

## **A New Platform for Process Design & Optimization**

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Senior Fellow National Energy Technology Laboratory





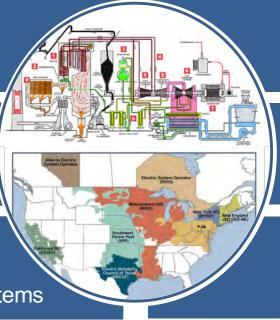


Carnegie Mellon 🔆 West Virginia University.

Increasingly dynamic operations

Greater linkages among scales

Support for innovative concepts, systems, and technologies: Process Intensification; Hybrid Systems



30+ years of progress in algorithms, hardware, modeling approaches

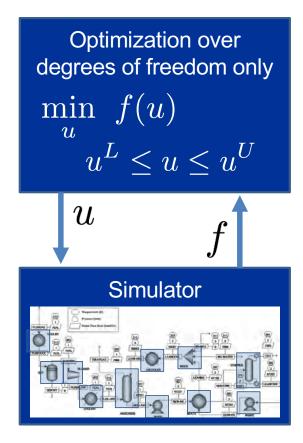
NOTRE DAME

Advances in continuous nonlinear optimization (dynamics, uncertainty)

Advances in discrete optimization (algorithms and formulation)

DOE Office of Fossil Energy Simulation-Based Engineering/Crosscutting R&D Program

### **Process Optimization: Transition to EO (algebraic) models**





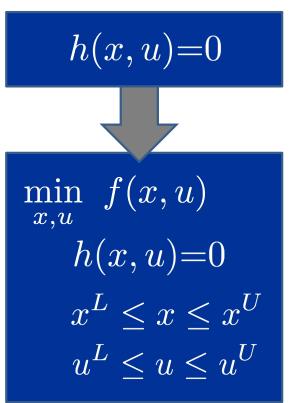
Black-box optimization (DFO) ~ 100-1000 simulations

Glass-box optimization ~ 1-5 STE

Optimization with embedded algebraic model as constraints  $\min_{x,u} f(x,u)$ h(x,u)=0 $x^{L} \leq x \leq x^{U}$  $u^{L} \leq u \leq u^{U}$ 

[Adapted from Biegler, 2017]

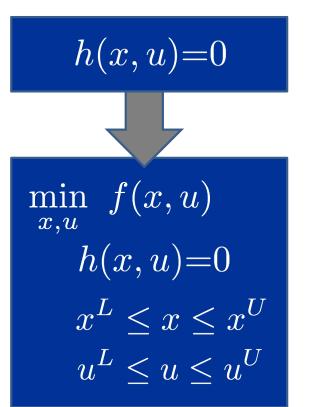
### **Equation-Oriented (algebraic) models: Benefits**



- Explicit equations exposed to general numerical solvers and analysis tools
- Significantly faster computational performance: automatic differentiation, exposed structure
  - Fully integrated complex facilities (enterprise-wide)
  - DAE and uncertainty can be addressed in this form
- Separation of model from solver
  - Supports a wide range of Newton-based solvers
  - Same model used for different analyses (simulation, optimization, sensitivity, UQ)
- Automatic model transformation and reformulation
- (e.g., MPEC, GDP, DAE, Stochastic Programming)
- MINLP / global optimization with explicit expressions



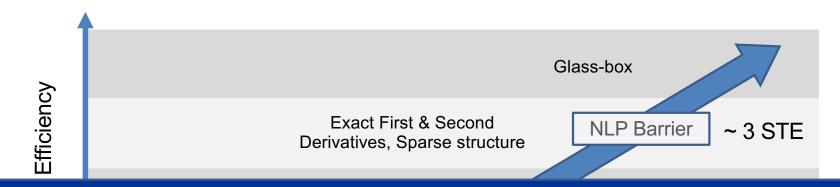
### **Equation-Oriented (algebraic) models: Challenges**



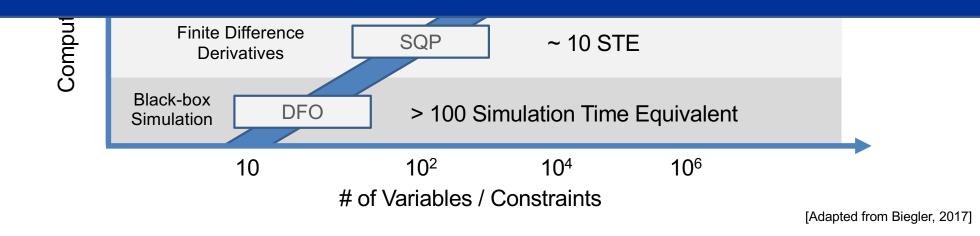
- Effective initialization critical for reliable convergence
- Not everything can (easily) be made equation-oriented
   Need a strategy for black-box sub-components
- Nonlinear simulation and optimization formulations are much larger than black-box counterparts



### **Process Optimization Environments and NLP Solvers**



Can now treat millions of variables ... on your desktop ... in minutes





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Existing process unit model library for rapid assembly and modeling of flowsheets

Flexible capabilities to model novel technologies and optimize new materials

Efficient optimization tools to explore large space of potential process flowsheets

Construction of optimization-ready surrogates and physical property relations

Scalable identification and handling of uncertainty inherent in novel design



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Flexible capabilities to model novel technologies and optimize new materials

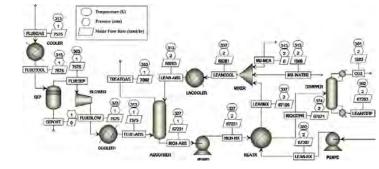
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### Sequential Modular Flowsheeting Tools

Very capable for steady-state modeling of existing processes and techno-economic analysis



- Simulation-based, black-box analysis does not support "glass-box" optimization-based approaches
- Insufficient flexibility for easy creation of tailored models from existing sub-components
- Difficult to explore large space of potential flowsheets, typically focus on a few (design rules and experience)



Strong process modeling libraries – missing full "glass-box" for advanced optimization

Image from: Kundu, Prodip & Chakma, Amit & Feng, Xianshe. (2014). Effectiveness of membranes and hybrid membrane processes in comparison with absorption using amines for post-combustion CO2 capture. International Journal of Greenhouse Gas Control. 28. 248–256

Existing process unit model library for rapid assembly and modeling of flowsheets

Flexible capabilities to model novel technologies and optimize new materials

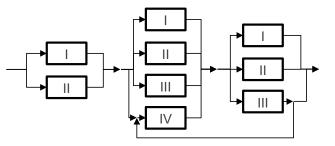
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#### General Algebraic Modeling Tools (e.g., GAMS, AMPL)

 Superstructure optimization (reformulated as MINLP) well-supported by algebraic modeling tools (e.g., AMPL, GAMS)



- Algebraic modeling tools lack component-based, process engineering model libraries
- Significant expertise required to formulate the (manual) transformation to MINLP
- No capabilities for developing advanced algorithms



Strong "glass-box" capabilities – missing model libraries and extensibility for advanced algorithms

Existing process unit model library for rapid assembly and modeling of flowsheets



IDAES Steady-state and dynamic equationoriented model library and modular structure

**IDAES** Steady-state and dynamic

equation-oriented modeling framework

Flexible capabilities to model novel technologies and optimize new materials

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Next Generation Integrated Platform for Modeling and Optimization

IDAES PyoSyn framework for superstructure optimization with Pyomo.GDP and GDPOpt

ALAMO, HELMET, RIPE, PySMO: Optimizationbased AI/ML approaches for kinetics, surrogate models, and thermo-physical properties

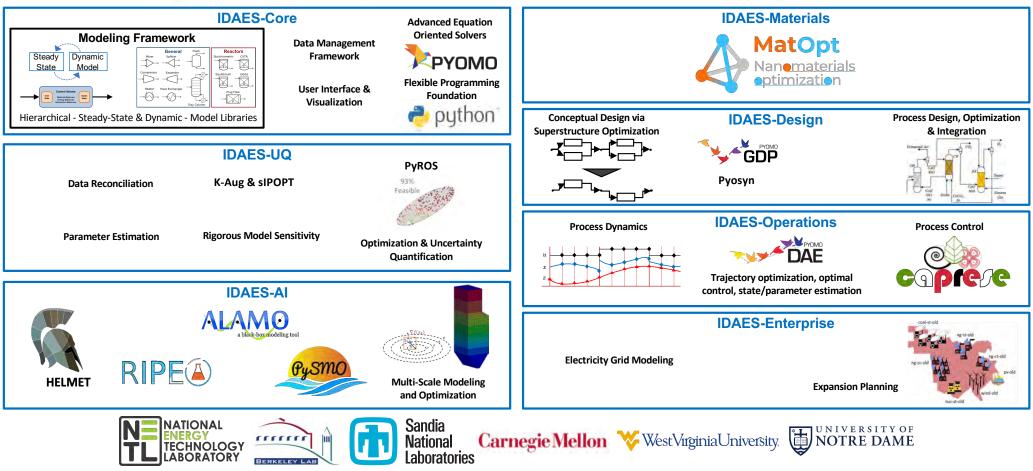
Stochastic prog. & adaptive robust optimization for scalable, rigorous treatment of uncertainty



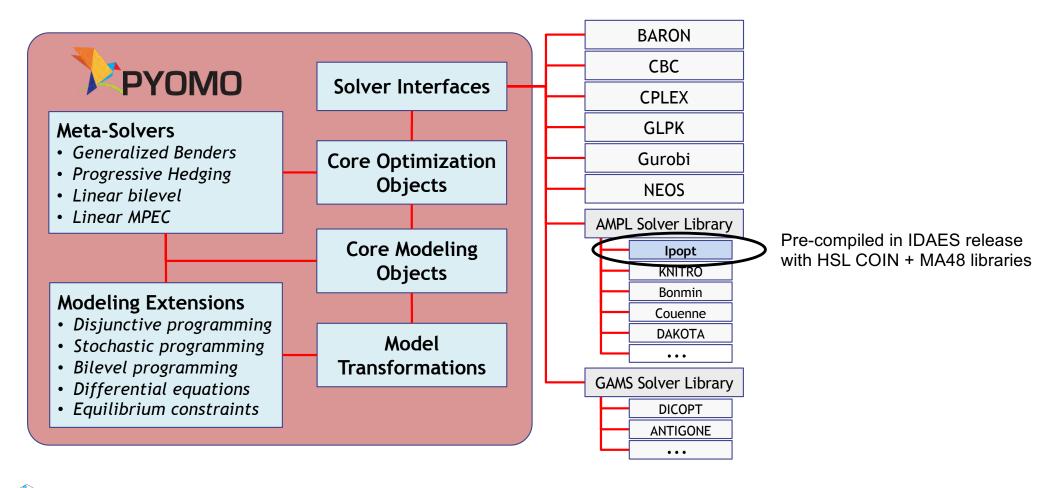


Advanced Energy Systems

# IDAES Integrated Platform



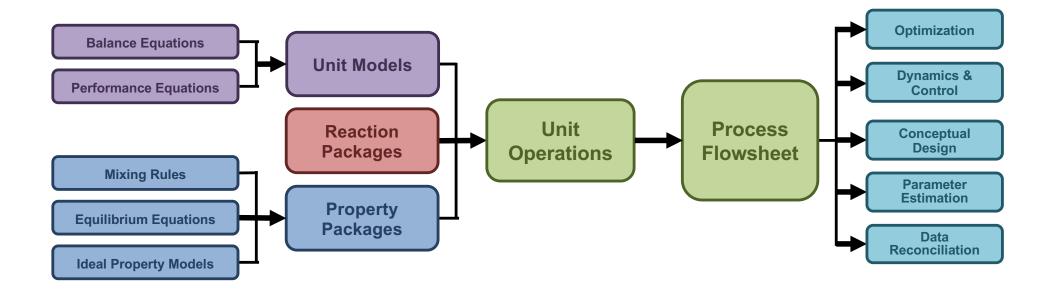
### **Pyomo: Python Optimization Modeling Objects**





### **IDAES Model Structure**

Flexibility and power of an equation-oriented modeling package Supports the block structure of a process simulator





### **Recent Applications and Impact**

- Existing Plant Process Improvements & Optimization
- Design & Optimization of Complex, Interacting Systems
  - Design space exploration
  - Optimization of carbon capture systems
  - Robust design to reduce technical risk
- Bridging timescales between power plant and grid
  - Energy storage to reduce cycling / wear
  - Insights on optimal bid strategies to increase revenue



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### **Support for the Existing Coal-Generation Fleet**

#### Partnership with Tri-State Generation and Transmission Association



Escalante Generating Station, Prewitt, NM

245 MW Subcritical Plant

Frequent Cycling





- Major focus areas
  - Reducing minimum load

Demonstrated 44% improvement upon correcting deaerator water hammer issue

Improving heat rate

Up to 2% improvement with a steeper sliding pressure approach to load following

- Fault detection and diagnosis

Alarm settings can identify reheater plugging 4-5 days in advance (previously 1-2 days)

Extending equipment life

#### Public releases

- 🎸 Jan 20: Steady-state power plant model library
- July 20: Code for data reconciliation,
  - parameter estimation, and optimization
- Dec 20: Dynamic power plant model library

### **IDAES Enables Complete Workflow from Analysis to Optimization**

#### **Data Reconciliation**

#### "Ensure data is reliable"

 $\underbrace{\text{Minimize}}_{\substack{\{temps, pressures, \\ flows\}}} \sum_{data} (error_{meas})^2$ 

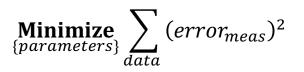
#### subject to

- Flowsheet connectivity
- Mass and energy balances
- Physical property calculations

error<sub>meas</sub> = <u>measurement – model prediction</u> measurement uncertainty

#### **Parameter Estimation**

"Make models predictive"



#### subject to

- Flowsheet connectivity
- Mass and energy balances
- Physical property calculations
- Performance equations for unit models

#### System-wide Optimization

"Identify optimal operation"

Minimize *Heat Rate {temps,pressures,* 

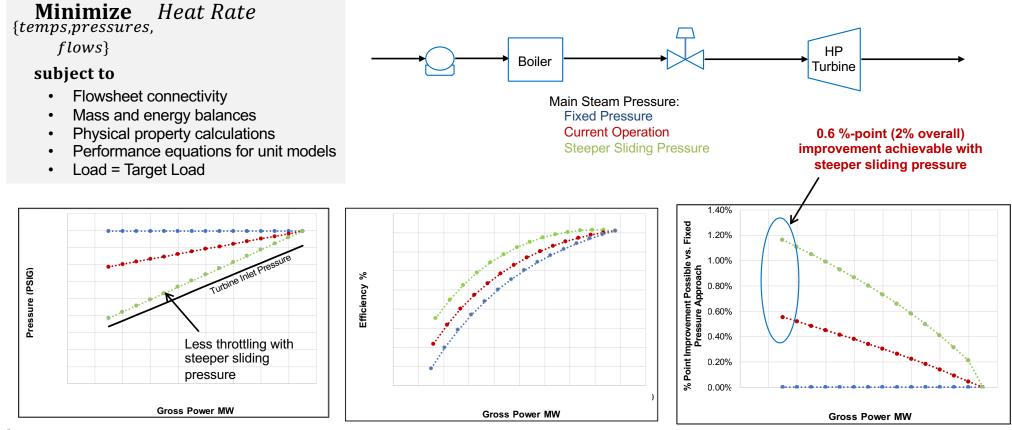
flows}

#### subject to

- Flowsheet connectivity
- Mass and energy balances
- Physical property calculations
- Performance equations for unit models
- Load = Target Load
- Operational Constraints (e.g., T<T<sub>max</sub>)
- Emissions < Emission Limits



### System-wide Optimization Revealed Heat Rate Improvements Achievable through Steeper Sliding Pressure Operation



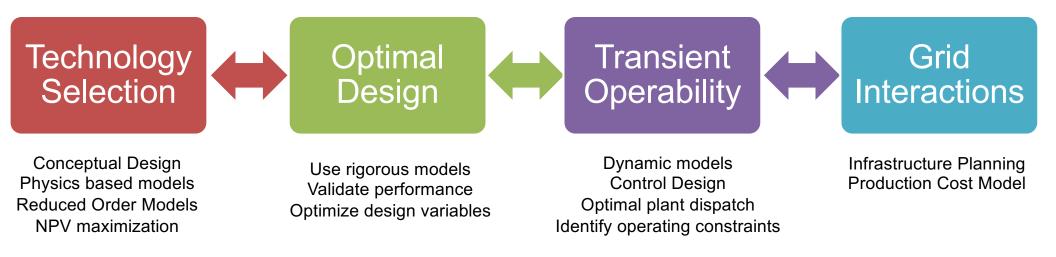


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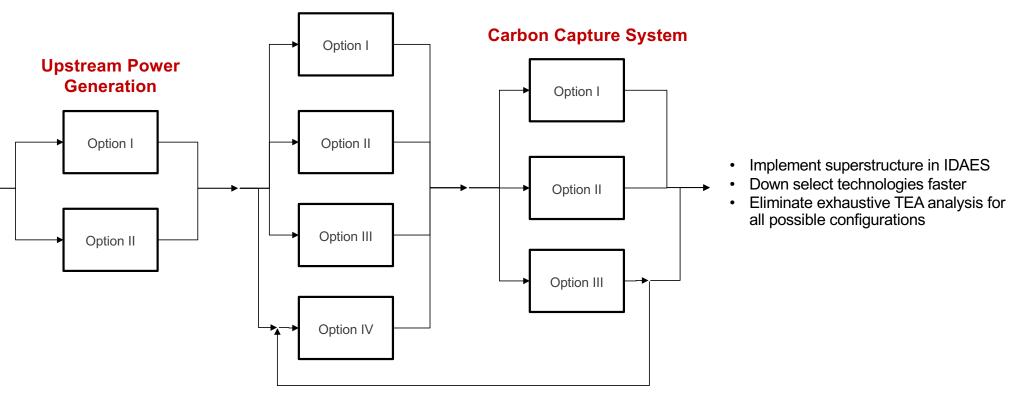


### **Design & Optimization of Complex, Interacting Systems**





### **Design Space Exploration of Options and Configurations**



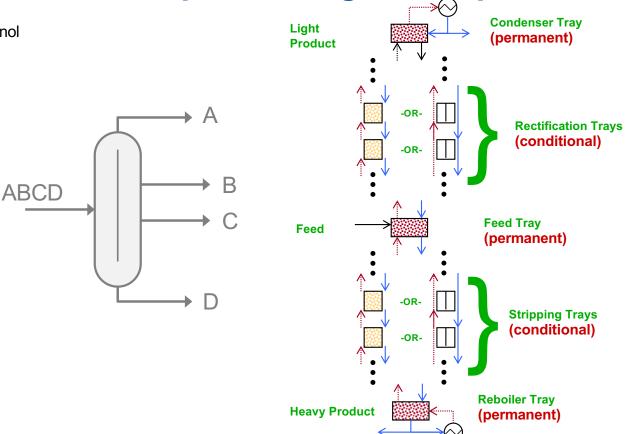
#### Storage Technology

#### 9 disjunctions, 18 binary variables $\rightarrow$ 315 flowsheets to evaluate



### **PyoSyn: Kaibel Column Conceptual Design Example**

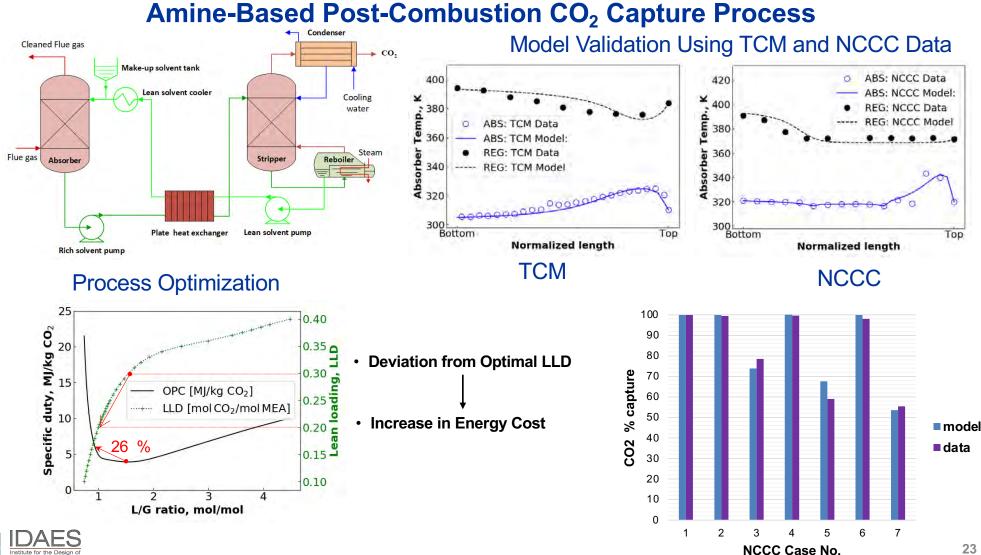
- Components: Methanol, ethanol, n-propanol, n-butanol
  - 99% purity for each component
- 42 million combinations
- GDP model written using Pyomo.GDP
  - 5715 constraints
    - 2124 nonlinear
  - 100 disjunctions
    - 3599 variables
      - 178 binary
      - 3421 continuous
- Solved in <u>639 sec using GDPopt-LOA solver</u>
  - Logic-based outer approximation algorithm
  - 4 iterations
- Resulting design:
  - 46 trays (21% reduction vs. base case)
  - Dividing wall between 12th and 26th tray
  - Feed at 18th tray
  - Side outlets at 13<sup>th</sup> and 22<sup>nd</sup> trays



#### Optimal Design Kaibel Column reduces energy consumption by more than 40% compared to 2 columns



Rawlings, Chen, Grossmann, Caballero, Computers & Chemical Engineering, 125, 2019, 31-39.

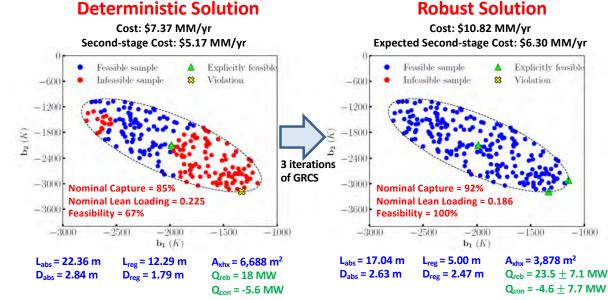


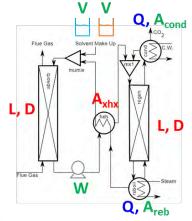
stitute for the Design o dvanced Energy System

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### **PyROS:** Robust Design CO<sub>2</sub> Capture System

- Design Variables (First-Stage)
  - Columns dimensions (D,A), heat exchanger areas (Axhx)
  - hold-up tank volumes (V), pump power (P)
- Control Variables (Second-Stage)
  - Duties (Qreb, Qcon)
- Uncertain Parameters
  - Equilibrium constant parameters (b1, b2)





#### Deteministic design fails to meet CO<sub>2</sub> capture performance requirement with a 33% probability

#### **Robust design**

guarantees CO<sub>2</sub> capture in all scenarios; cost increase is kept to the minimum necessary to achieve this

#### **Robustness achieved**

by increasing reboiler/condenser duties, which also lead to lower lean-loading (due to shorter regenerator column)



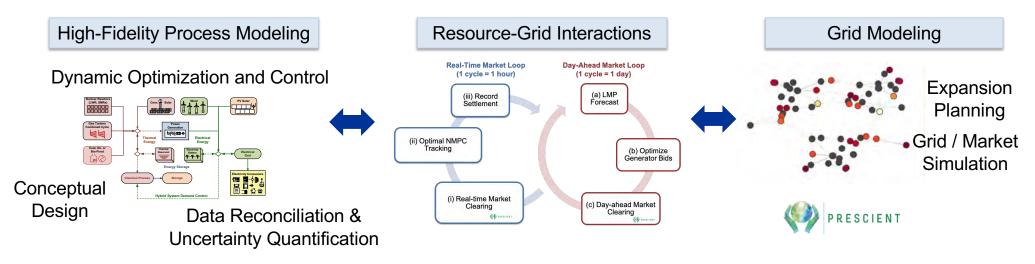
Isenberg, N.. I., Akula, P., Eslik, J., Bhattacharyya, Miller, D. C., Gounaris, C. E. (2020). Under Review.

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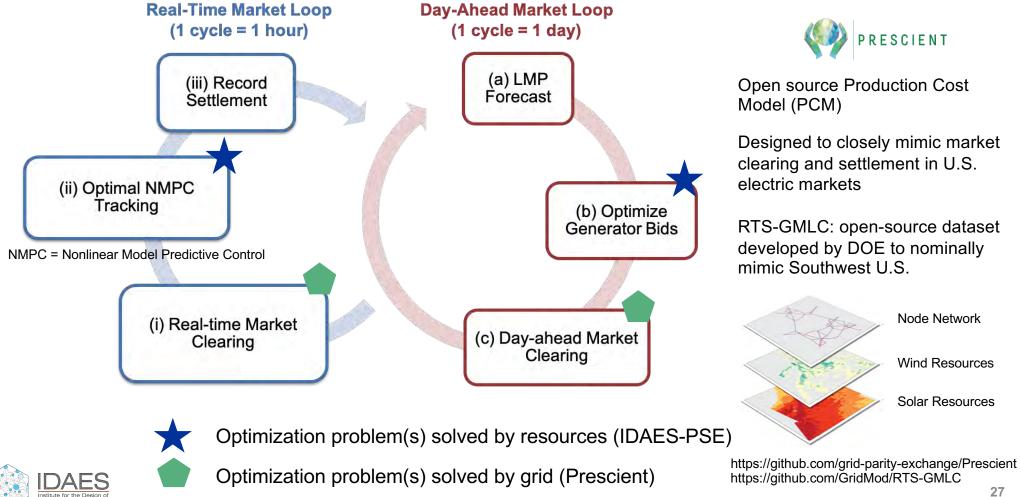
### **Bridging Timescales in IDAES Enables Unique Analyses**



- 1. Elucidate complex relationships between resource dynamics and market dispatch (with uncertainty, beyond price-taker assumption)
- 2. Predict the economic opportunities and market impacts of emerging technologies (e.g., Coal FIRST, tightly-coupled hybrid energy systems)
- 3. Guide conceptual design & retrofit to meet current and future power grid needs

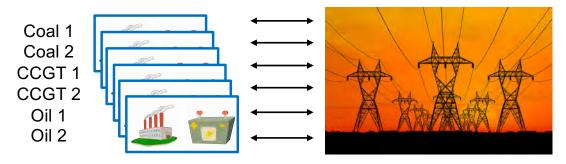


### Modeling Multiscale Resource and Grid Decision-Making



### Thermal generators with energy storage

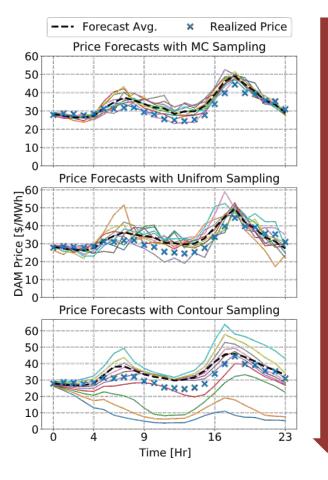
• Evaluate the impact of pairing thermal generators with electricity storage



- Optimize combined generator profit, subject to
  - Ramping limits
  - Minimum up/down time constraints
  - Storage energy balance
- Under two operating modes:
  - Self-schedule
  - Bidding



### Forecast: Sampling strategies



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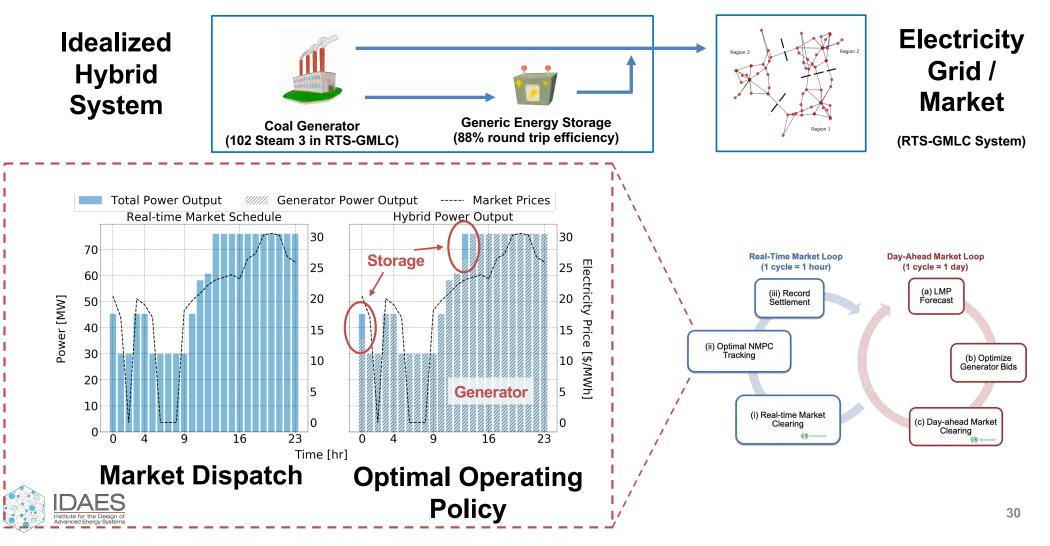
### Quantifying the opportunity of integrated analysis

Model	Participation Mode	Perfect Information (M\$)	MC Sampling (M\$)	Uniform Sampling (M\$)	Contour Sampling (M\$)
Thermal Generators	Bid Curve Self-	51.8 (100%)	46.2 (89.3%) 42.1	47.3 (91.3%) 41.0	47.5 (91.7%) 41.3
	schedule		(81.3%)	(79.2%)	(79.6%)
Thermal Generators + Storage	Bid Curve	54.1 (100%)	46.6 (86.2%)	48.2 (89.0%)	47.9 (88.6%)
	Self- schedule		43.6 (80.5%)	41.3 (76.3%)	42.5 (78.5%)

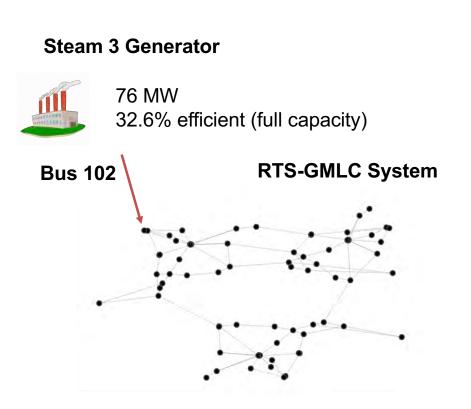
Bidding (direct market participation) is more robust to market price uncertainty.



### Hybrid system tracked market dispatch with 30% less ramping



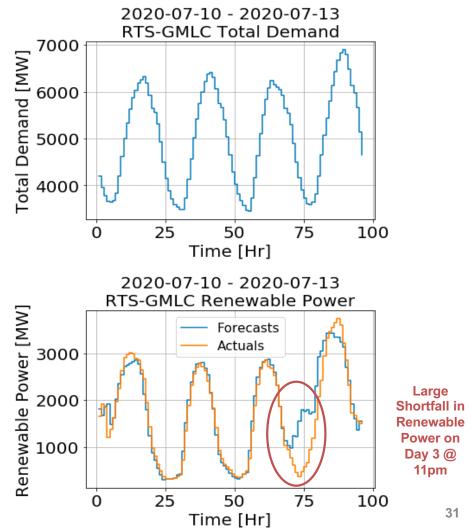
### **Optimize Bidding Strategy for Coal Steam 3 Generator**



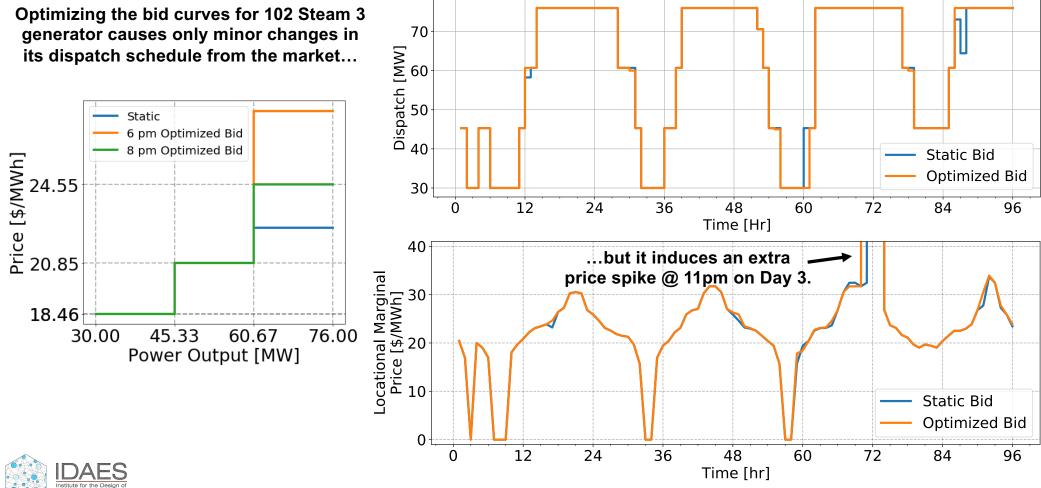
158 generators (42% dispatchable) 14,550 MW capacity (54% dispatchable)



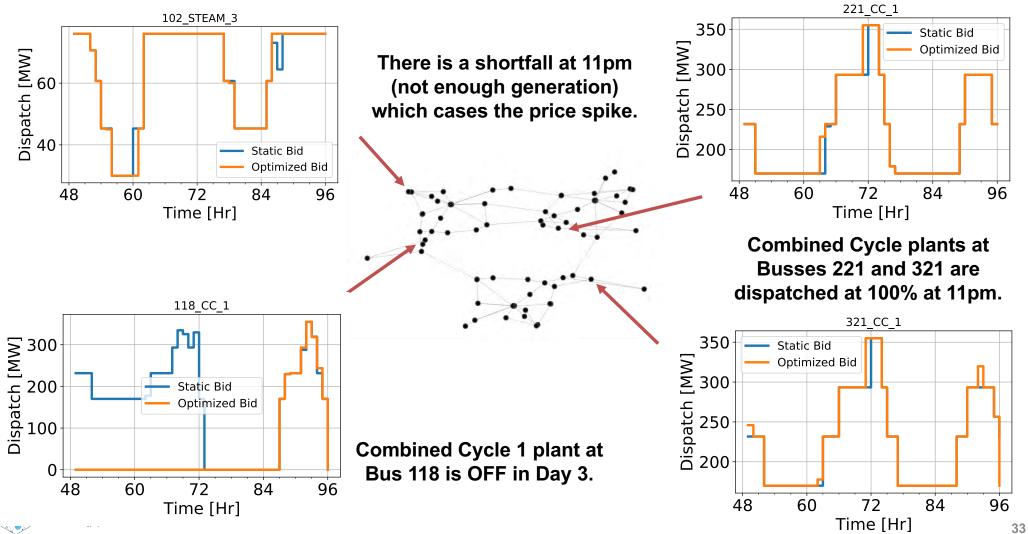
Data: RTS-GMLC, https://github.com/GridMod/RTS-GMLC



### **Optimal Bid Changes Dispatch & Increases Revenue**



### Changes in a single generator impacts entire network



### **Conclusions: Recent Applications and Impact**

- Existing Plant Process Improvements & Optimization
  - Improved minimum operating load by 44%
  - Opportunity to increase overall efficiency by 2%
- Design & Optimization of Complex, Interacting Systems
  - Design space exploration
    - Reduced energy demand by >40% through automated exploration of 42 million alternatives
  - Optimization of carbon capture systems
    - Reduced operating cost by 15-18%
  - Robust design to reduce technical risk
    - Inherently robust against uncertainties in the core process thermophysical properties
- Bridging timescales between power plant and grid
  - Energy storage
    - Increased revenue opportunities
    - Reduced equipment wear and tear by >30%
  - Insights on optimal bid strategies to increase revenue
    - Captures complex interactions among generators & bulk power market
    - Analysis of emerging flexible energy systems must capture interactions with the balance of the grid



### **Extended Applications of IDAES**



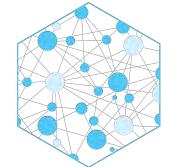






### **Virtual Joint Stakeholder Workshop**

- October 1 @ 11-2:15 Eastern
  Plenary presentations
- October 8 @ 11-1:20 Eastern
   Topical presentations
- October 15 @ 11 1:20 Eastern
  - Topical presentations









### **Available Videos and Tutorials**

#### Overview Video

- <u>https://youtu.be/28qjcHb4JfQ</u>
- **Tutorial 1:** IDAES 101: Python and Pyomo Basics
  - <u>https://youtu.be/\_E1H4C-hy14</u>
- **Tutorial 2:** IDAES Flash Unit Model and Parameter Estimation (NRTL)
  - <u>https://youtu.be/H698yy3yu6E</u>
- Tutorial 3: IDAES Flowsheet Simulation and Optimization; Visualization Demo

<u>https://youtu.be/v9HyCiP0LHg</u>





### idaes.org

### github.com/IDAES/idaes-pse





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- Carnegie Mellon University: Larry Biegler, Nick Sahinidis, Chrysanthos Gounaris, Ignacio Grossmann, Owais Sarwar, Natalie Isenberg, Chris Hanselman, Marissa Engle, Qi Chen, Cristiana Lara, Robert Parker, Ben Sauk, Vibhav Dabadghao, Can Li, David Molina Thierry
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- University of Notre Dame: Alexander Dowling, Xian Gao

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