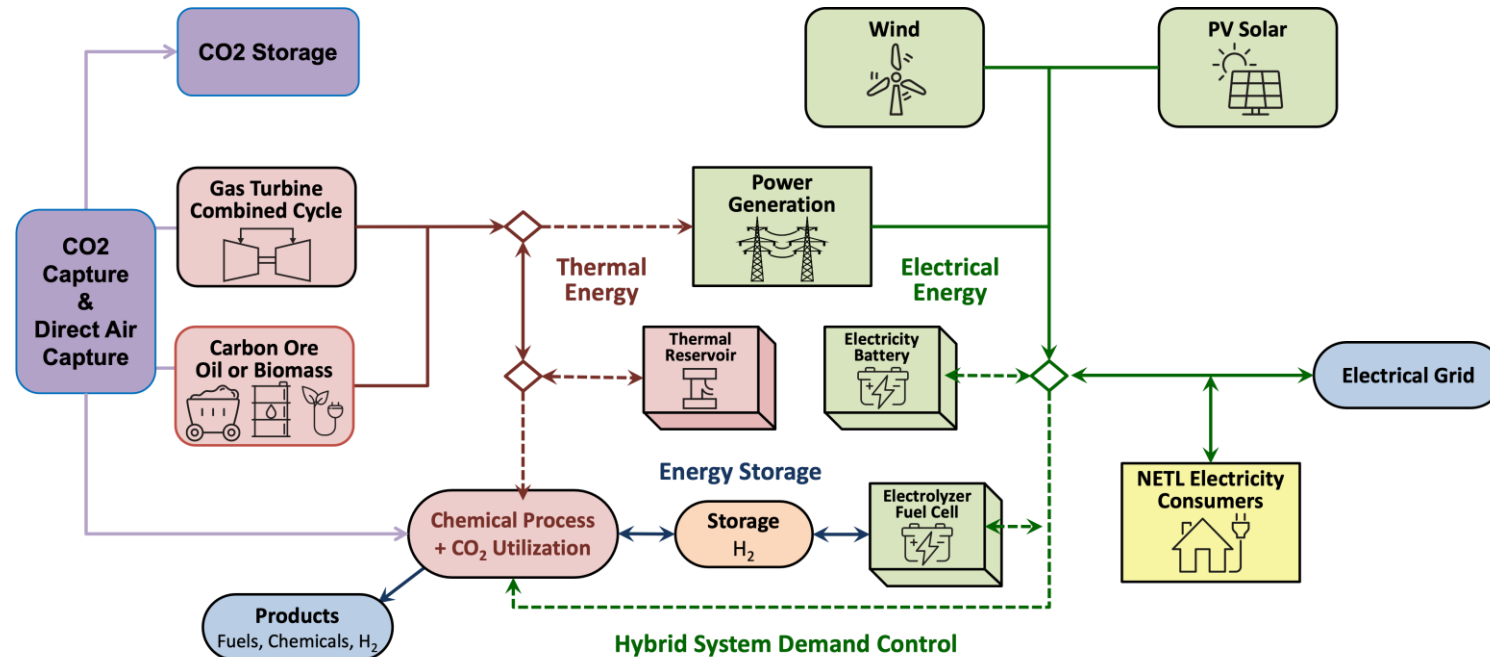
November 8, 2023



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 renewable integration
- Reduce carbon emissions
- Reduce grid operation costs

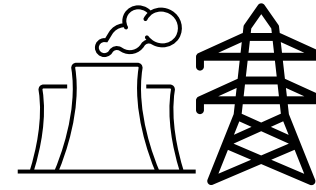
Challenge:

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

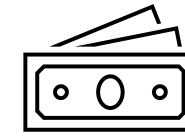
Traditional IES Optimization Approaches Have Limitations

Traditional Techno-Economic Analysis:

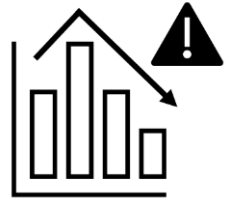
- Fixed selling price of electricity and IES capacity factor.
- Lack information about the electricity grid.
- Static analysis that assumes the constant input parameters.



Technical
Analysis

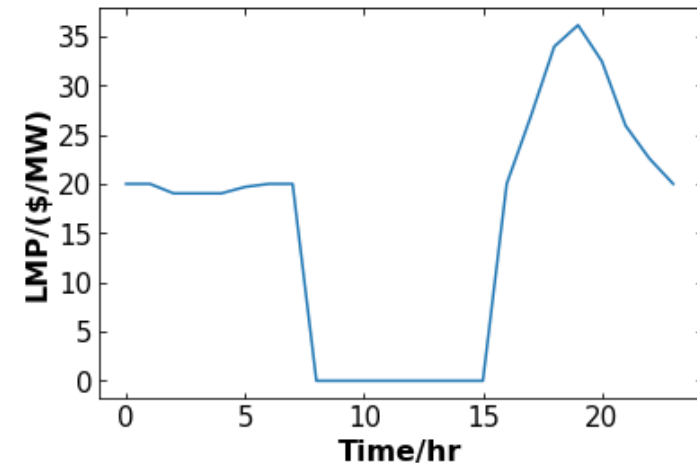


Economic/Financial
Analysis



Risk
Analysis

Price-taker Analysis:



Historical Locational
Marginal Price $\pi_{s,t}$ (LMP)

Data
Analysis

$\max_{LMP} NPV$
 $s. t.$ Process Constraints
Economic Constraints
Environment Constraints

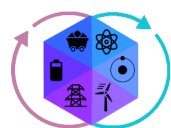
Price-taker
Optimization Models

Solve

Optimal design
Optimal operation
Net present value
...

Optimal Decisions

Both methods fail to consider **dynamic interactions** between market and IES.



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Platform to Advance Tightly
Coupled Hybrid Energy Systems

Gooty, Radhakrishna Tumbalam, et al. "Incorporation of market signals for the optimal design of post combustion carbon capture systems." *Applied Energy* 337 (2023): 120880.

Developing Optimization Environments for Scale-bridging

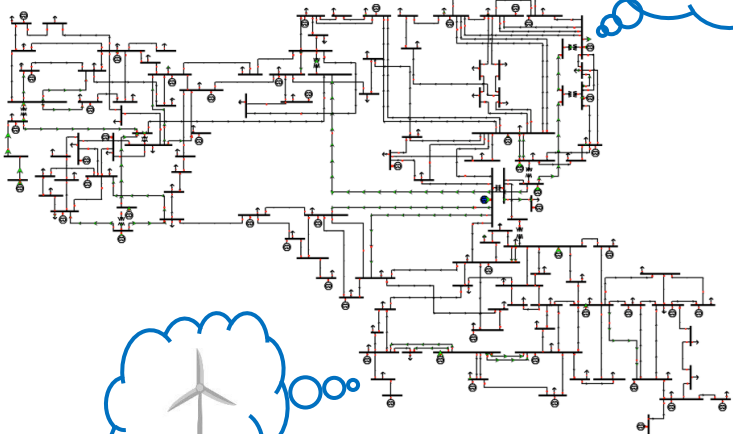
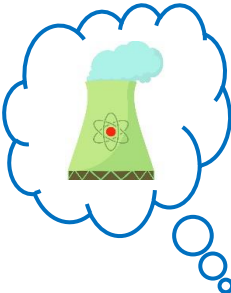
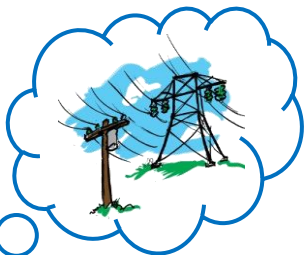
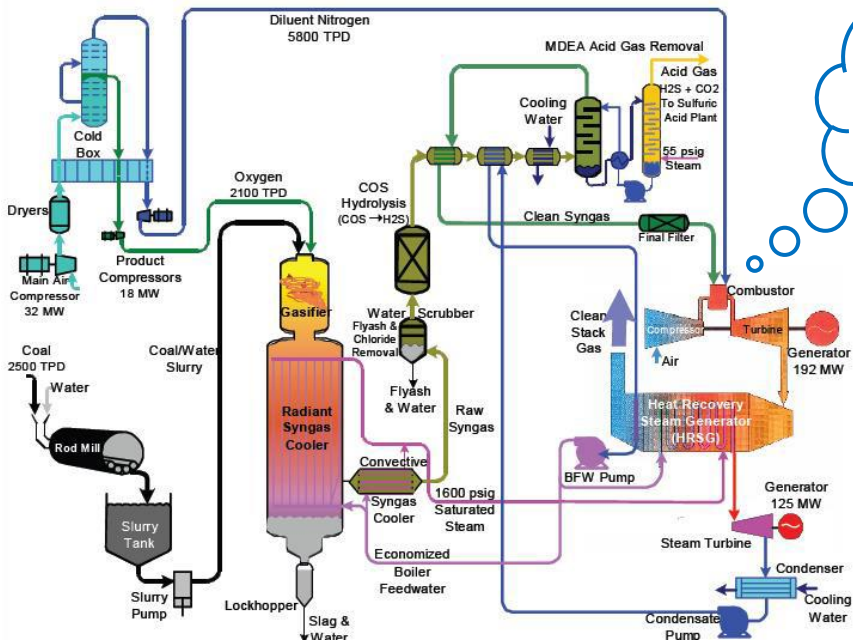
Process-centric Modeling

Detailed plant model assuming grid as an infinite capacity bus
Price-taker model

Market Interactions

Grid-centric Modeling

Detailed power flow models, with individual generators modeled
Product cost models (PCM)

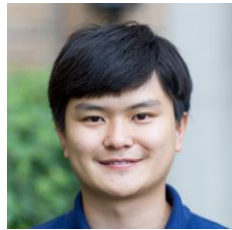


Hybrid System Operations

<https://www.netl.doe.gov/research/coal/energy-systems/gasification/gasifipedia/igcc-config>

<https://icseg.iti.illinois.edu/files/2013/10/IEEE118.png>

Multiscale Simulation Framework Moves Beyond Price-taker




Dr. Gao, Xian

Real-Time Market Loop

(1 cycle = 1 hour)


Day-Ahead Market Loop

(1 cycle = 1 day)




PRESCIENT

(iii) Settle




balance:

- cost
- health
- tracking penalty



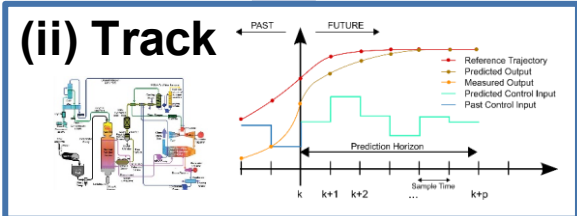
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min **system generation costs**
(economic dispatch)

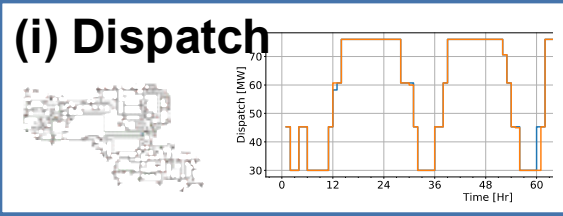


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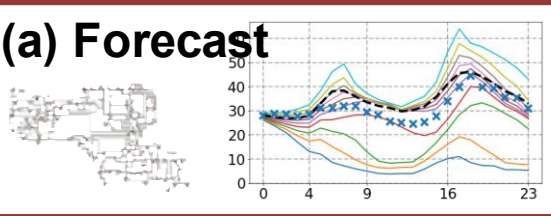
(ii) Track




(i) Dispatch



(a) Forecast

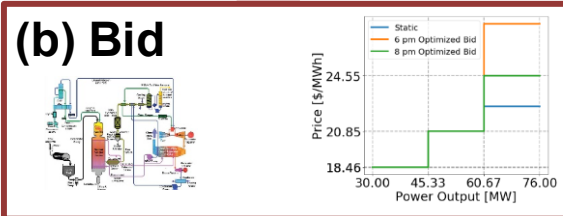


Forecast the LMP for the certain time periods.




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(b) Bid

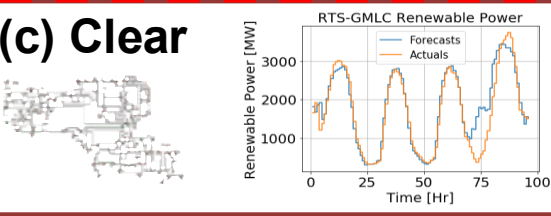


max $E[\text{Profit}]$




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(c) Clear



min **system generation costs**
(unit commitment)

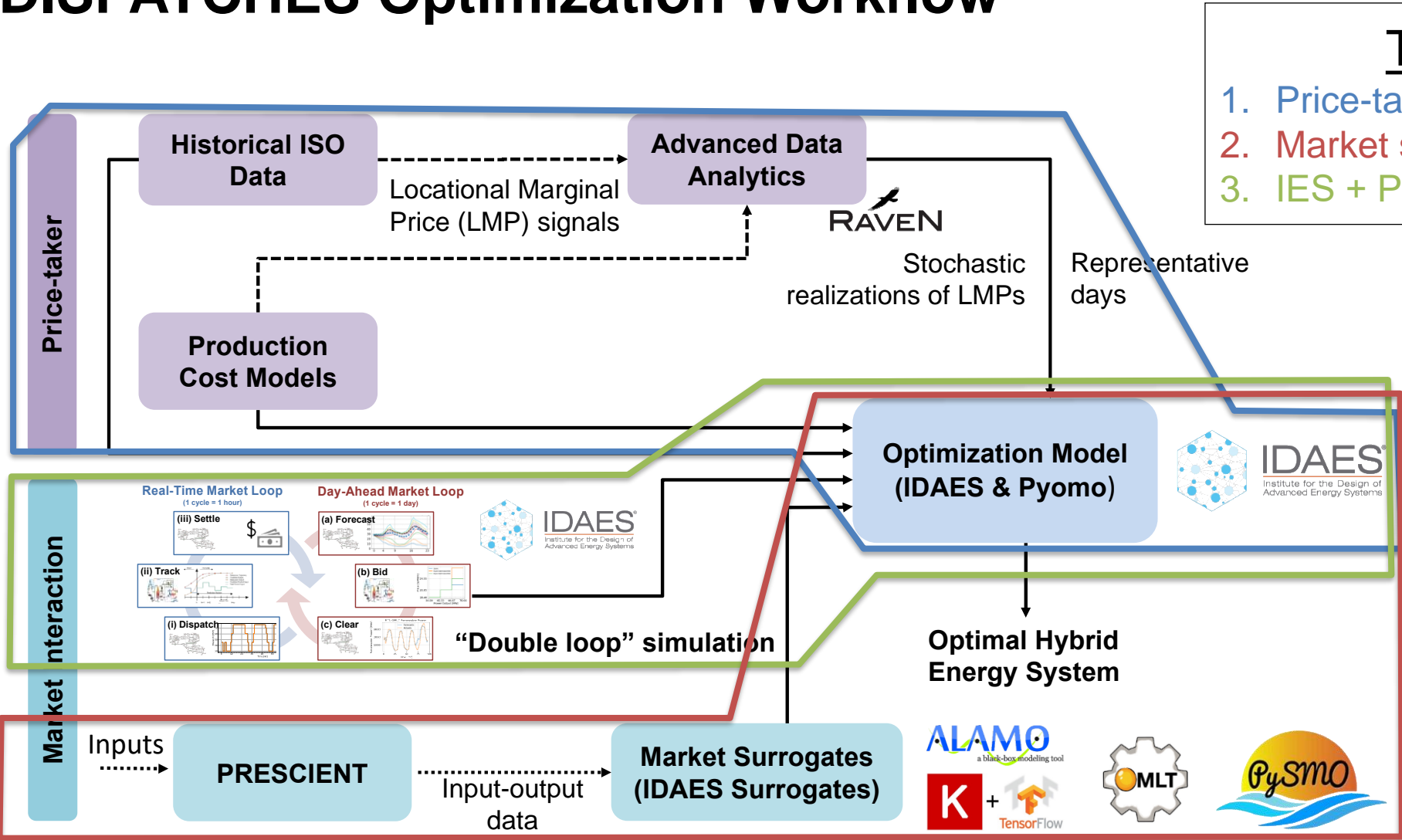


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Key take away:

The multiscale simulation framework mimics how independent system operators (ISO) operate the U.S. wholesale electricity markets and provides generator-level operation information.

DISPATCHES Optimization Workflow



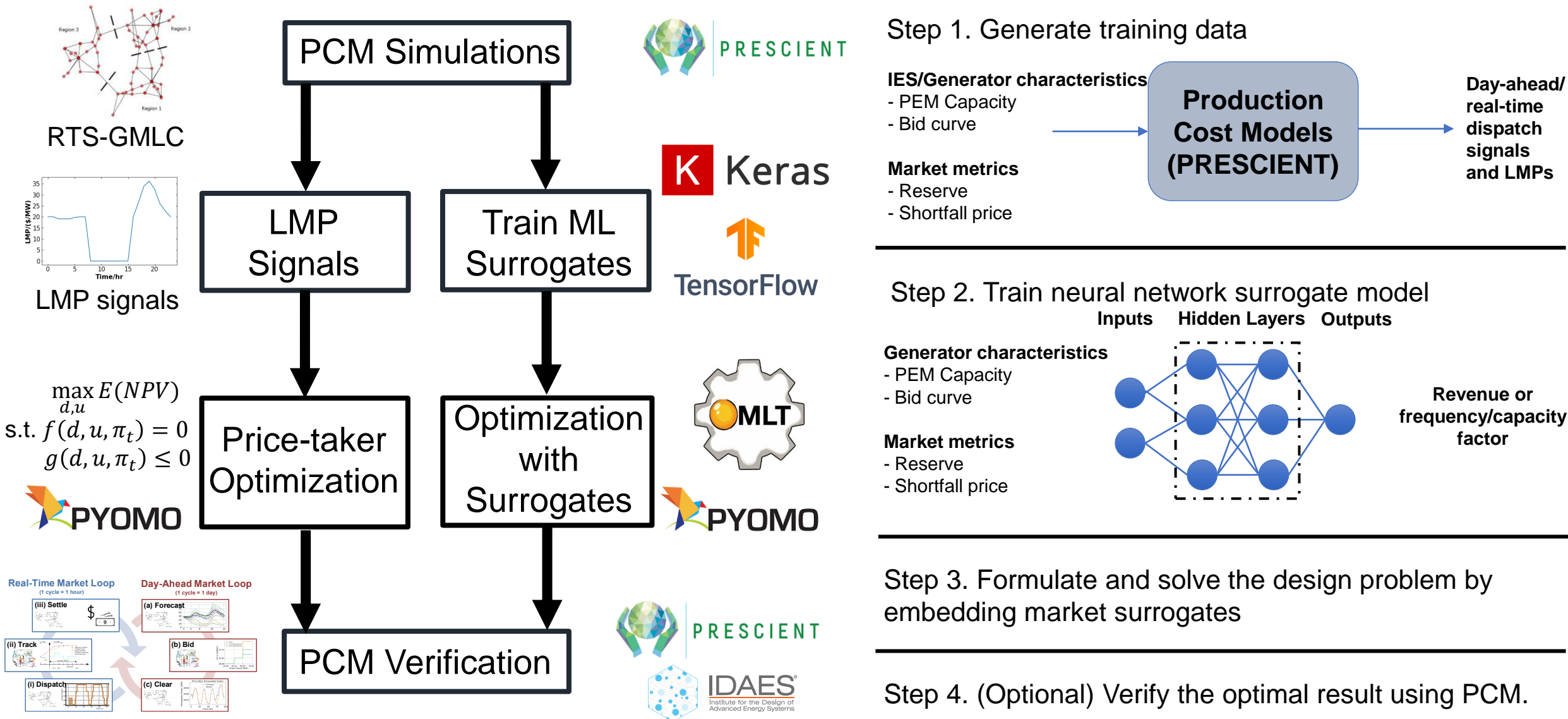
Three Workflows:

1. Price-taker
2. Market surrogates + design
3. IES + PCM "double-loop" optimization

Advantages of each workflow

- Price-taker: Low complexity.
- Surrogate: More accurate.
- Double-loop: Provide insights into how operation (bidding) impacts the IES economics and the grid.

IES Conceptual Design Optimization with Surrogate Models



Step 1. Generate training data

IES/Generator characteristics

- PEM Capacity
- Bid curve

Production
Cost Models
(PRESCIENT)

Day-ahead/
real-time
dispatch
signals
and LMPs

Market metrics

- Reserve
- Shortfall price

Step 2. Train neural network surrogate model

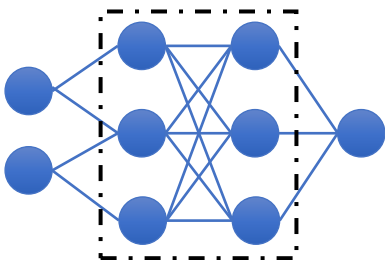
Inputs Hidden Layers Outputs

Generator characteristics

- PEM Capacity
- Bid curve

Market metrics

- Reserve
- Shortfall price

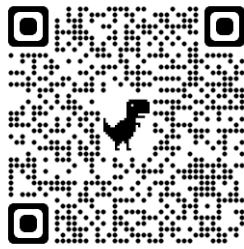


Revenue or
frequency/capacity
factor

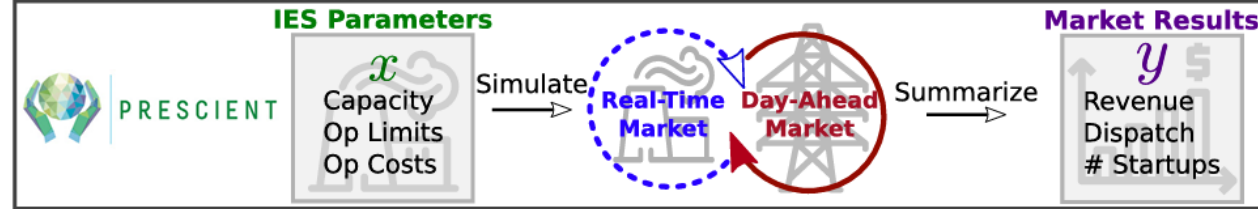
Step 3. Formulate and solve the design problem by embedding market surrogates

Step 4. (Optional) Verify the optimal result using PCM.

Recent Paper: Beyond Price-taker, Co-Optimization of a Thermal Power Plant (Power Only)

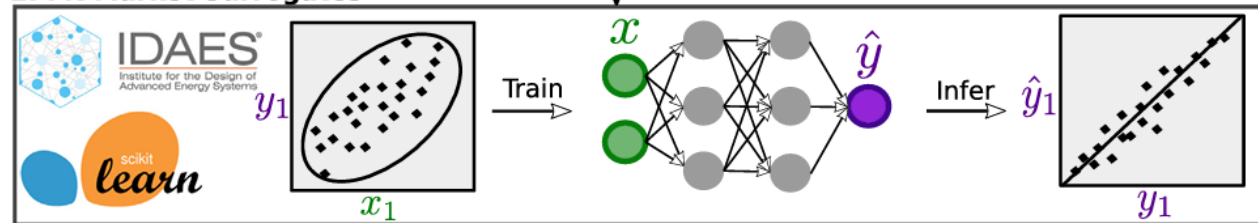


1. Run Market Simulations



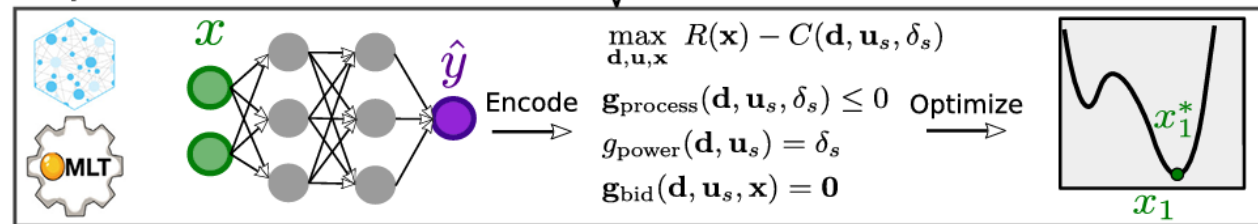
Totally 64000 annual PCM simulations of a **Rankine cycle** thermal power plant.

2. Fit Market Surrogates



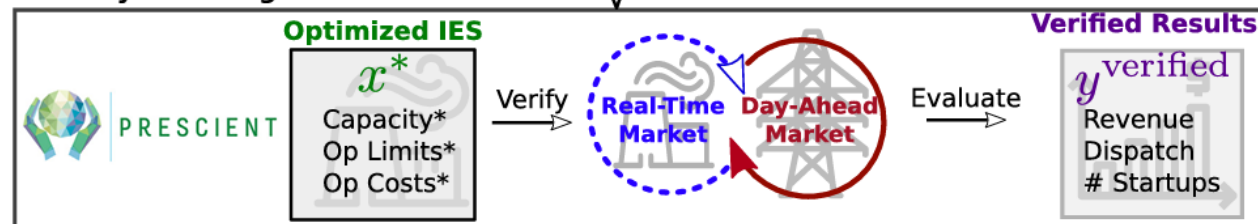
Three surrogate models (**revenue, start-up, frequency**) to model the IES/market interaction.

3. Optimize IES



Price-taker **overestimates** the revenue because large generators will **suppress** the market electricity price.

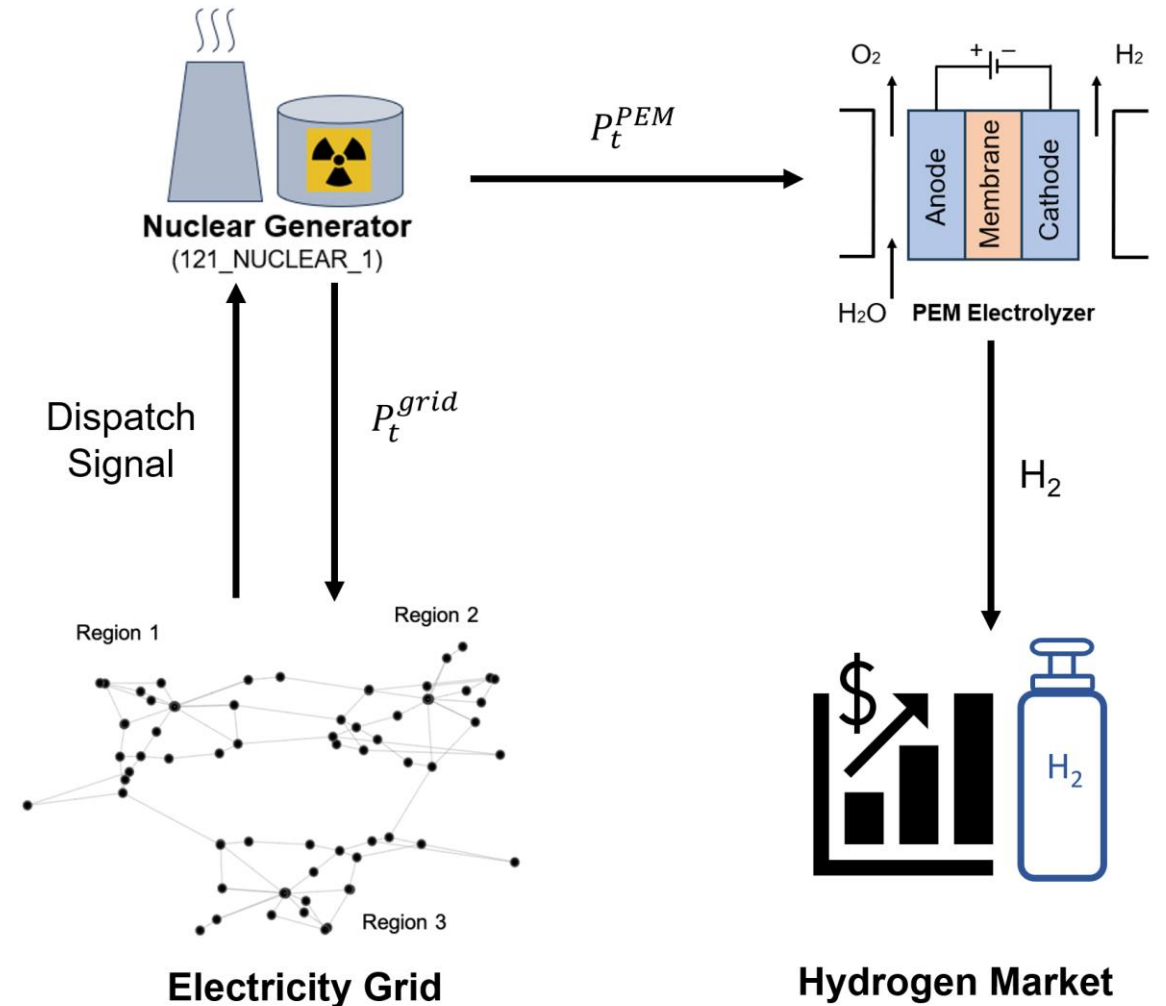
4. Verify IES Design



Optimization with market surrogates is **accurate** over a wide range of conditions.

Nuclear Energy (NE) Model (Co-produce Power + Hydrogen)

- Increasing renewables → volatile grid conditions
 - Nuclear generators cannot respond (baseload)
- Participate in alternate markets, e.g., H_2
 - Increases profitability, efficiency and flexibility
- Need to co-optimize design and operating decisions of IES due to dynamic markets
- Need to consider how IES influence markets, e.g., change electricity prices
- Simplified H_2 market (constant H_2 price)
 - Price-taker



Price-taker and Conceptual Design Optimization Model

Price-taker Model

$$\begin{aligned} \max_{d,u} \varphi \sum_{t \in T} & \left(R(d, u_t, \pi_t) + R_{H2}(d, u_t) - C_{OPEX}(d, u_t) \right) - C_{CAPEX}(d) \\ \text{s.t.} \quad & g_{process}(d, u_t) \leq 0 \quad t \in T \\ & g_{process}(d, u_t) = 0 \quad t \in T \end{aligned}$$

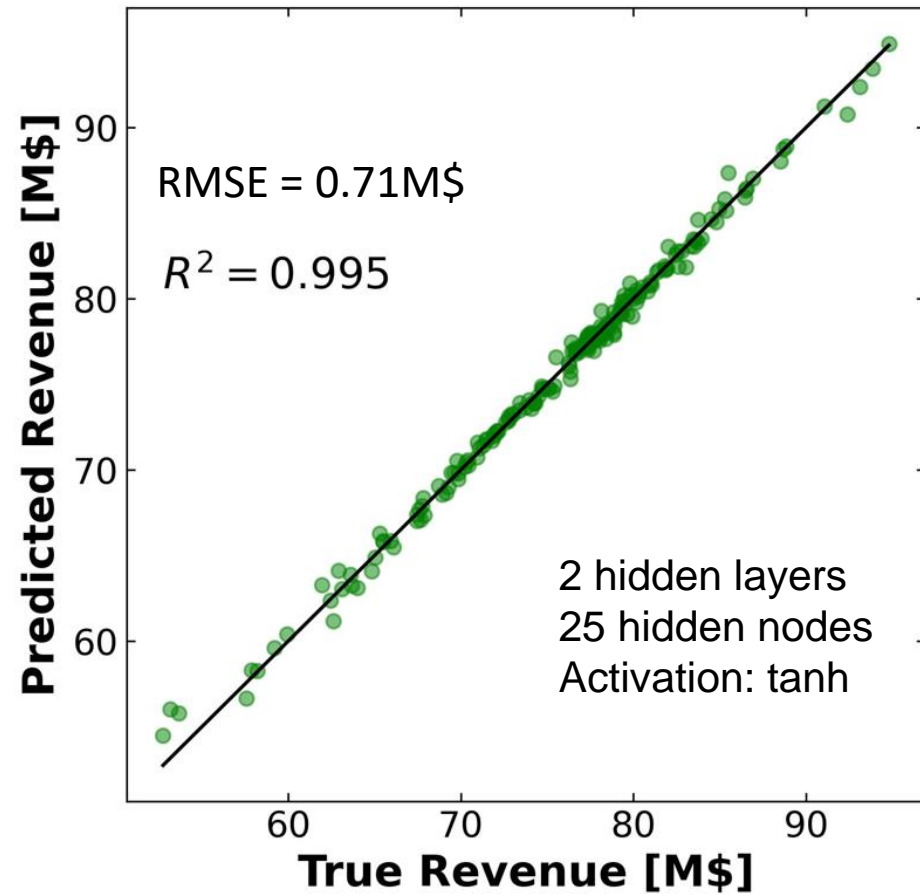
Functions/Variables/ Parameters/Sets	Description
f_{rev}	Revenue surrogate
f_{freq}	Frequency surrogate
R	Electricity revenue
R_{H2}	Hydrogen revenue
C_{OPEX}	Operation cost
C_{CAPEX}	Capital cost
d	IES design variables
u_s, u_t	IES Operation variables
ω_s	Weights of scenarios
x	Surrogate inputs
π_s	LMP signals
δ_s	Representative operation profiles
φ	NPV multiplier
S	Scenarios
T	Time periods

Conceptual Design Model with Surrogates

$$\begin{aligned} \max_{d,u,\delta} \varphi & \left[R(x) + \sum_{s \in S} \omega_s(x) \left(R_{H2}(d, u_s, \delta_s) - C_{OPEX}(d, u_s, \delta_s) \right) \right] - C_{CAPEX}(d) \\ \text{s.t.} \quad & g_{process}(d, u_s) \leq 0 \quad s \in S \\ & g_{power}(d, u_s) = \delta_s \quad s \in S \\ & R(x) = f_{rev}(x) \\ & \omega_s(x) = f_{freq}(x) \quad s \in S \end{aligned}$$

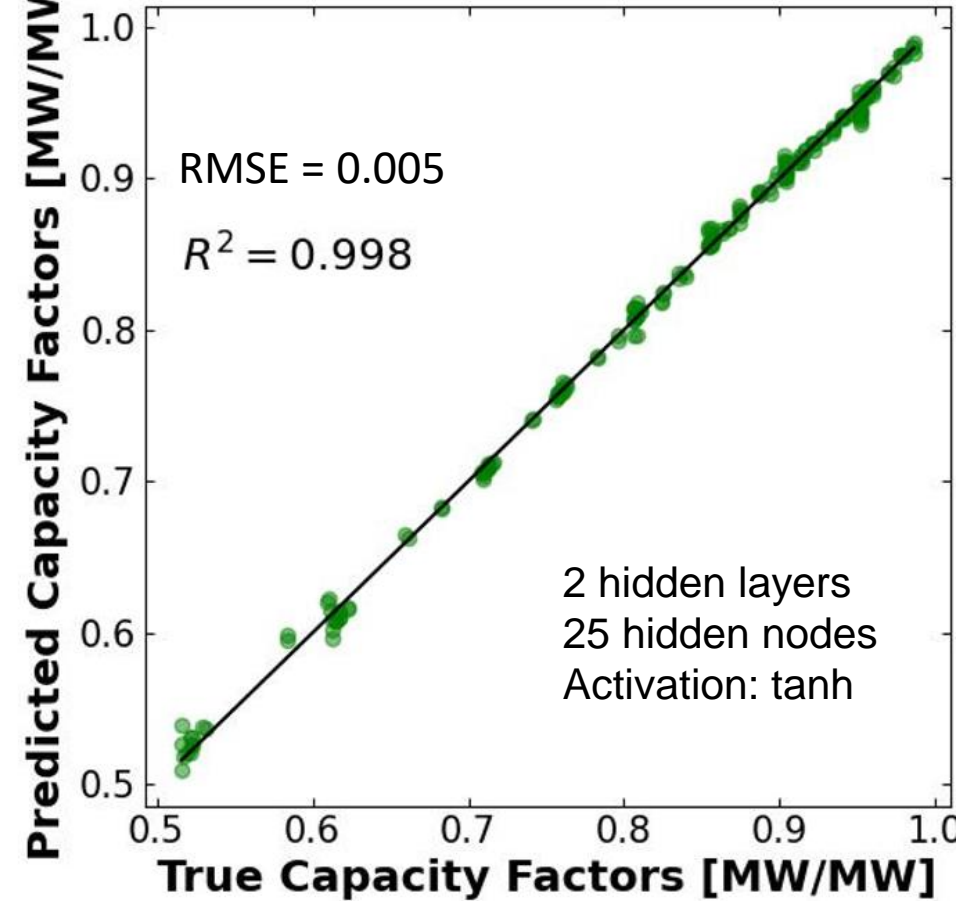
Surrogate Models Have Good Regression Performance

Revenue Surrogate



Predict the electricity revenue according to the IES design.

Capacity Factor Surrogate



Predict the annual capacity factor according to the IES design.

 Keras


TensorFlow



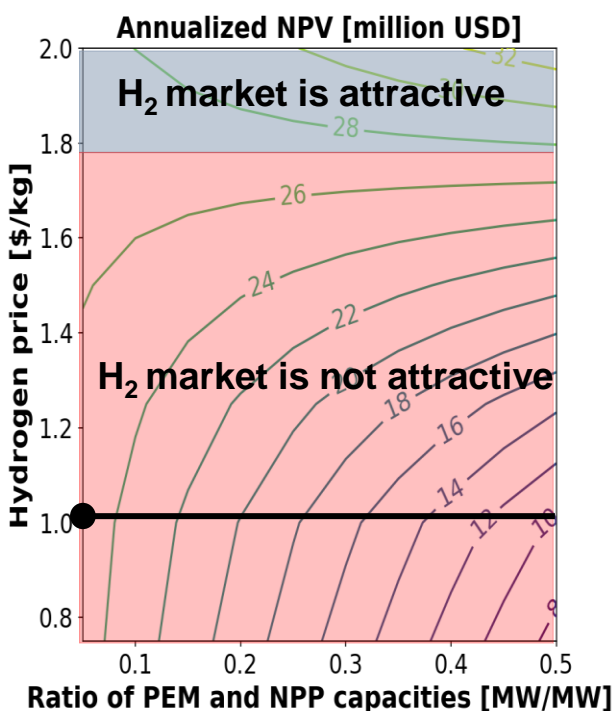
Price-taker Gives Inaccurate Economic Analyses

- Difference in the **net present value** and breakeven H_2 price

Price-taker **overestimates** the breakeven H_2 price

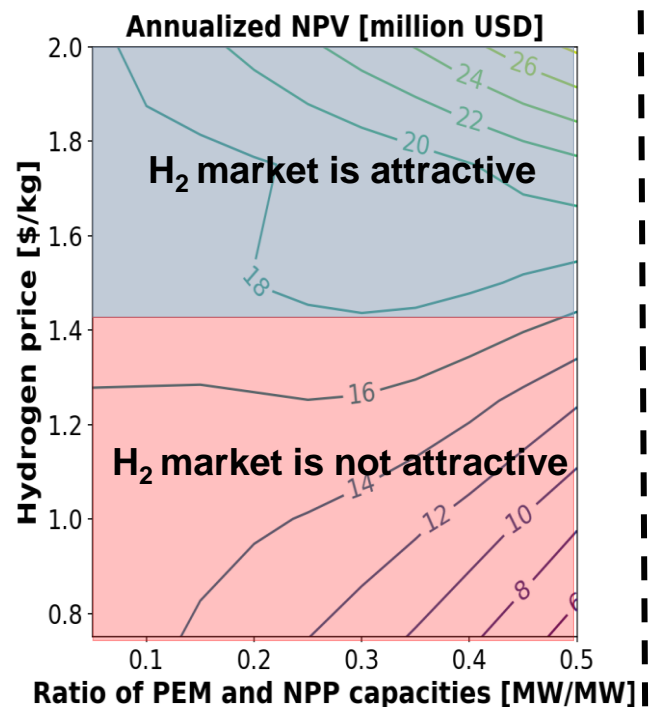
Price-taker

~\$1.8/kg



Market Surrogate

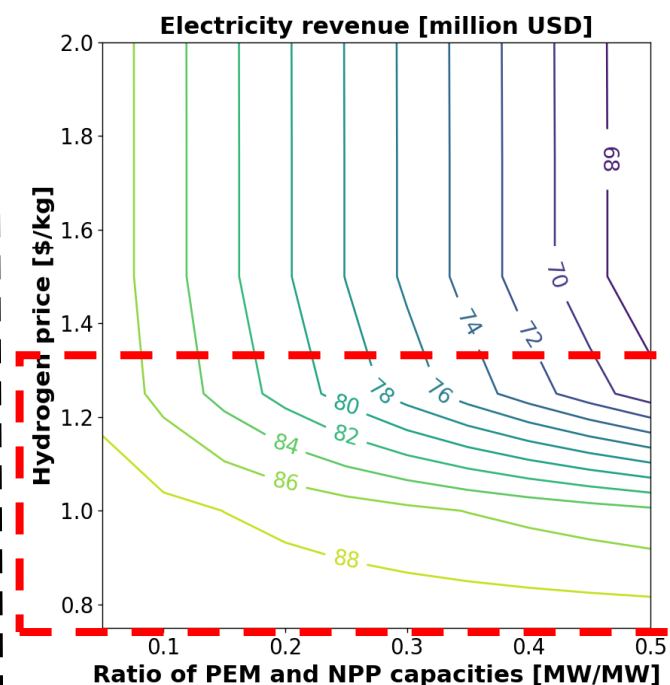
~\$1.4/kg



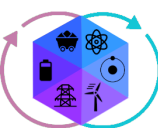
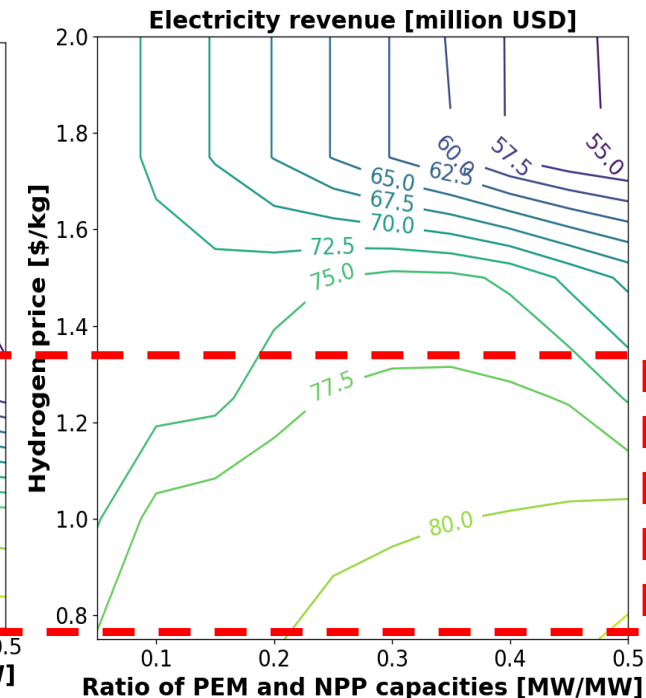
- Difference in **electricity revenue**

Electricity revenue depends on H_2 vs electricity production schedule – **nuanced interactions**

Price-taker



Market Surrogate



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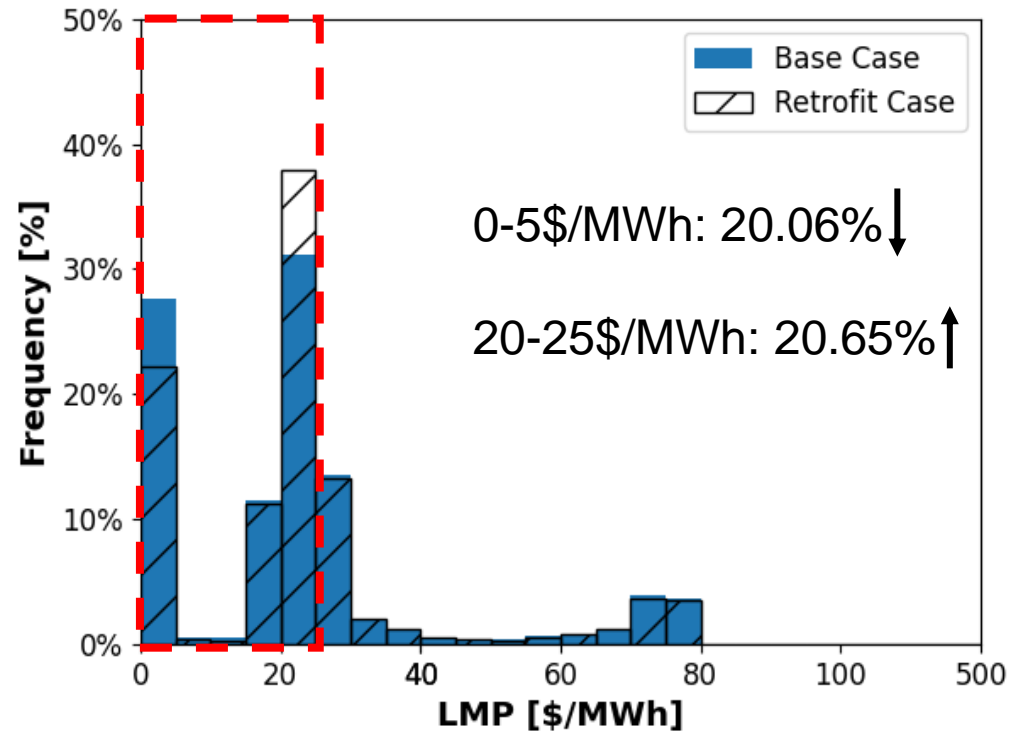
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IES-Market Interactions Change the LMP Distribution

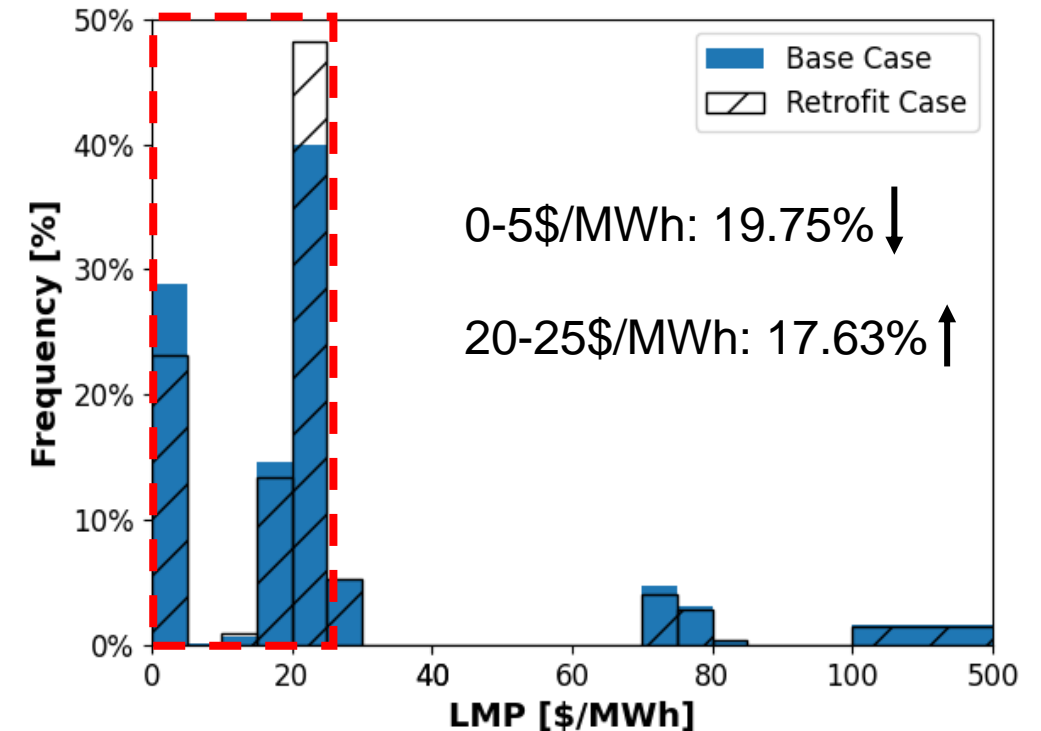
Base case (400 MW baseload nuclear generator without an electrolyzer)

Retrofitted case (400 MW nuclear generator equipped with a 200 MW electrolyzer – H₂ sold at \$1/kg)

Day-ahead Prices



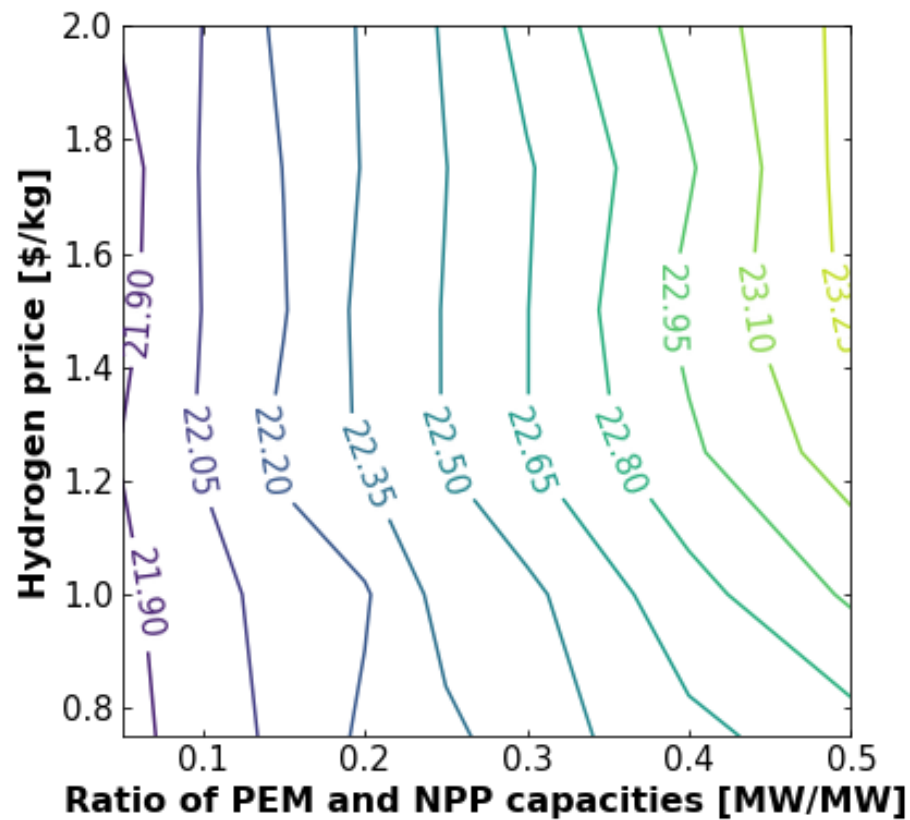
Real-time Prices



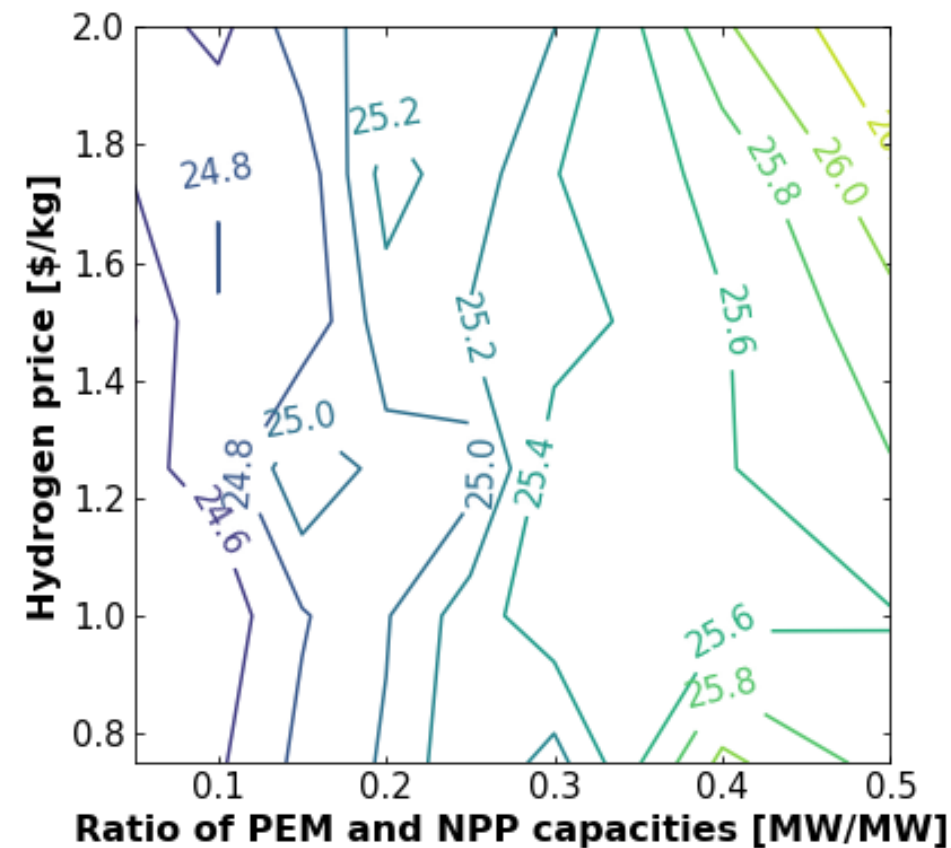
Fewer periods near **0 \$/MWh** and **more** periods near **20 \$/MWh**.
IES **reduces** the electricity supply at low LMP periods and increases the price.

A Larger PEM Tends to Increase the Average LMP

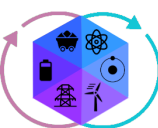
Day-ahead Prices



Real-time Prices



The annual average LMP at the node is impacted by IES designs. However, price-taker model ignores this interaction.



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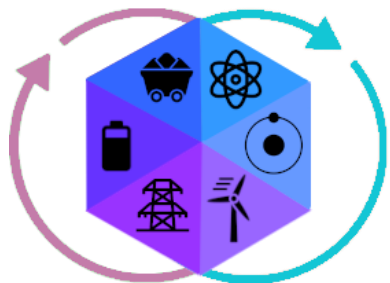
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Conclusion

- The price-taker optimization overestimates the economic performance of IES, which may mislead the decision making.
 - The interactions between IES and market will impact the electricity price and eventually affect the electricity revenue, where the price-taker model can't capture this.
 - Using the market surrogate framework will enable us to have a more accurate economic analysis of IES.
-

Future Work

- How to apply the surrogate-assisted workflow to the IES with storage systems.
- How to develop a general form of the surrogate model to describe all IES.



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We graciously acknowledge support from the Grid Modernization Laboratory Consortium through FECM, NE, & EERE

National Energy Technology Laboratory: David Miller, Radhakrishna Gooty, Andrew Lee, Naresh Susarla, (Jaffer Ghouse)

Sandia National Laboratories: John Siirola, Darryl Melander, Edna Rawlings, Kyle Skolfield, (Jordan Jalving)

Idaho National Laboratory: Aaron Epiney, Joshua Cogliati (Andrea Alfonsi, Konor Frick, Jason Hansen, Cristian Rabiti)

National Renewable Energy Laboratory: Wes Jones, Darice Guittet, Ben Kneuen, Ignas Satkauskas, (Abinet Eseye)

Lawrence Berkeley National Laboratory: Dan Gunter, Oluwamayowa Amusat, Keith Beattie, Ludovico Bianchi

University of Notre Dame: Alexander Dowling, Xinhe Chen, (Xian Gao)



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Acknowledgements

This work was conducted as part of the Institute for the Design of Advanced Energy Systems (IDAES) with support from the U.S. Department of Energy's Office of Fossil Energy and Carbon Management (FECM) through the Simulation-based Engineering Research Program.

Office of Fossil Energy and Carbon Management: Eva Rodezno, Robert Schrecengost

National Energy Technology Laboratory: David Miller, Tony Burgard, Benjamin Omell, Steve Zitney, John Eslick, Andrew Lee, Miguel Zamarripa, Jinliang Ma, Jaffer Ghouse, Chinedu Okoli, Arun Iyengar, Anca Ostace, Anuja Deshpande, Alex Noring, Naresh Susarla, Radhakrishna Gooty, Doug Allen, Ryan Hughes, Andres Calderon, Brandon Paul, Adam Atia, John Brewer, Nadejda Victor, Maojian Wang, Peng Liu, Sydni Credle, Dave Lyons, Nate Weiland

Sandia National Laboratories: John Siirola, Bethany Nicholson, Michael Bynum, Jordan Jalving, Emma Johnson, Katherine Klise, Shawn Martin, Miranda Mundt, Edna Soraya Rawlings, Kyle Skolfield

Lawrence Berkeley National Laboratory: Deb Agarwal, Dan Gunter, Keith Beattie, John Shinn, Hamdy Elgammal, Joshua Boverhof, Karen Whitenack, Oluwamayowa Amusat, Sarah Poon

Carnegie Mellon University: Larry Biegler, Chrysanthos Gounaris, Ignacio Grossmann, Carl Laird, John Eason, Owais Sarwar, Natalie Isenberg, Chris Hanselman, Marissa Engle, Qi Chen, Cristiana Lara, Robert Parker, Ben Sauk, Vibhav Dabadghao, Can Li, David Molina Thierry, Mingrui Li, Seolhee Cho, Georgia Stinchfield, Jason Sherman, San Dinh

West Virginia University: Debangsu Bhattacharyya, Paul Akula, Quang-Minh Le, Nishant Giridhar, Matthew Alastanos

University of Notre Dame: Alex Dowling, Xian Gao, Nicole Cortes, Xinhe Chen

Georgia Tech: Nick Sahinidis, Yijiang Li, Selin Bayramoglu



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

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Acknowledgements



I would like to express my special thanks to the following people and organizations:

- Prof. Dowling and Dowling Lab members.
- Department of Chemical and Biomolecular Engineering, University of Notre Dame.

