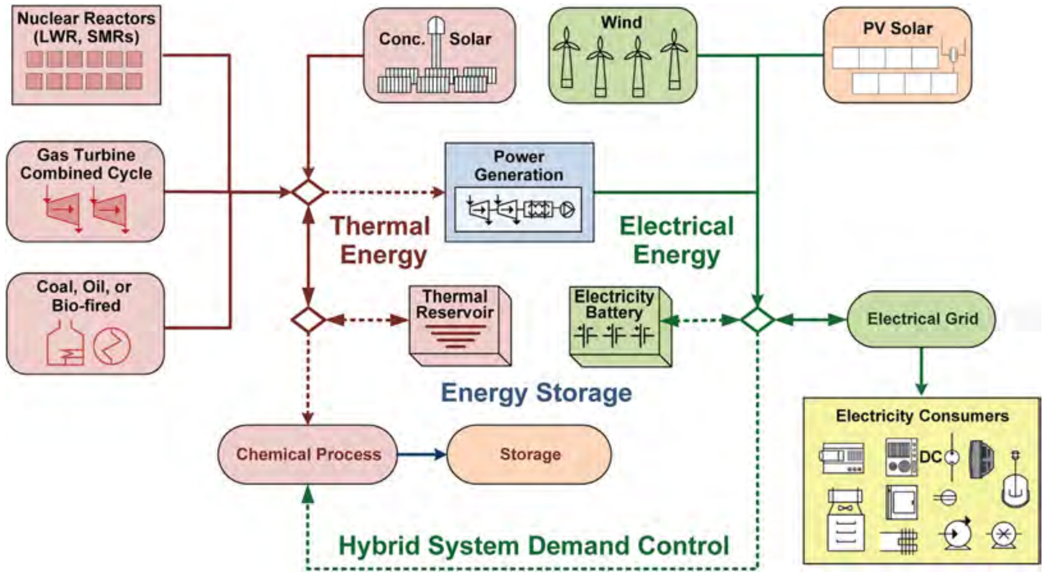
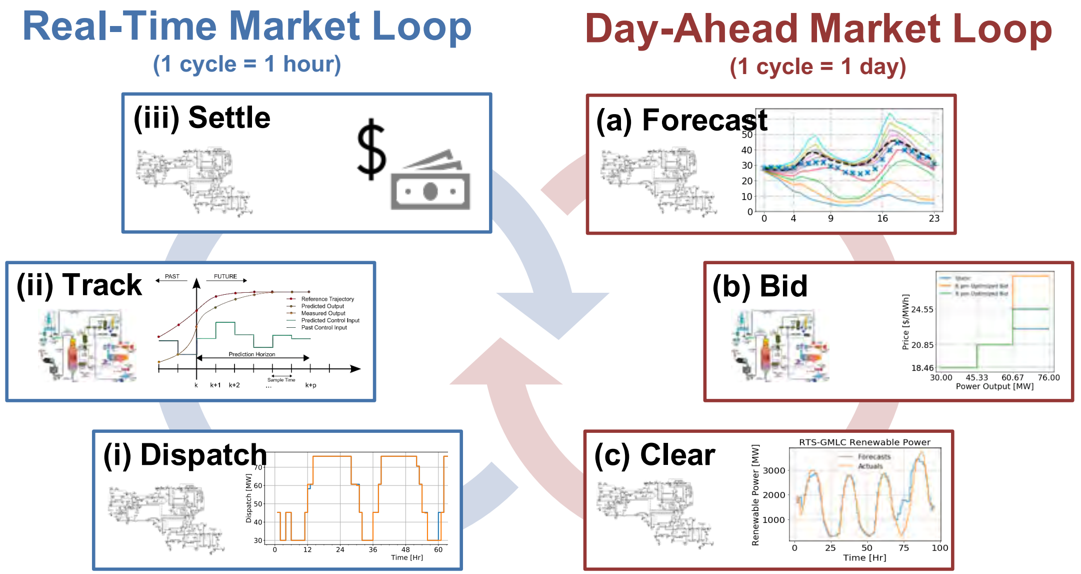
Multiscale Design, Operations, and Control Optimization of Integrated Energy Systems Considering Energy Market Interactions





Prof. Alexander (Alex) Dowling

CAPD ESI Seminar / April 5, 2022

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GRID MODERNIZATION LABORATORY CONSORTIUM
U.S. Department of Energy

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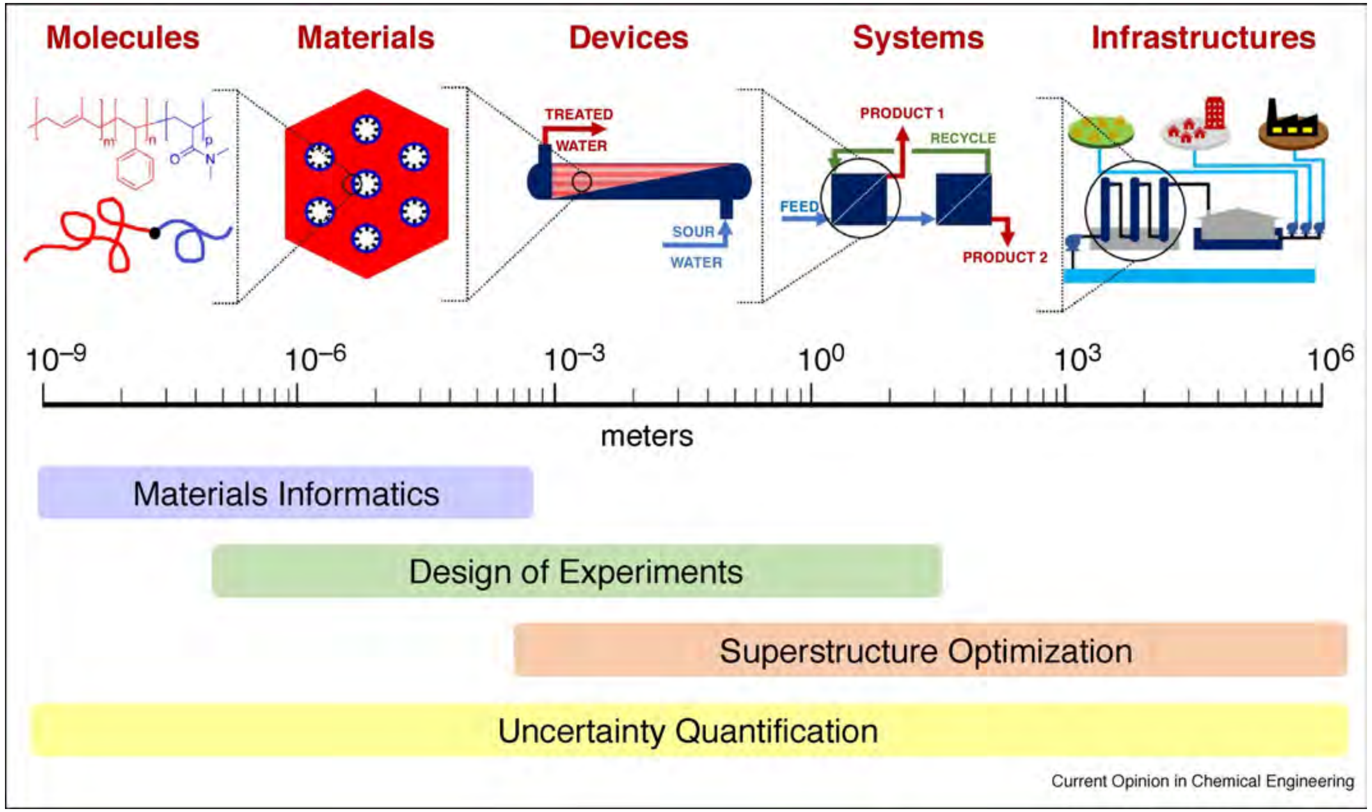
IDAES
Institute for the Design of Advanced Energy Systems

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

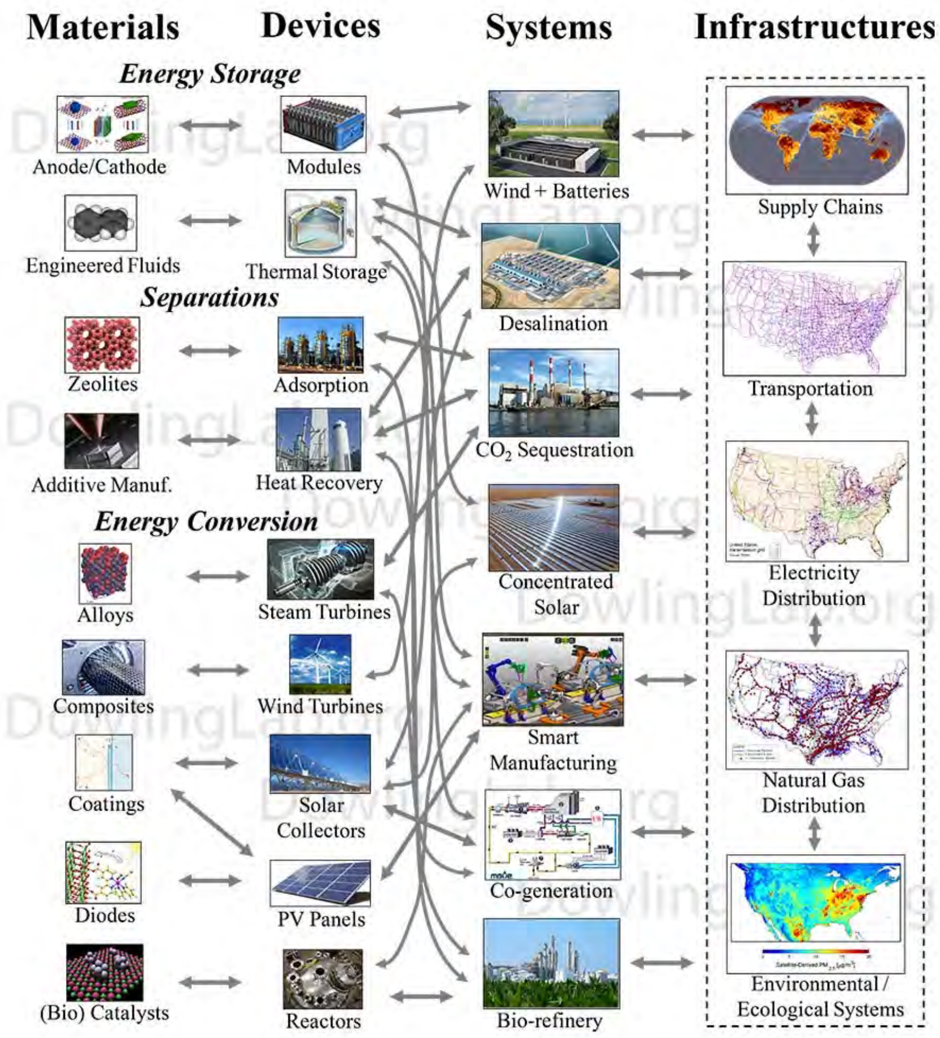
Dowling Lab: Molecular-to-Systems Engineering

Mission: accelerate sustainable/green innovations

Methods: multiscale modeling, optimization, uncertainty quantification, data science

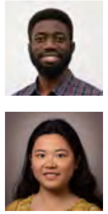


Eugene, Phillip, Dowling (2019), *COCHE*.

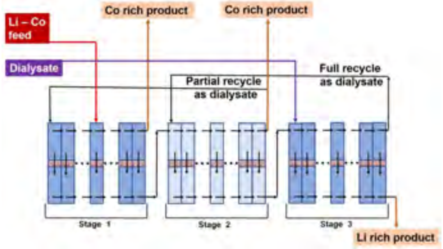


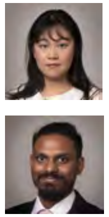
Modeling and Optimization for Data-Driven Decision-Making

CO_2 Capture

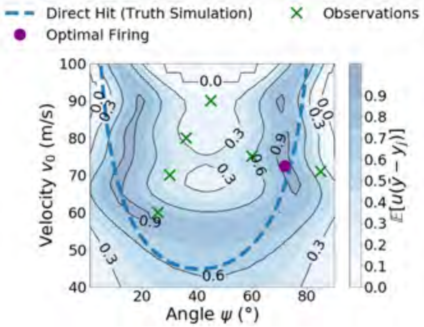



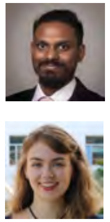
Novel Membrane Separations





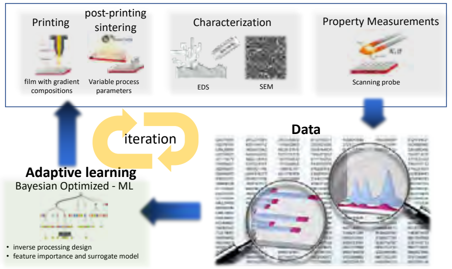
Uncertainty Quantification





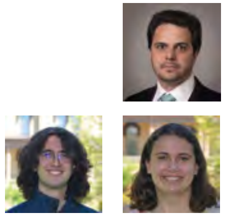
Electric Grid & Energy Markets


Additive Manufacturing of Thermoelectric Devices

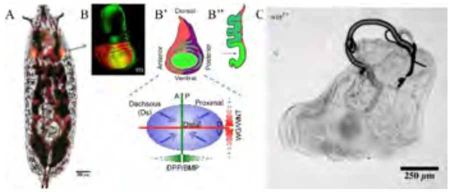



$$
\begin{aligned}
\min \quad & f(x,y) \\
\text{s.t.} \quad & g(x,y) \le 0 \\
& h(x,y) = 0 \\
& x \in \mathbb{R}^n, \; y \in \mathbb{Z}^m
\end{aligned}
$$

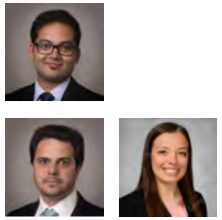
Sustainable Desalination



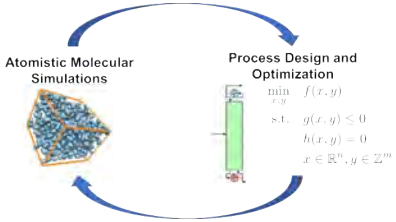

Systems Biology

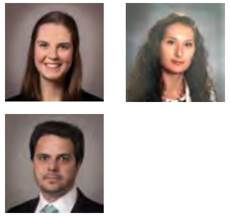


Responsible Shale Gas Utilization

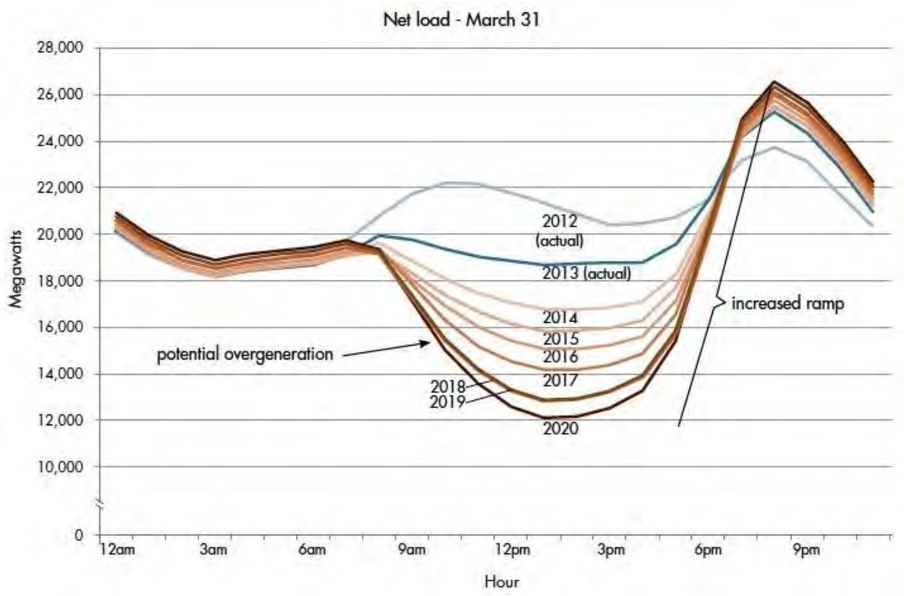


Molecular Design

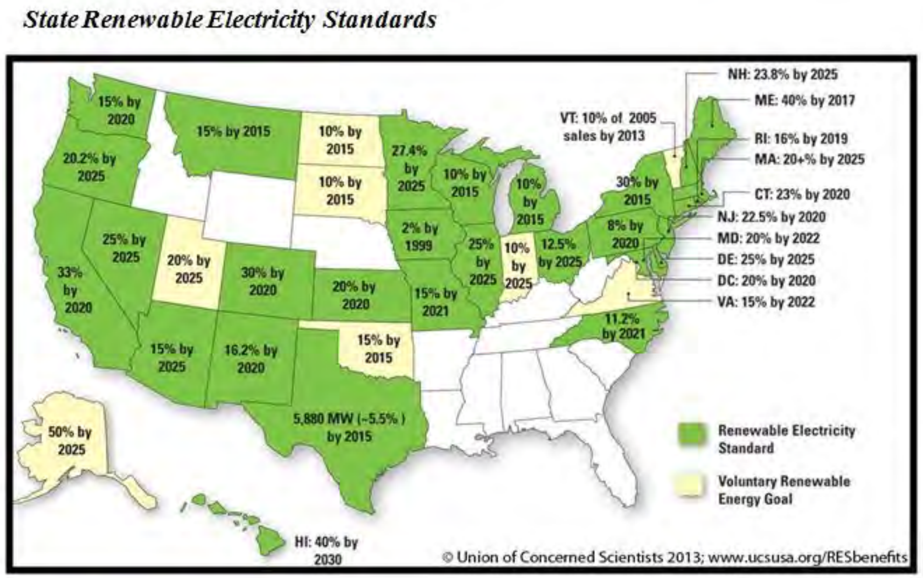




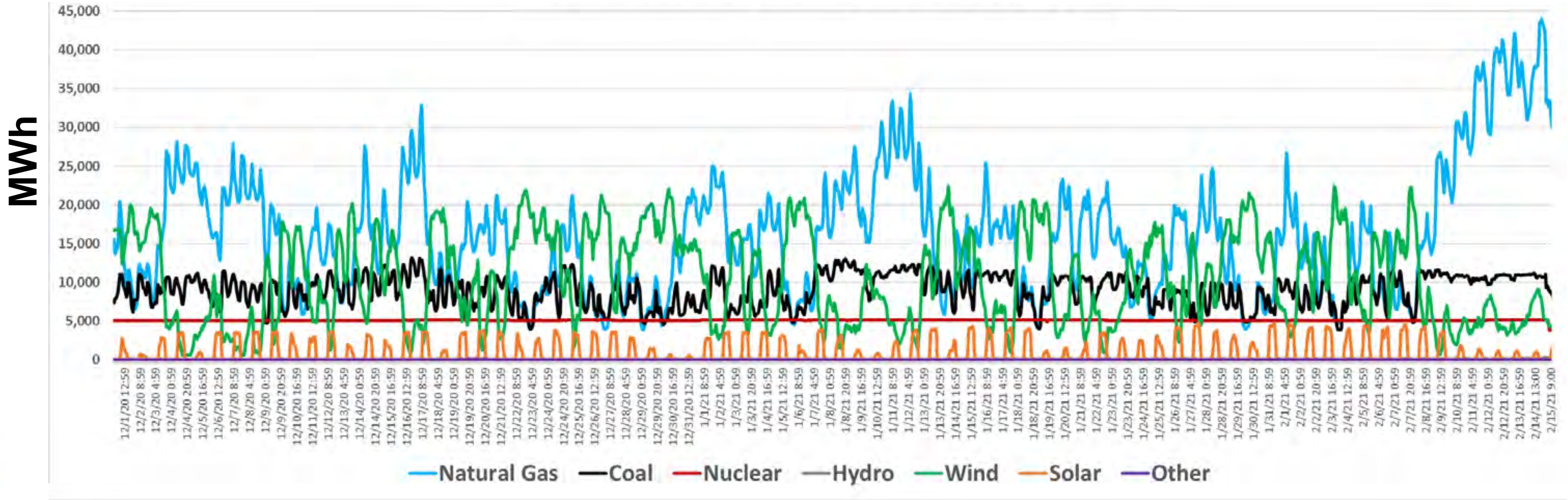
Challenge of increasingly integrated & dynamic grid/generation



Daily Variability Increases with More Renewables



Seasonal & Annual Variations



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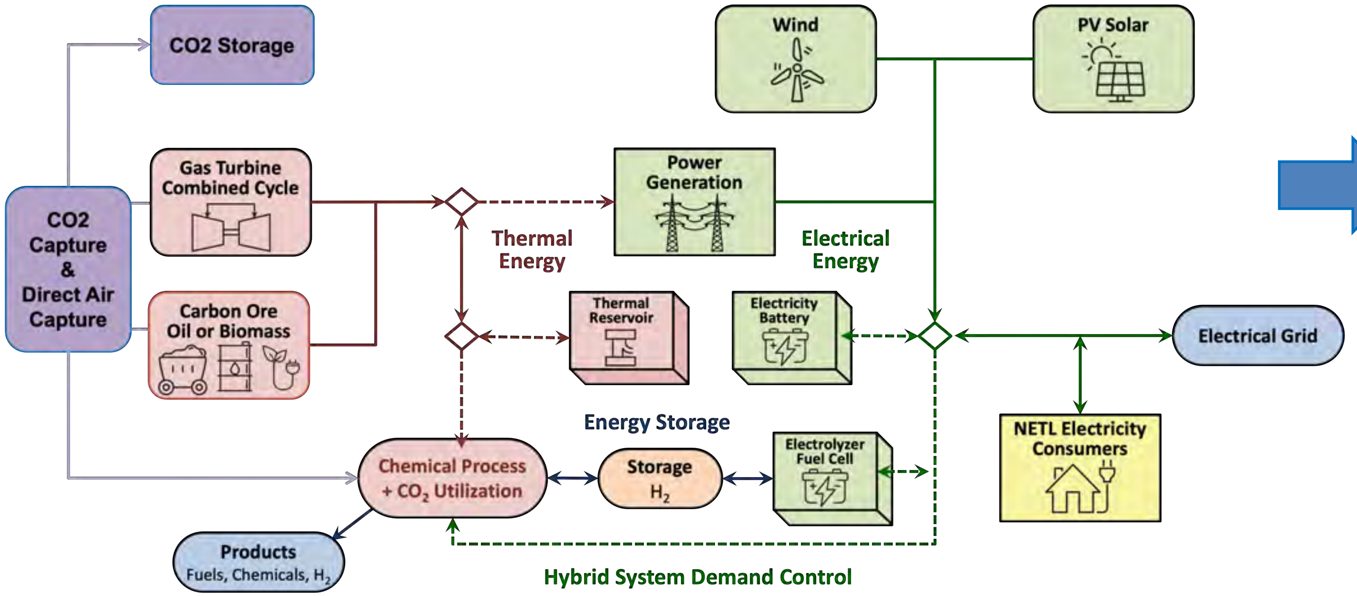
Integrated Energy Systems (IES) Provide Dynamic Flexibility

IESs provide **greater operational flexibility** by optimally coordinating material flows and energy conversions, **multiple value streams**

Multiple inputs and technologies:

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



Multiple outputs and markets:

Electricity energy
Ancillary services
H_2
Chemicals
Heating
Cooling

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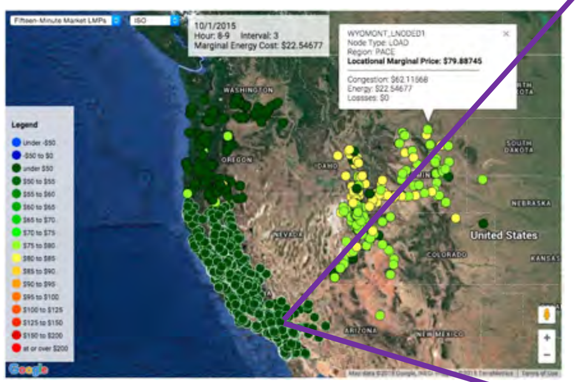
DISPATCHES Design Integration and Synthesis Platform to Advance Tightly Coupled Hybrid Energy Systems

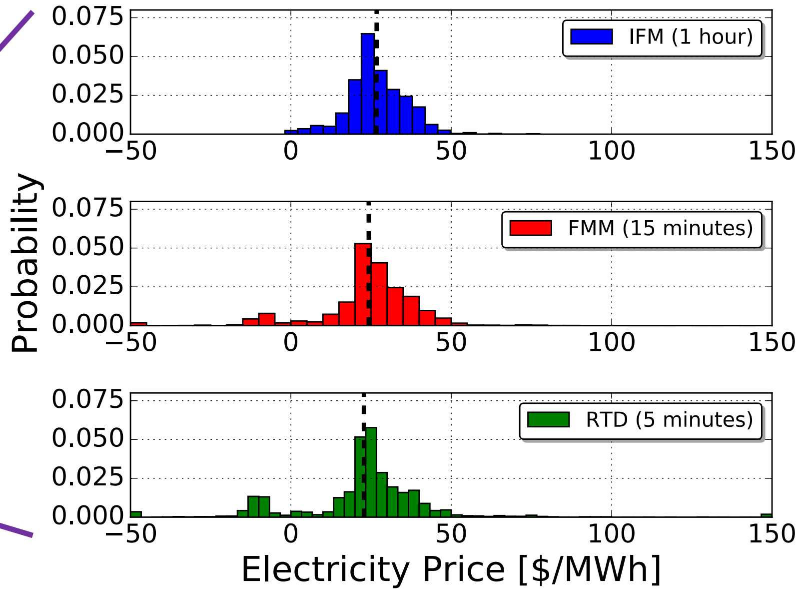
Figure: Arent, Bragg-Sitton, Miller, Tarka, Engel-Cox, Boardman, Balash, Ruth, Cox, and Garfield. (2020). *Joule*.

California (CAISO) Energy Prices

Data from http://oasis.caiso.com

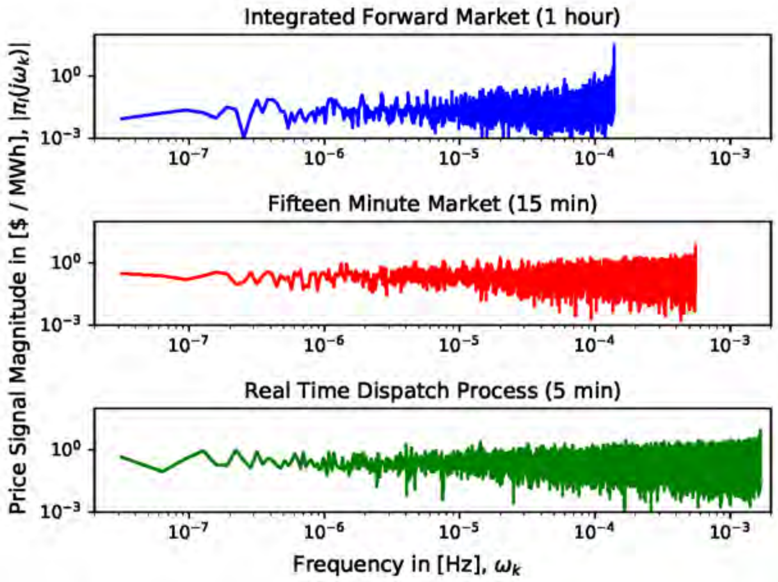


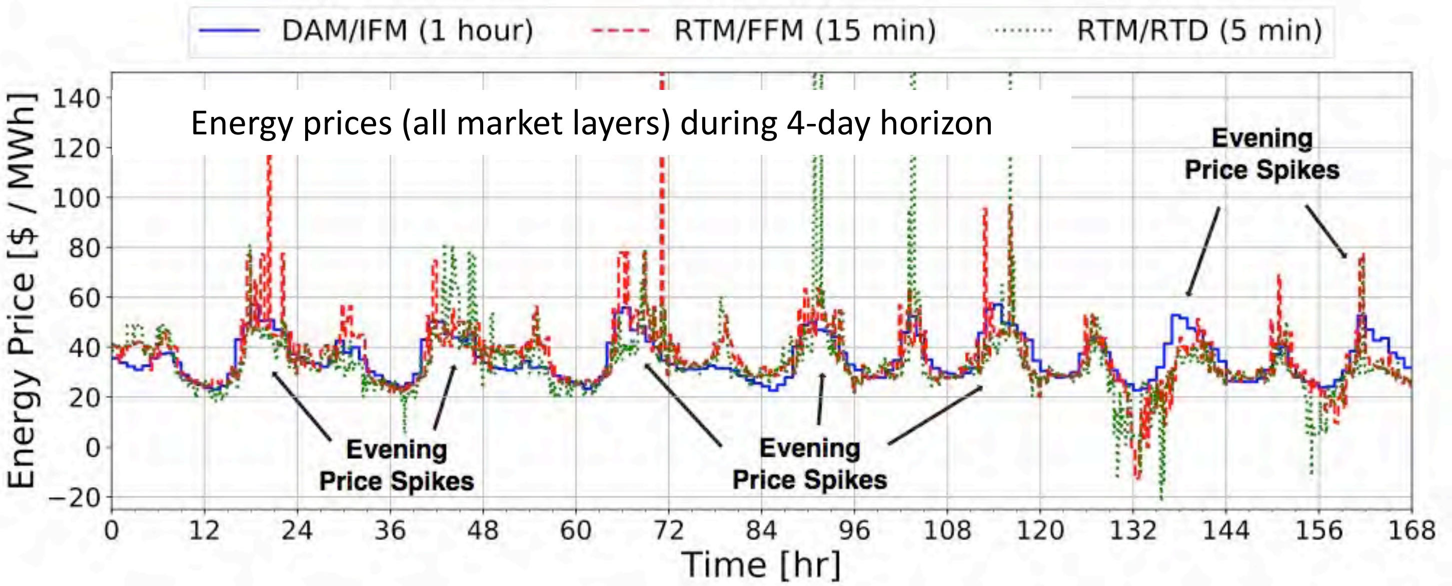
Annual price distribution for 1-3pm



Day-Ahead Market

Real-Time Market





Fourier Analysis

$$\pi(t) = \sum_{k=0}^{N} A_k \sin(\omega_k t) + B_k \cos(\omega_k t)$$

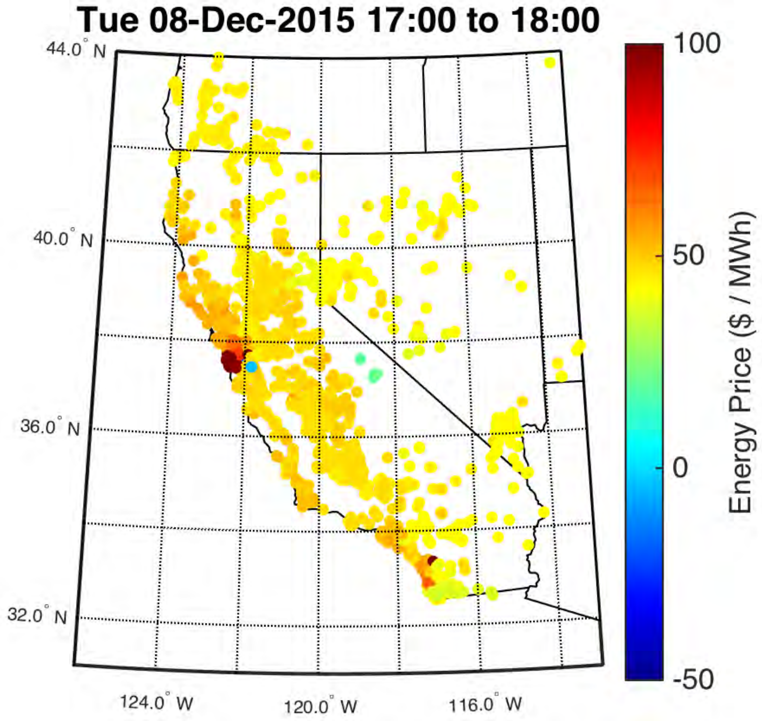
$$|\pi(j\omega_k)| = \sqrt{A_k^2 + B_k^2}$$

97% of signal magnitude is from 10^{-5} Hz (day-to-day) and faster frequencies

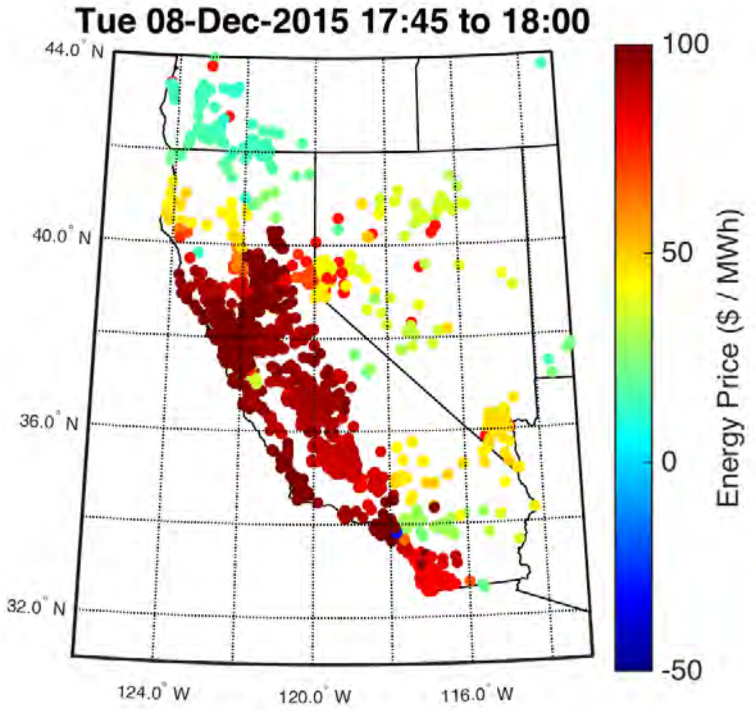
Figures:
Dowling, Kumar, & Zavala (2017), *Applied Energy*
Dowling & Zavala (2018), *Comp. & Chem. Eng.*

Spatiotemporal Price Variations Create New Opportunities

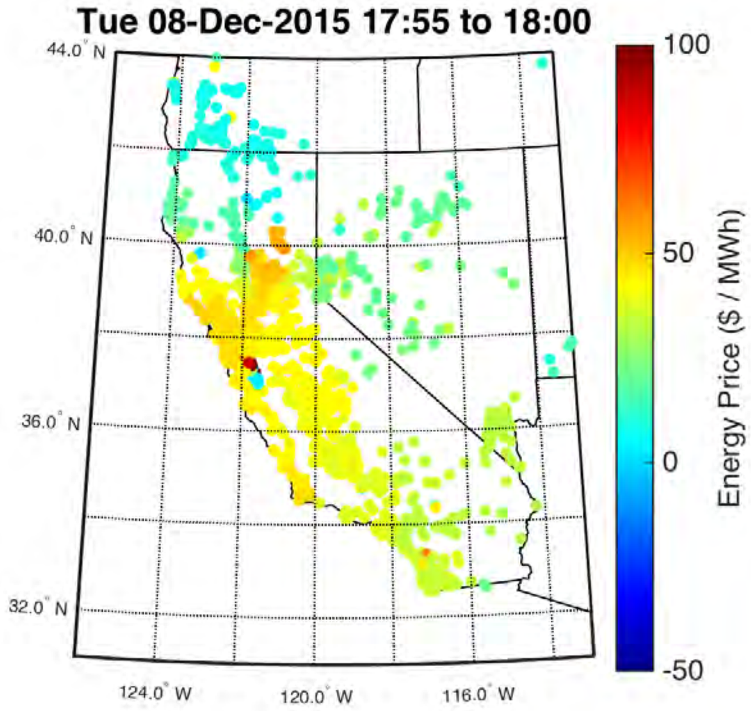
Integrated Forward Market
(1-hour intervals)



Fifteen Minute Market
(15-min. intervals)



Real-Time Dispatch Process
(5-min. intervals)



Observations:

- Over **1 trillion** prices for CA system in 2015 (500 GB uncompressed text)
- Localized volatility at slower timescales
- System-wide volatility at faster timescales

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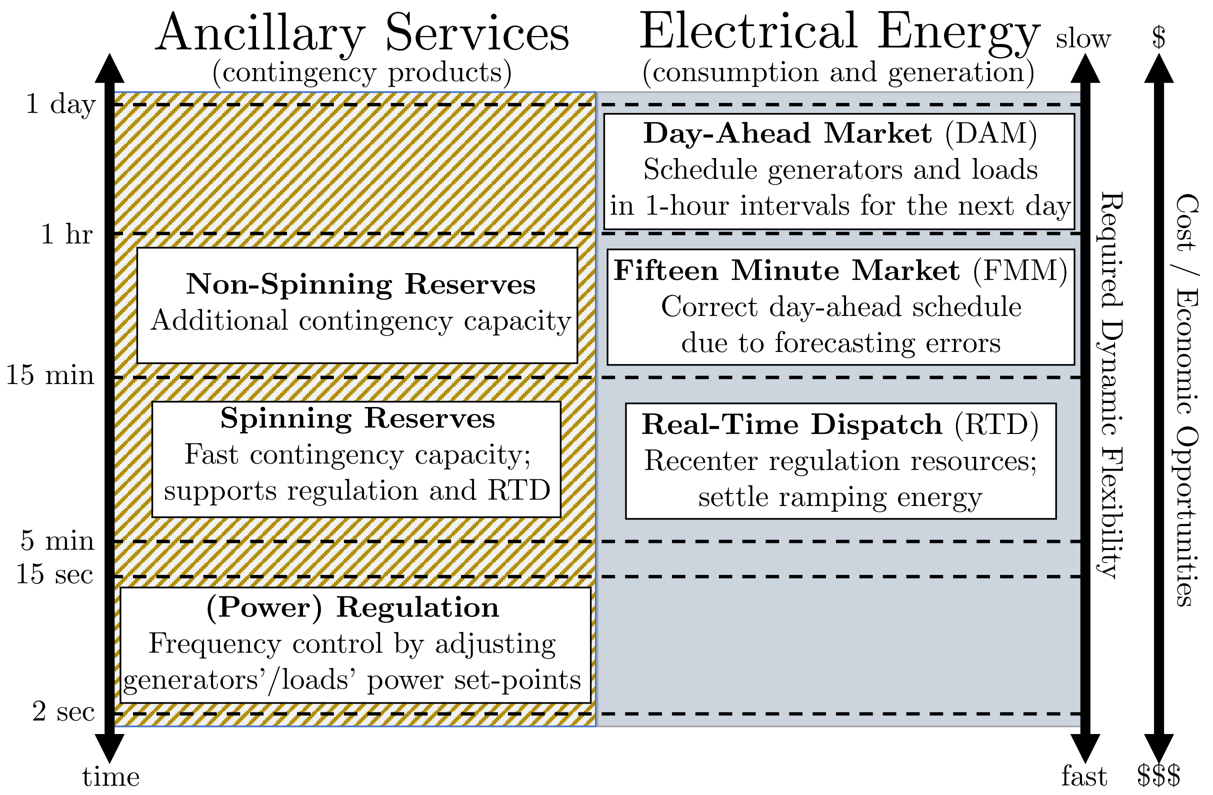
Market Hierarchy and Literature Review (Resource Perspective)

California (CAISO) circa 2015



Similar structure in Texas (ERCOT), New York (NYISO), Midwest (MISO), Eastern US (PJM), etc.

Figure: Dowling, Kumar, & Zavala (2017), *Applied Energy*

Scheduling with Time-Varying Prices (and Uncertainty)

Ashok & Banerjee (2001), *IEEE Tran. Power Sys.*
Ierapetritou, Wu, Vin, Sweeney, & Chigirinskiy (2002), *IERC*
Ashok (2008), *Applied Energy*
Castro, Harjunkoski, & Grossmann (2009), *IECR*
Castro, Harjunkoski, & Grossmann (2011), *CACE*
Mitra, Grossmann, Pinto, & Arora (2012), *CACE*
Mitra, Sun, & Grossmann (2013), *Energy*
Zhang, Cremer, Grossmann, Sundaramoorthy, & Pinto (2016), *CACE*

Reserves / Interruptible Loads

Zhang & Hug (2015), *IEEE PES ISGT*
Zhang, Morari, Grossmann, Sundaramoorthy, & Pinto (2016), *CACE*

Frequency Regulation

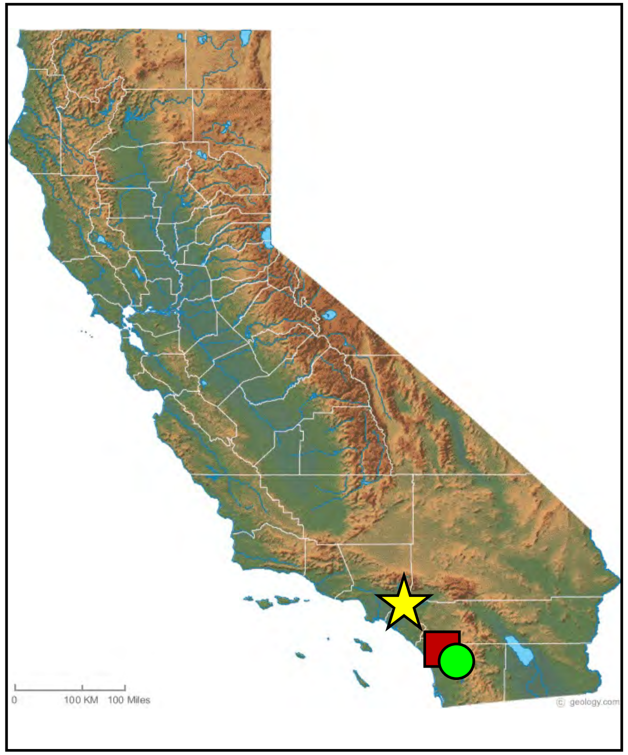
Fares, Meyers, and Webber (2014), *Applied Energy*
Zhang & Hug (2015), *IEEE PES Gen. Meet.*
Lin, Barooah, Meyn, & Middelkoop (2015), *IEEE Trans. Smart Grid*
Dowling & Zavala (2018), *CACE*

Energy Markets & Distillation Systems (e.g., ASU)

Zhang, Grossmann, Heuberger, Sundaramoorthy, & Pinto (2015), *AIChE J.*
Cao, Swartz, Baldea, & Blouin (2015), *J. Process Control*
Cao, Swartz, & Flores-Cerrillo (2015), *IECR*
Pattison, Touretzky, Johansson, Harjunkoski, & Baldea (2016), *IECR*

Example: Energy Storage Investments in California

Mandate: procure **1,325 MW** of battery energy storage by 2024



	Escondido, CA	**El Cajon, CA**	**Chino, CA**
Utility	San Diego Gas & Electric	San Diego Gas & Electric	Southern California Edison
Opened	Feb. 2017	Feb. 2017	Dec. 2016
Storage Size	120 MWh	30 MWh	80 MWh
Power Rating	**30 MW**	**7.5 MW**	**20 MW**
Cost	Not Disclosed	Not Disclosed	$45 million (estimate)
Supplier	AES	AES	Tesla
Technology	Li-ion	Li-ion	Li-ion

Market-Based Incentives for Battery Energy Storage Systems

max Market Revenue
(*perfect information*)

s.t. Market Rules
(*is the bid legal?*)

Market Dynamics
(*price-taker,*
ignore FR signals)

Resource Physics
(*no degradation,*
constant efficiency)

CAISO Markets
(IFM, FMM, RTDP)

Energy Purchases

Energy Sales

Ancillary Service Sales
- Regulation Up
- Regulation Down
- Spin. Reserves
- Non-spin. Reserves

Tesla PowerPack

Efficiency: η

Power Rating: $1\ \mathrm{MW}$

Max Storage: $\bar{S}$

Goal: Maximize Revenue

Decision Variables:
- Market participation schedule

Constraints:
- California market rules
- Battery physics

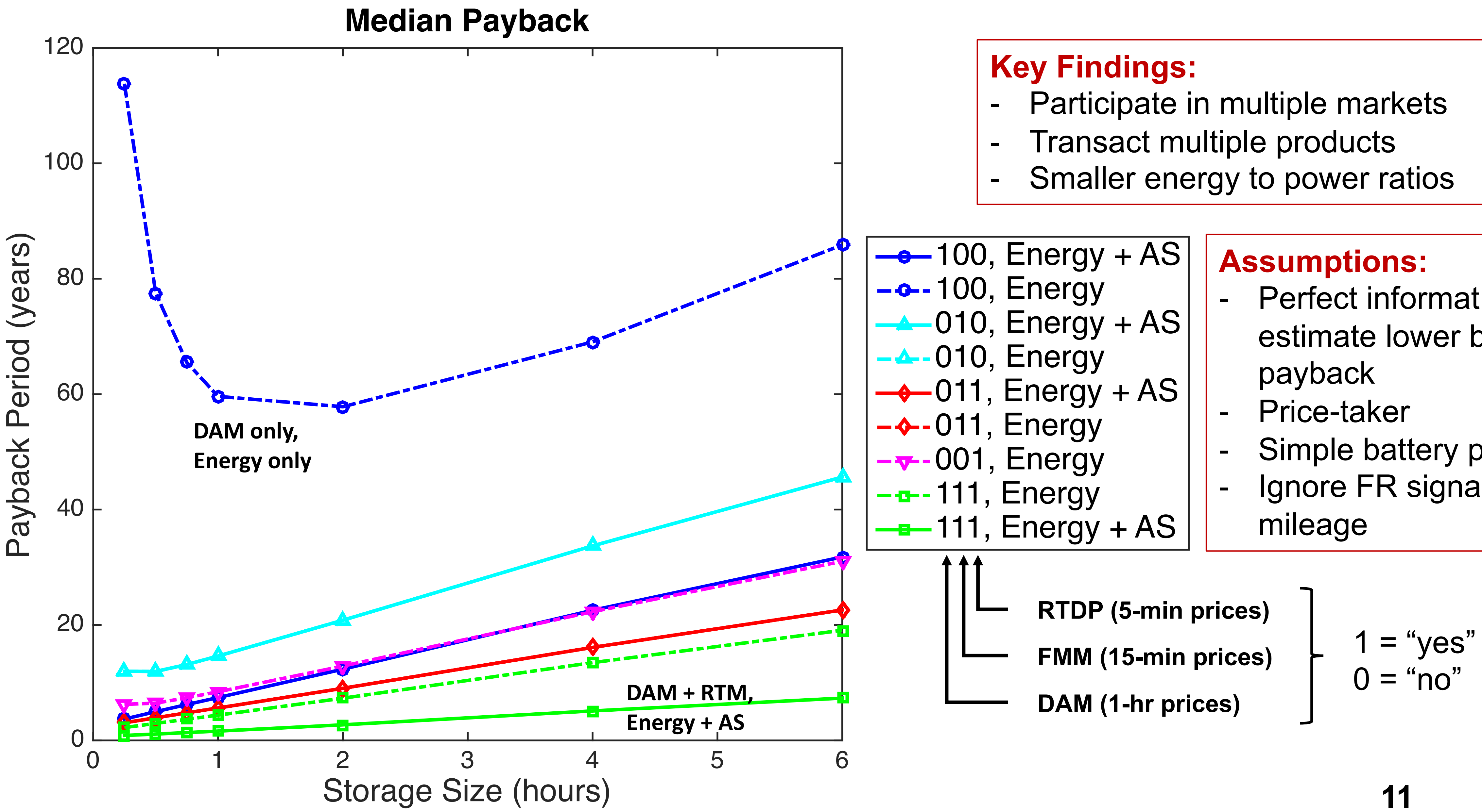
Input Data:
- Which markets/products to transact?
- Location in CAISO
- Storage size (in hours)

Time horizon: 1 year

Tesla PowerPack System
- 88% to 89% round trip efficiency
- 50 kW to 2.5 MW
- 2 hr to 6 hr of storage
- 900 $/kW to 2,700 $/kW

Data from **www.tesla.com/powerpack**, accessed March 2017

What Size and How to Interact with Markets?



Key Findings:
- Participate in multiple markets
- Transact multiple products
- Smaller energy to power ratios

Assumptions:
- Perfect information → estimate lower bound for payback
- Price-taker
- Simple battery physics
- Ignore FR signals and mileage

Where to Locate?

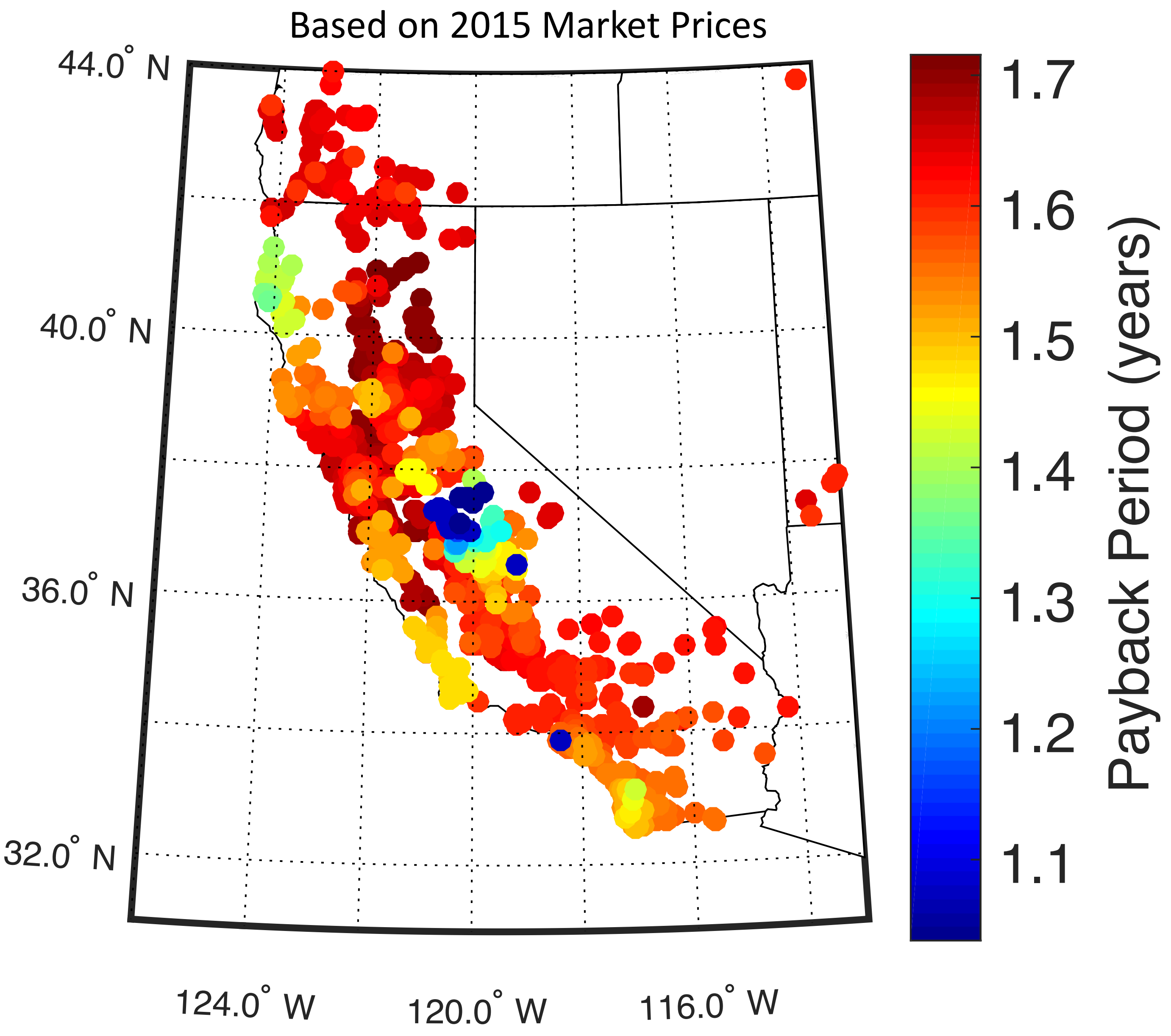
Full Market Participation
DAM and RTM
Energy and Ancillary Services

Storage Size:
1 hour

Investment:
$570,000 / MW

Revenue:
$330,000 to $550,000 / MW / yr

Computational Stats:
- 6,600 nodes analyzed
- 10s to 24s per node (Gurobi 7.0)
- 200 CPU-hours (serial) for map



Is **central CA** optimal location for storage from **grid operator's perspective**?
(e.g., maximize overall reliability, minimize overall system cost)

Interdependencies of Sizing, Degradation, and Replacement Strategy

$$\begin{aligned} \max \quad & \textcolor{blue}{\textbf{Net Present Value}} \\ & \quad (\textit{perfect information}) \\ \text{s.t.} \quad & \text{Market Rules} \\ & \quad (\textit{is the bid legal?}) \\ & \text{Market Dynamics} \\ & \quad (\textit{price-taker}, \\ & \qquad \textit{ignore FR signals}) \\ & \text{Resource Physics} \\ & \quad (\textcolor{blue}{\textbf{\textit{linear degradation}}}, \\ & \qquad \textit{constant efficiency}) \end{aligned}$$

Sodium Sulfur Battery
69% round trip efficiency
4,000 cycles to *failure* (80% loss in capacity)
$370,000 investment for 1 MWh system

Degradation Model

$$\begin{aligned} \text{Energy Counter :} \quad & C_t = |S_t - S_{t-1}| + C_{t-1}, \\ \text{Max. Storage :} \quad & S_t \le \bar{S} - \varepsilon_d C_t, \quad t \in \mathcal{T}. \end{aligned}$$

Goal: Maximize Net Present Value

Decision Variables:
- Market participation schedule
- **Storage size** (design)

Constraints:
- California market rules
- Battery physics

Input Parameters:
- Which markets/products to transact?
- Replacement horizon (N)
- Degradation rate (ϵ_d)

Problem Stats. ($N = 5$ yrs):
- Linear program
- 3 to 5 million variables
- 4 to 7 million constraints
- 2 CPU-hours (mean) per instance

Degradation Data: Rodrigues et al (2015), *Energy* Cost Data: Dicorato et al (2012), *IEEE Trans. STE*

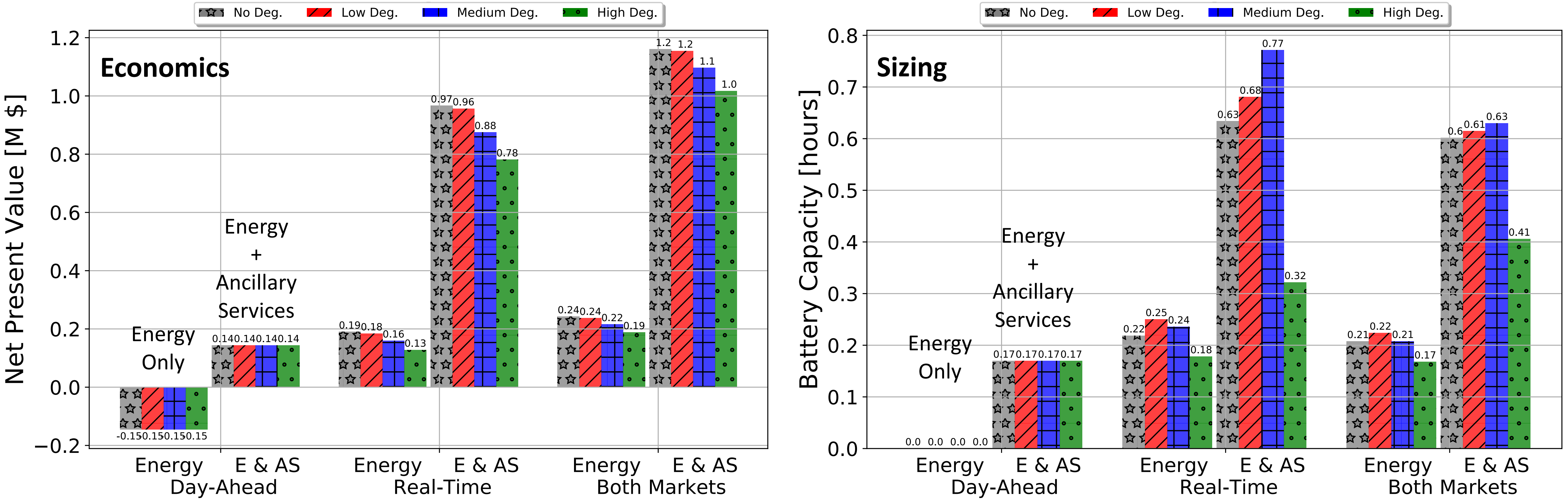
Degradation Effects for Sodium Sulfur Batteries

Degradation Case	Cycles to Failure
None	∞
Low	40,000
Medium	4,000
High	400

Key Findings

- **AS and RTM** drive economics
- Only **10% NPV improvement** from *technology breakthrough*
- **NPV** is most sensitive to **market participation mode**
- **AS** revenues justify 3 to 4x times larger battery

Results: 5-year replacement strategy

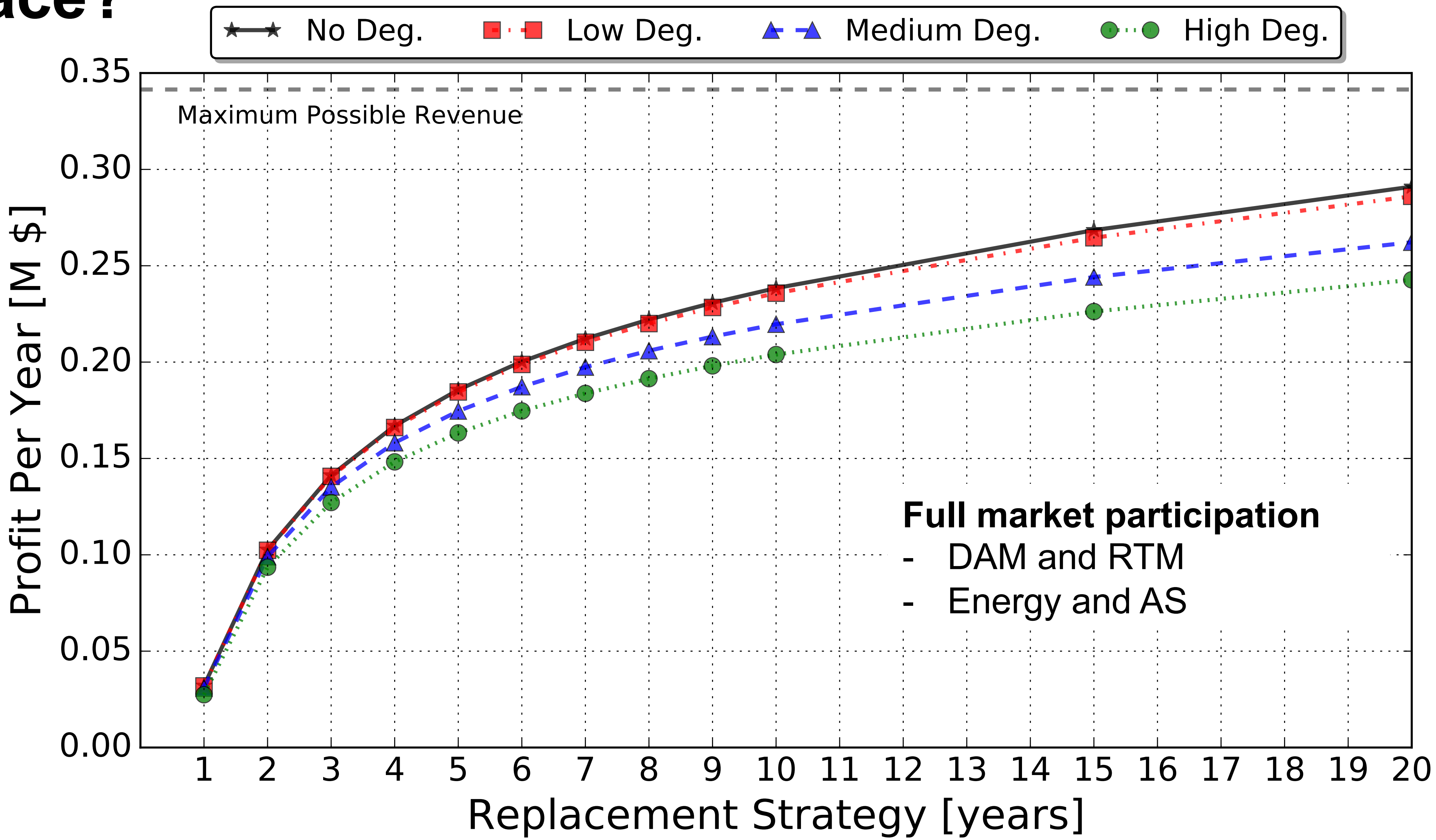


When to Replace?

Propose consistent metric to compare different replacement horizons:

$$PPY_Y = \frac{NPV_Y}{\sum_{y=1}^{Y} \left(\frac{1+i}{1+r}\right)^{y-1}}$$

Y: Investment horizon
NPV_Y: Net present value
i: inflation rate
r: discount rate



Observation: optimization exploits degrees of freedom in market participation to mitigate degradation

Optimal Multiscale and Multiproduct Market Participation

Optimization Framework for Market-Based Energy System Design

$$\begin{aligned} \max \quad & \text{Market Revenue} \\ & \quad (\textit{perfect information}) \\ \text{s.t.} \quad & \text{Market Rules} \\ & \quad (\textit{is the bid legal?}) \\ & \text{Market Dynamics} \\ & \quad (\textit{price-taker,} \\ & \qquad \textit{ignore FR signals}) \\ & \text{Resource Physics} \end{aligned}$$

Batteries are an attractive investment

- **Payback in 1 to 2 years** with optimized full market participation
- Smaller storage sizes are optimal
- Install in **central CA** (near Fresno)
- Only 10% higher NPV with 10x slower degradation

New opportunities for solar thermal

- Up to 50% higher revenues with ancillary services
- Decomposition algorithm for simultaneous scheduling, control, and market participation

Framework and Market Data Analysis
Dowling, Kumar, Zavala (2017), *Applied Energy*
Dowling and Zavala (2017), *CACE*

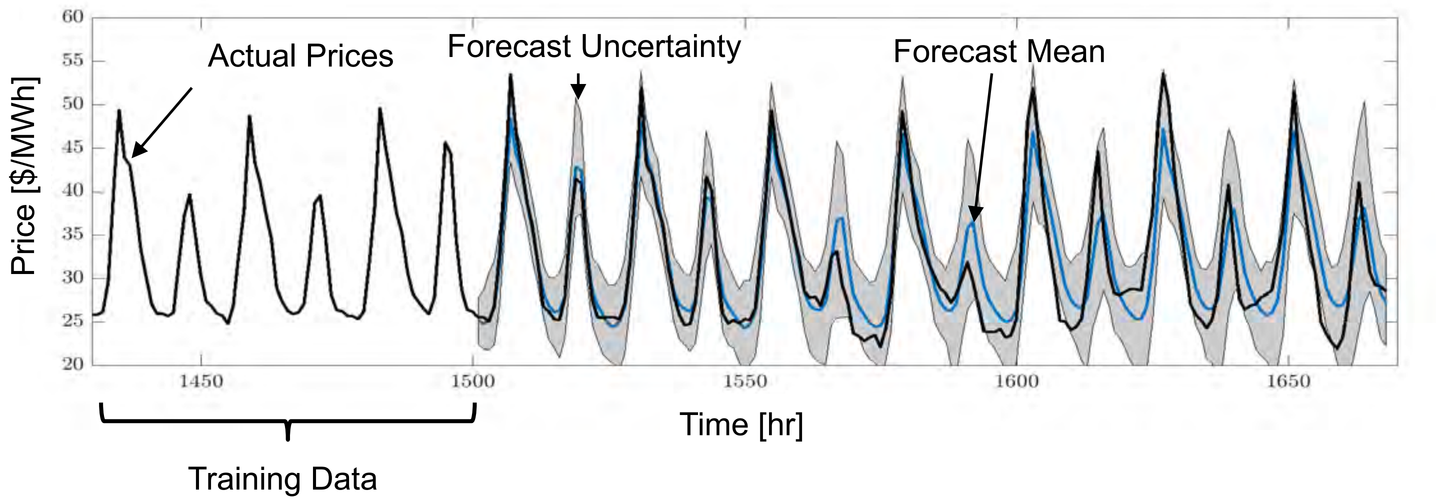
Batteries
Sorourifar, Zavala, Dowling (2020), *IEEE Trans. Suis. En.*

Concentrated Solar Thermal
Dowling, Zheng, Zavala (2017), *RSER*
Dowling, Zheng, Zavala (2018), *AIChE J.*

What about uncertainty?

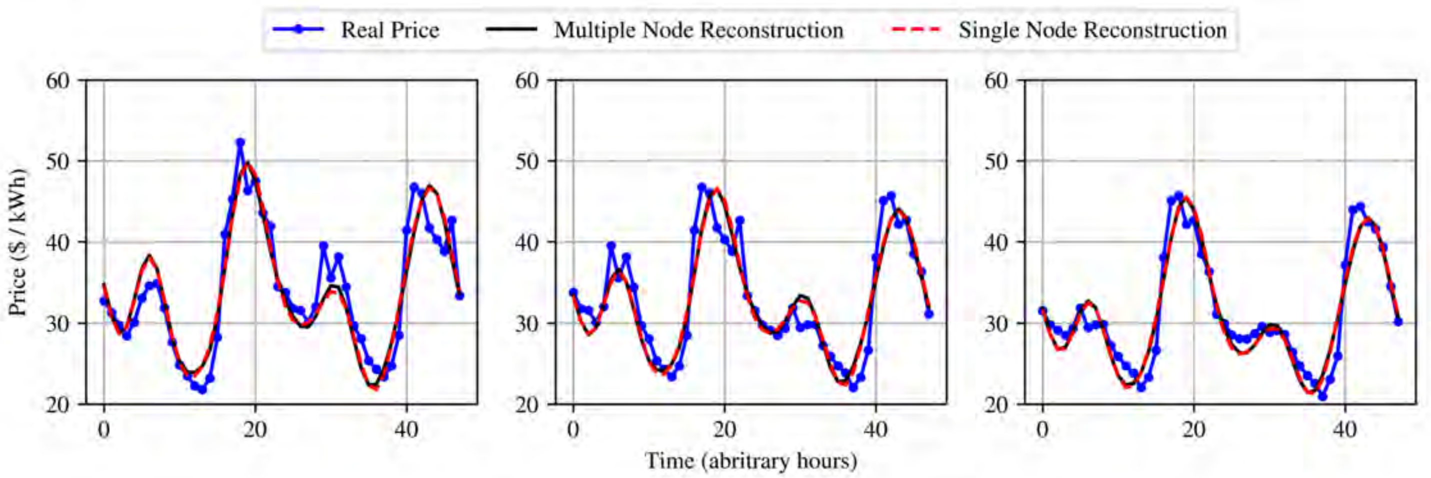
Autoregressive Gaussian Process (GP)

Gao & Dowling (2020),
Proc. American Control Conference.



Dynamic Model Decomposition

Elmore & Dowling (2021). *Energy.*



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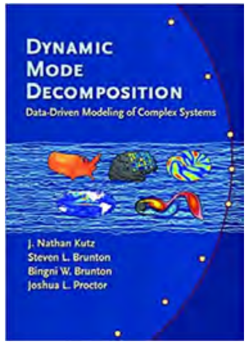
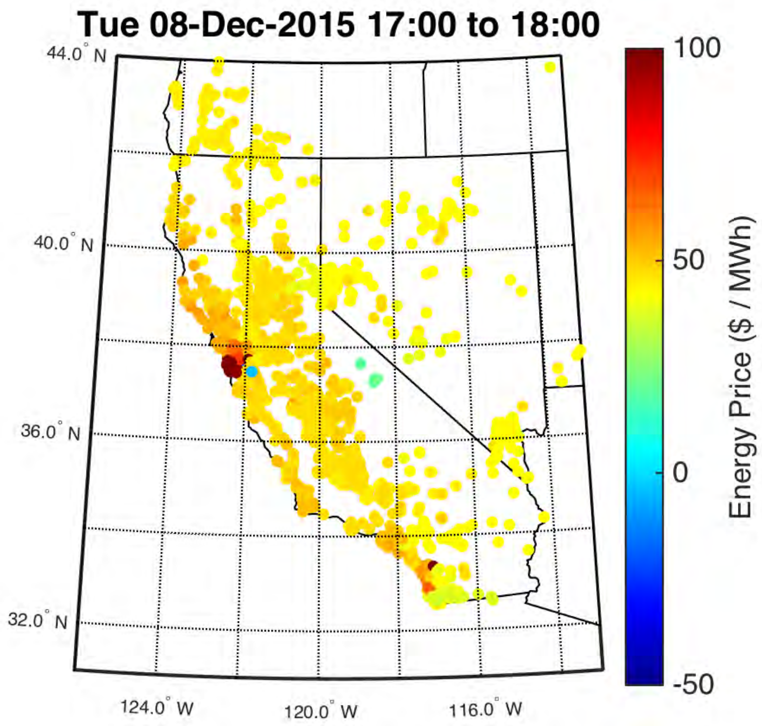
Dynamic Mode Decomposition

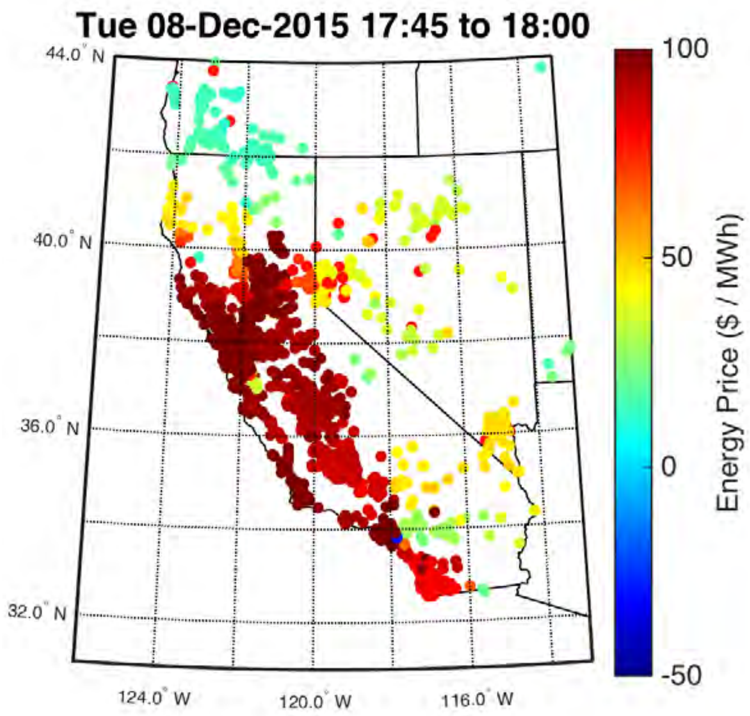
Book Sale @ SIAM UQ 2018



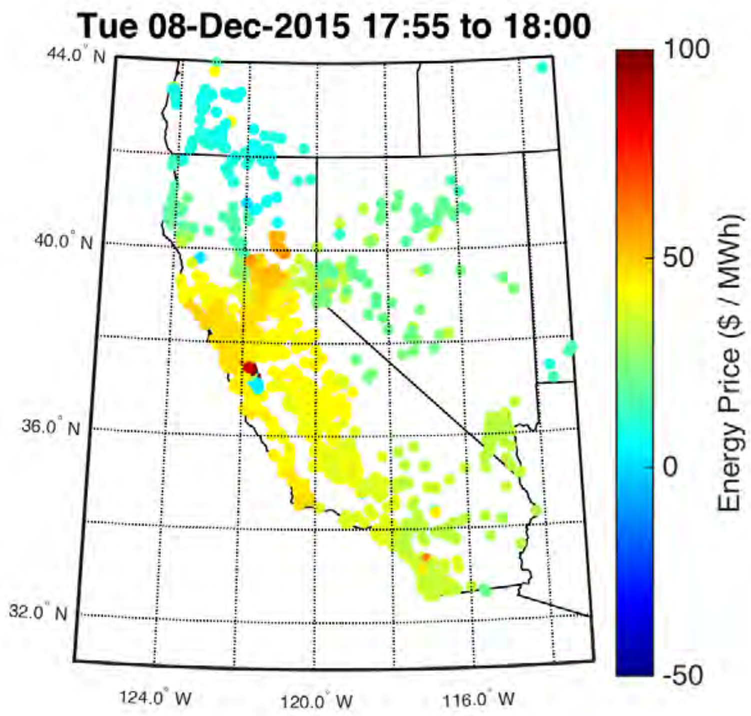
Integrated Forward Market
(1-hour intervals)



Fifteen Minute Market
(15-min. intervals)



Real-Time Dispatch Process
(5-min. intervals)



DMD: Find "Best" (Low Rank) Linear System Approximation

Define data matrices

$$\mathbf{X} = \left[\mathbf{x}_1 \cdots \mathbf{x}_{n-1}\right] \in \mathbb{R}^{m \times (n-1)}$$

$$\mathbf{X}' = \left[\mathbf{x}_2 \cdots \mathbf{x}_n\right] \in \mathbb{R}^{m \times (n-1)}$$

Best fit linear system

$$\mathbf{A}\mathbf{X} \approx \mathbf{X}'$$

Singular value decomposition

$$\mathbf{X} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^*$$

$$\mathbf{X} \approx \mathbf{X}_r = \mathbf{U}_r\mathbf{\Sigma}_r\mathbf{V}_r^* = \sum_{i=1}^{r} \mathbf{u}_i \sigma_i \mathbf{v}_i^*$$

Low-rank approximation

$$\tilde{\mathbf{A}} = \mathbf{U}_r^*\mathbf{A}\mathbf{U}_r = \mathbf{U}_r^*\mathbf{X}'\mathbf{V}_r\mathbf{\Sigma}_r^{-1}$$

DMD modes & forecasts

$$\tilde{\mathbf{A}}\mathbf{W} = \mathbf{W}\mathbf{\Lambda}$$

$$\mathbf{\Phi} = \mathbf{X}'\mathbf{V}_r\mathbf{\Sigma}_r^{-1}\mathbf{W}$$

$$\Omega_{ij} = \begin{cases} \frac{\ln(\Lambda_{ij})}{\Delta t} & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$$

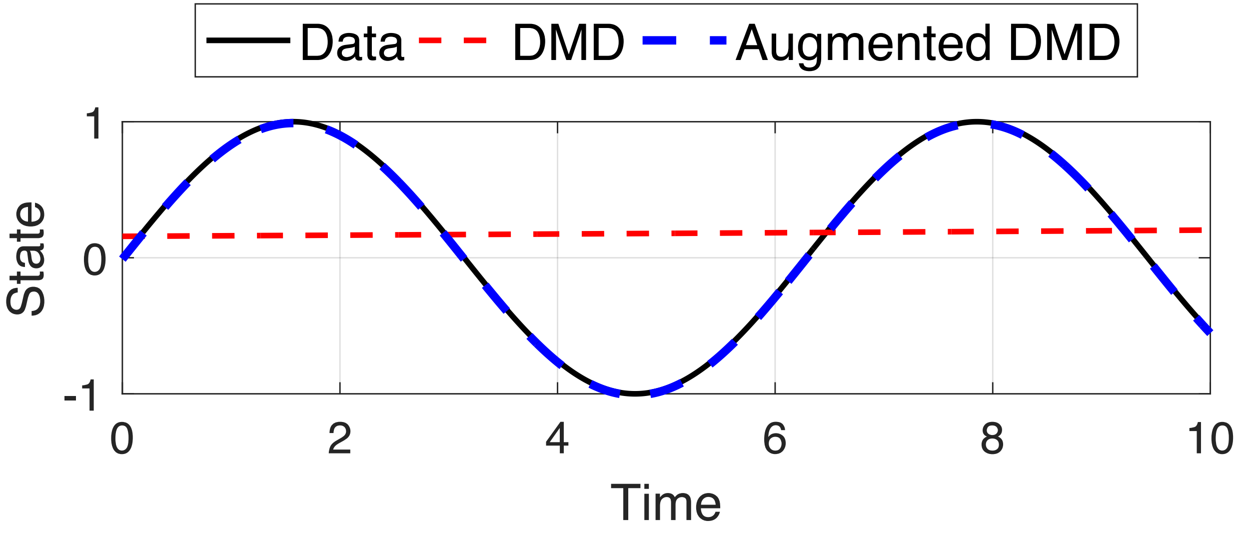
$$\mathbf{x}(t) = \mathbf{\Phi} e^{\mathbf{\Omega} t}\mathbf{b}$$

Elmore & Dowling (2021). *Energy, 232,* p. 121013.

Augmented DMD Overcomes "Standing Wave Problem"

Problem: DMD fails for

$$x(t) = \sin(t)$$



Solution: stack / time-shifted copies of data to create *augmented input matrix*

$$\mathbf{X}_{\text{aug}} = \begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_{n-l-1} \\ \mathbf{x}_2 & \mathbf{x}_3 & \cdots & \mathbf{x}_{n-l} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{x}_l & \mathbf{x}_{l+1} & \cdots & \mathbf{x}_{n-1} \end{bmatrix}$$

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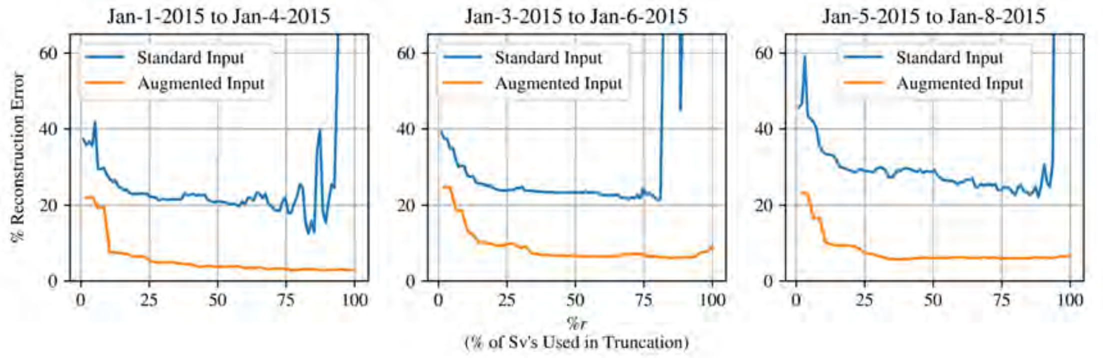
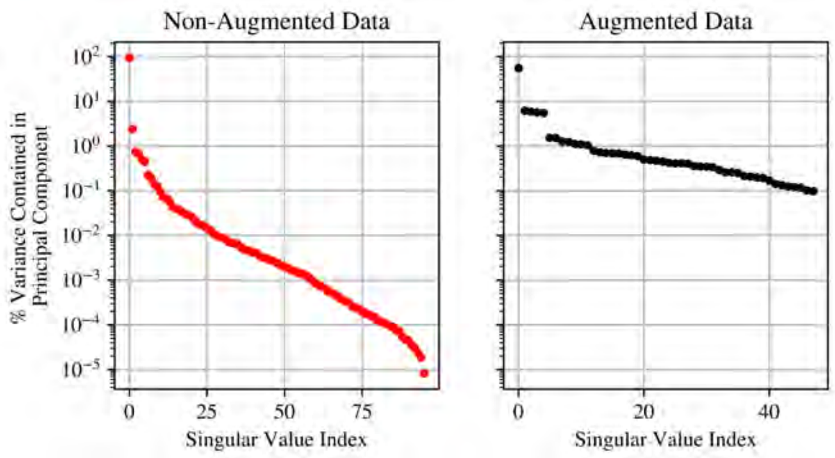
Elmore & Dowling (2021). *Energy, 232,* p. 121013.

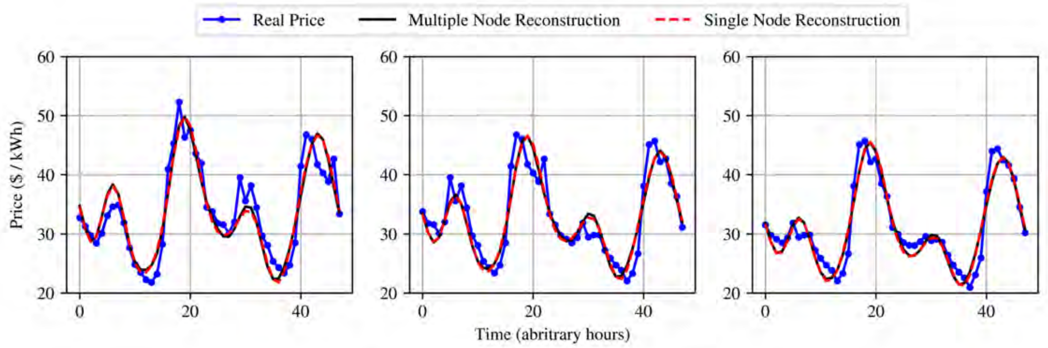
Augment DMD Is a Fast Forecaster, Superior to DMD



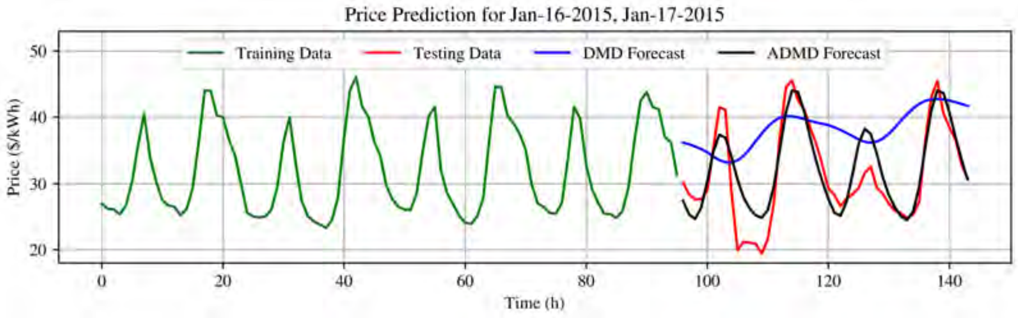
Reconstruction error with ADMD is less sensitivity to truncation level



ADMD identifies low rank structures



ADMD works well with data from individual nodes. There is negligible benefit to analyzing multiple nodes simultaneously.

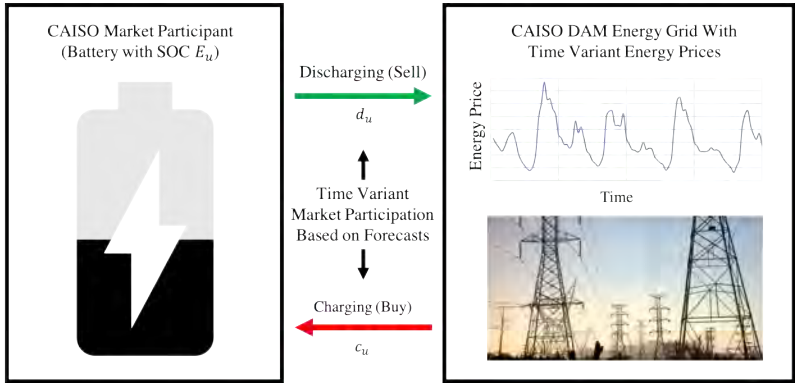


ADMD forecasts outperform DMD and recapitulate dominant timescales.

Elmore & Dowling (2021). *Energy, 232,* p. 121013.

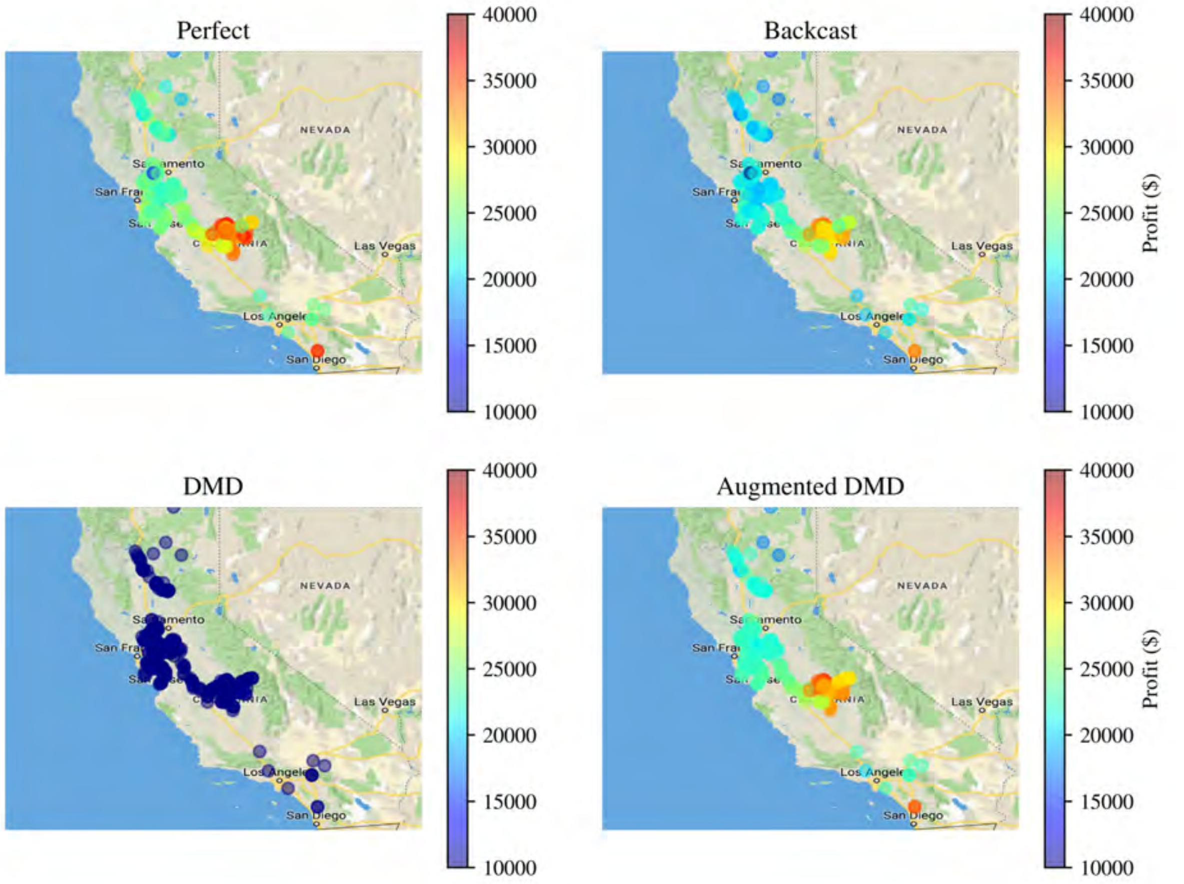
How much does uncertainty impact market revenues?

Optimal Energy Arbitrage (Control)



$$
\begin{aligned}
\max_{\mathbf{c},\mathbf{d},\mathbf{E}} \quad & \mathbf{p}^T(\mathbf{d}-\mathbf{c}) \\
\text{s.t.} \quad & E_u = E_{u-1} + c_u\sqrt{\eta} - \frac{d_i}{\sqrt{\eta}}, \\
& 0 \le E_u \le 4 \text{ MWh}, \\
& 0 \le c_u \le 1 \text{ MW}, \\
& 0 \le d_u \le 1 \text{ MW}, \\
& \forall u \in \{1, ..., N_c\}.
\end{aligned}
$$

Revenue Captured Relative to Perfect Information

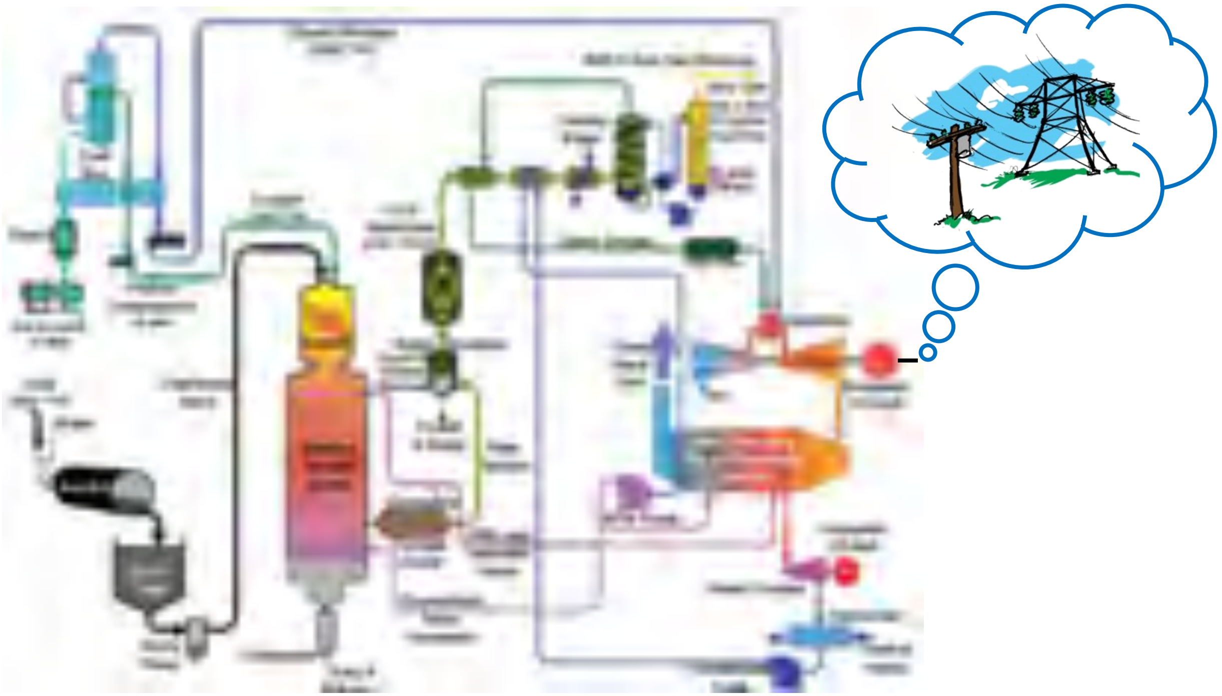


DMD	22% to 24%
Augmented DMD	81% to 92%
Backcasting	84% to 88%

Energy system analysis capabilities are applied in isolation

Process-centric Modeling

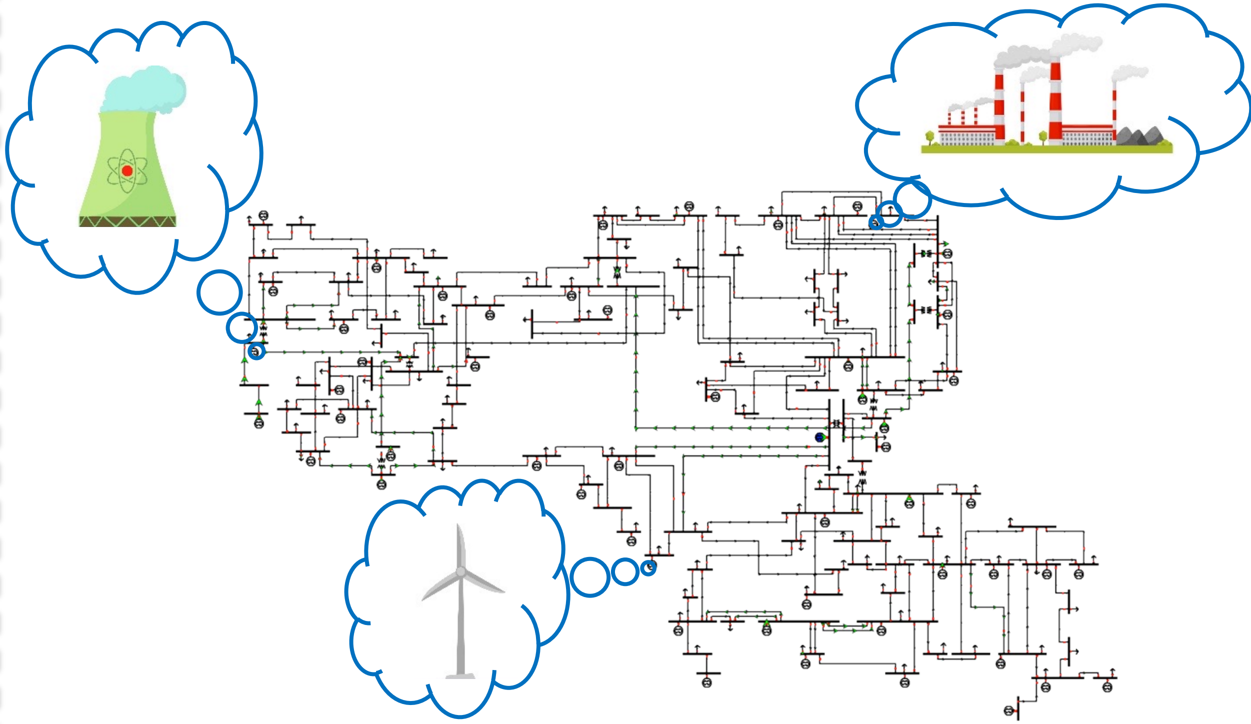
Detailed steady state or dynamic process models, with the grid modeled as an infinite capacity bus



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

Grid-centric Modeling

Detailed power flow models, with individual generators modeled as either dispatchable point sources or stochastic "negative loads"



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

IDAES Institute for the Design of Advanced Energy Systems

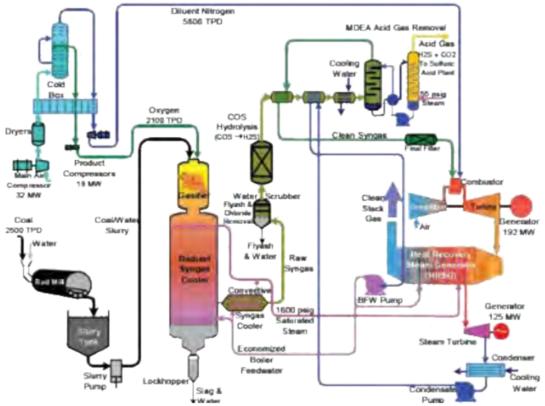
Gao, Knueven, Miller, Siirola, Dowling. (2022) *Applied Energy* (accepted)

Bridging timescales in IDAES enables unique analyses

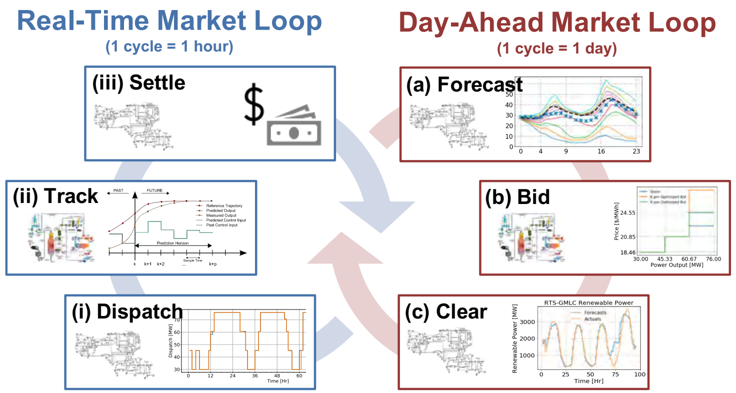
High-Fidelity Process Modeling

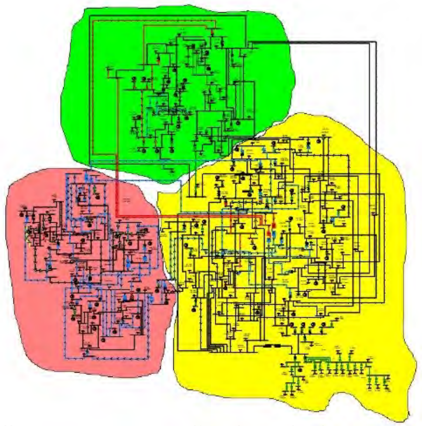
Integrated Resource-Grid Model

Grid Modeling



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





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

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., H_2 production, integrated energy systems)
3. Guide conceptual design & retrofit to meet current and future power grid needs

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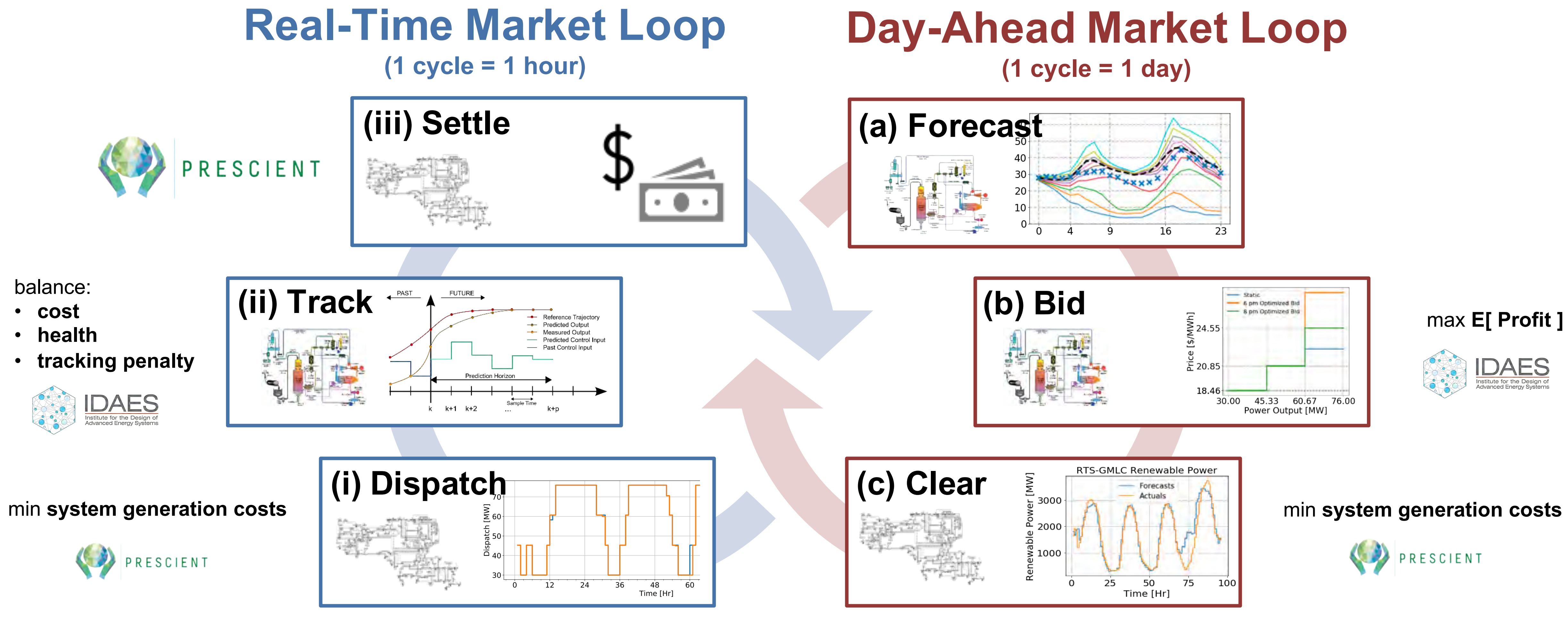
Institute for the Design of Advanced Energy Systems

Modeling multiscale resource and grid decision-making

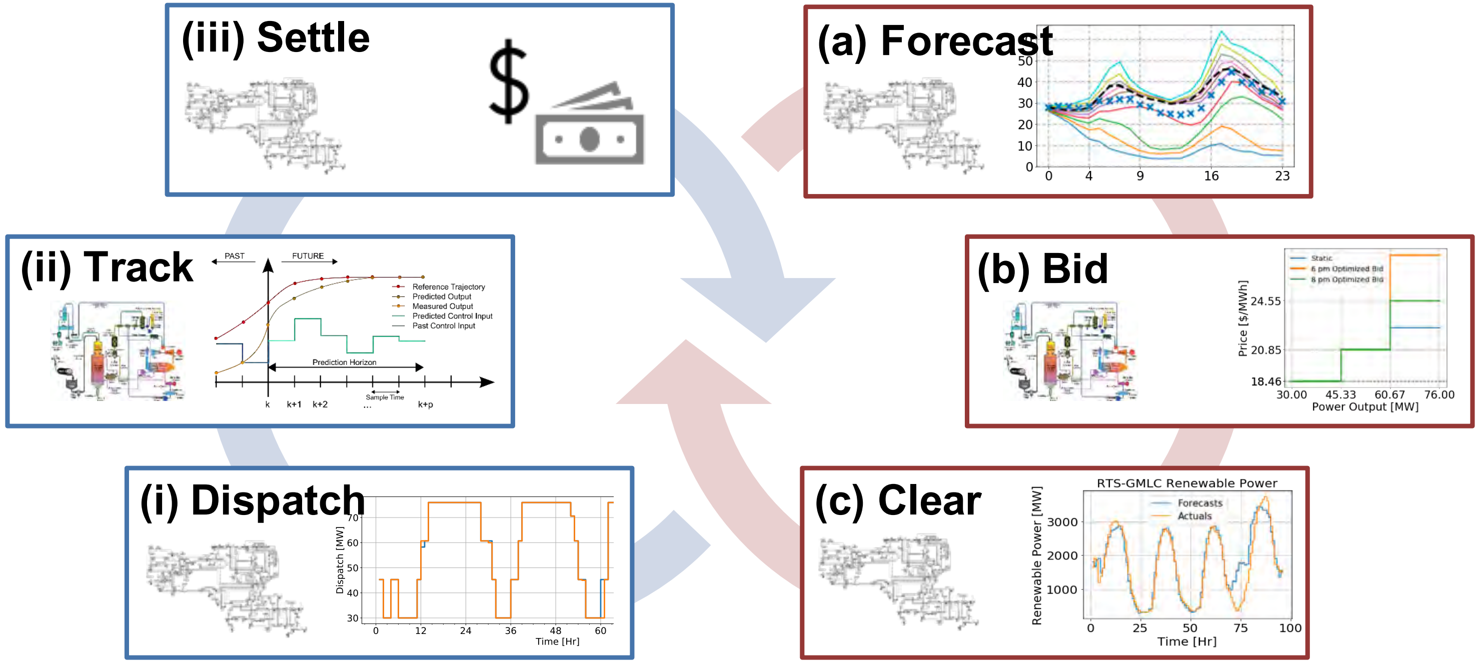


IDAES integrates detailed process models (b, ii) into the daily (a, c) and hourly (i, iii) grid operations workflows

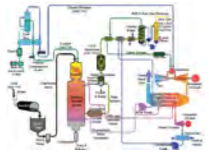
Case Study 1: Quantifying Resource-Grid Interactions

Real-Time Market Loop
(1 cycle = 1 hour)

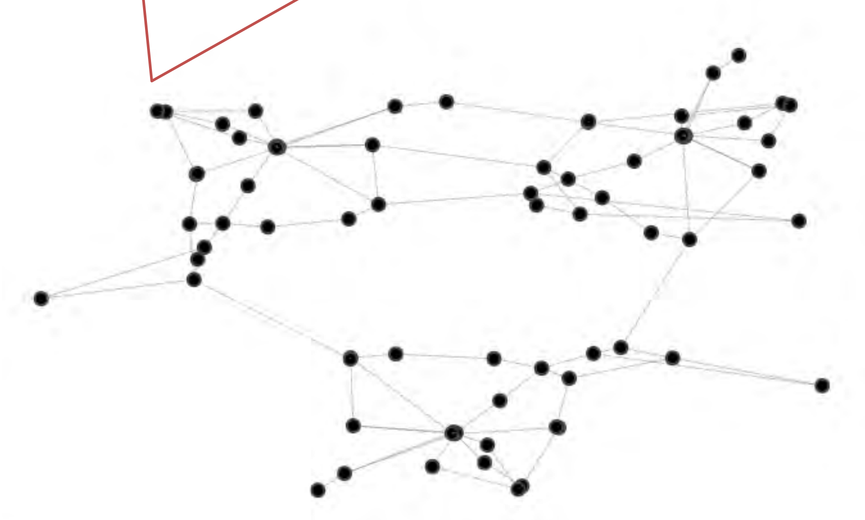
Day-Ahead Market Loop
(1 cycle = 1 day)



Bus 102 Steam 3: Optimizing Bids



76 MW
32.6% efficient (full capacity)



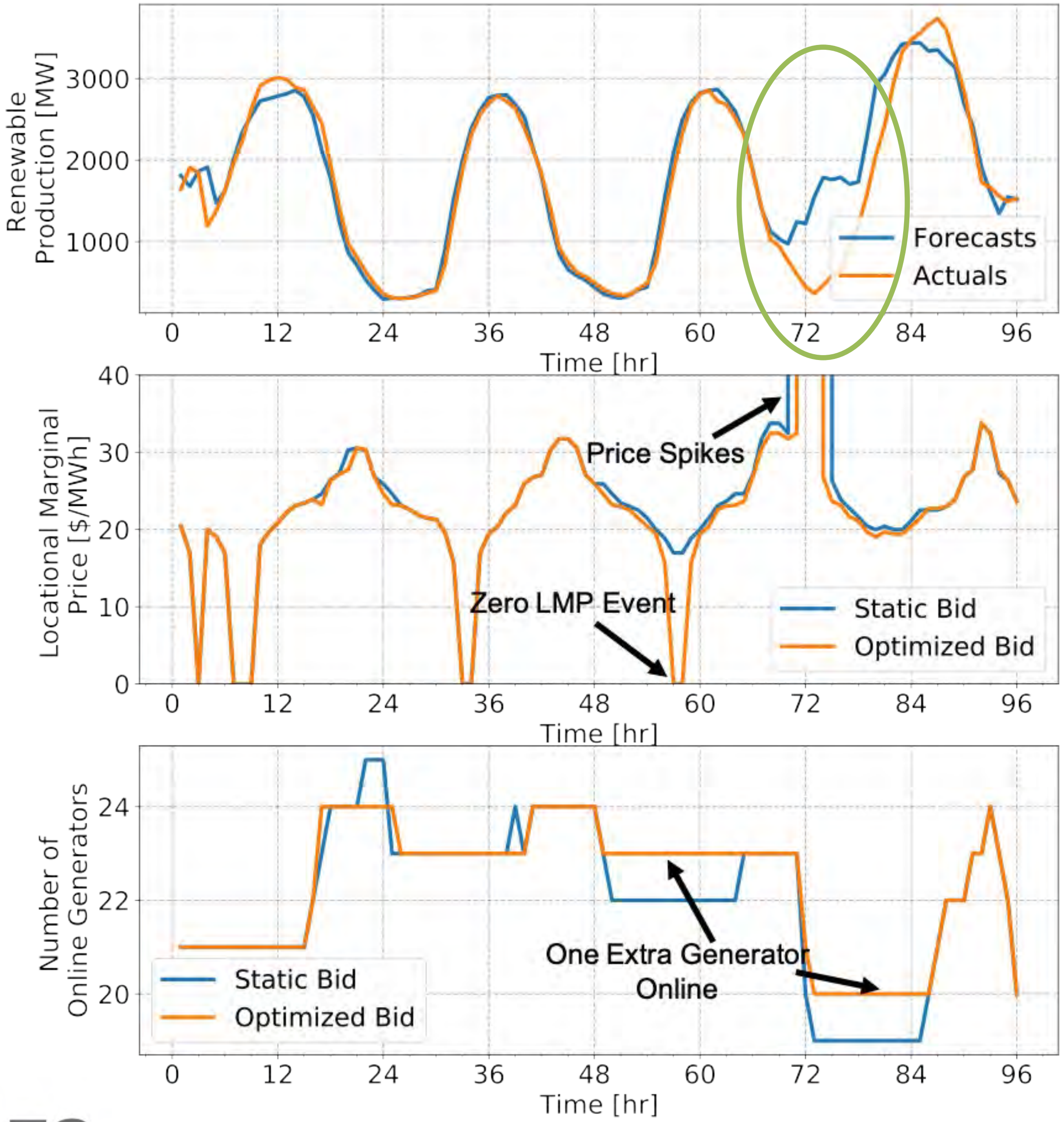
RTS-GMLC Test System

PRESCIENT

Case Study Setup:

1. Generator 102 Steam 3 optimizes bids using stochastic programming (time-varying)
2. Other generators use static bids
3. Simulation dates: 01/02/2020 – 12/29/2020

Optimized bidding changes extreme price events



26% shortfall of renewable energy production

Extreme price events near hour 72 shortens from 4 hours to 2 hours duration

Changes in bidding strategies can impact the commitment decisions across the entire grid/market network

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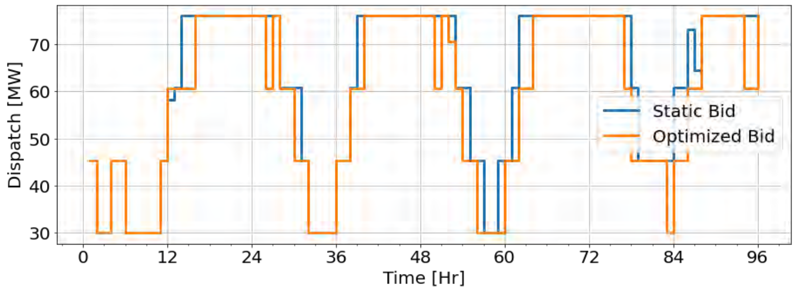
Optimized bidding changes unit commitment and dispatch decisions across the network

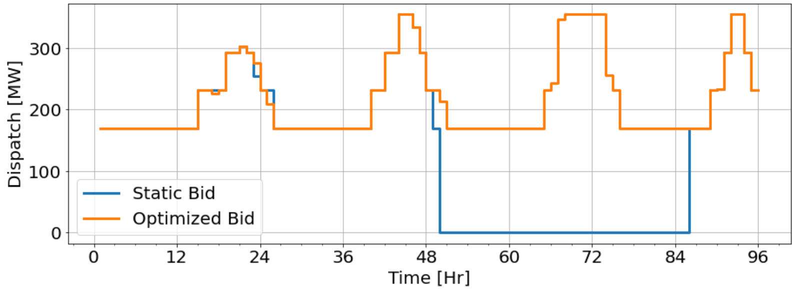
Bus 102 Steam 3: Optimizing Bids

76 MW
32.6% efficient (full capacity)

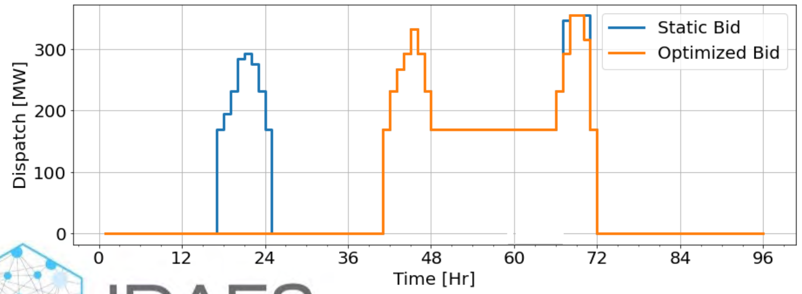


Demonstration Dates:
July 10 – July 14, 2020

Bus 107 Combined Cycle 1



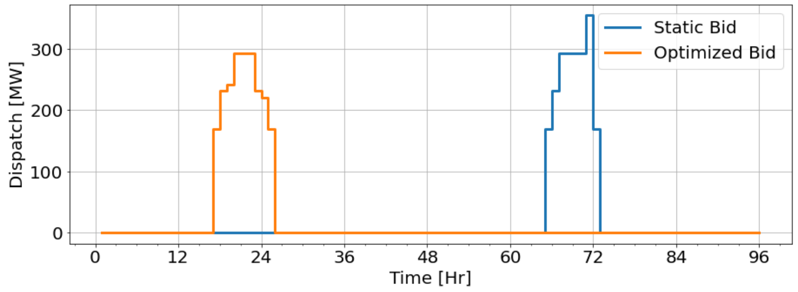
Bus 323 Combined Cycle 2



Effects ripple through grid:

- Commitment and dispatch decisions are impacted across the grid.

Bus 213 Combined Cycle 3



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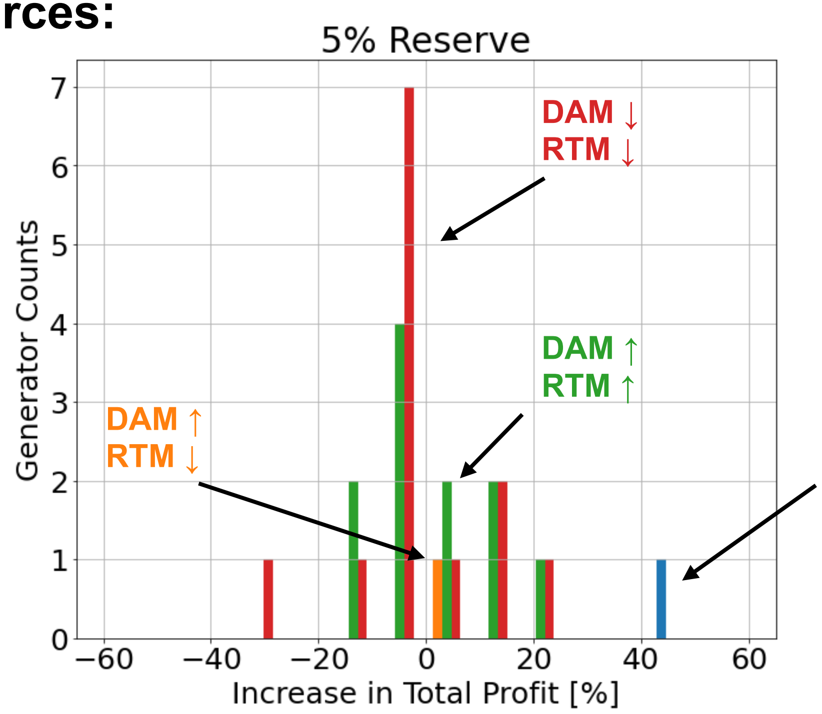
Case Study 1: Take Away Messages

A small change in the bid for a target thermal generator (Bus 102 Steam 3)…

Changes overall market statistics by less than 1%:
- Fixed, Generation, and Total Costs
- Load Shedding
- Reserve Shortfall
- Renewables Curtailment
- Total On/Offs
- Average Price

Conclusion: Ignoring bidding is reasonable for many aggregate modes.

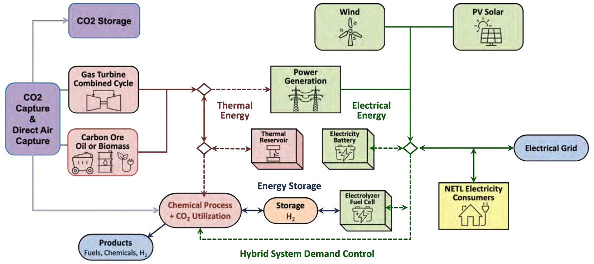
Shifts dispatches and profits across markets for all resources:



Resource with strategic bidding

DAM ↓
RTM ↑

20 to 40% increase in profits



Design and analysis of **integrating energy systems** must consider interactions with the grid to accurately capture economic impacts and rewards.

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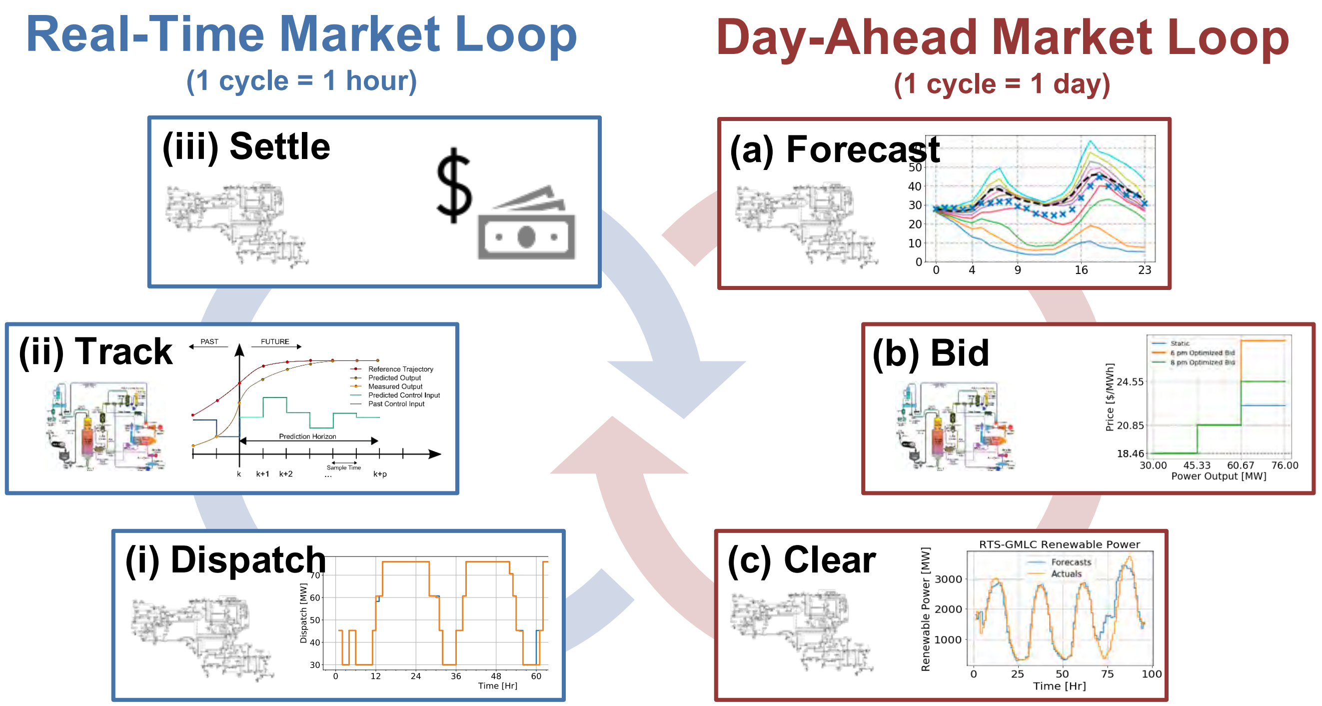
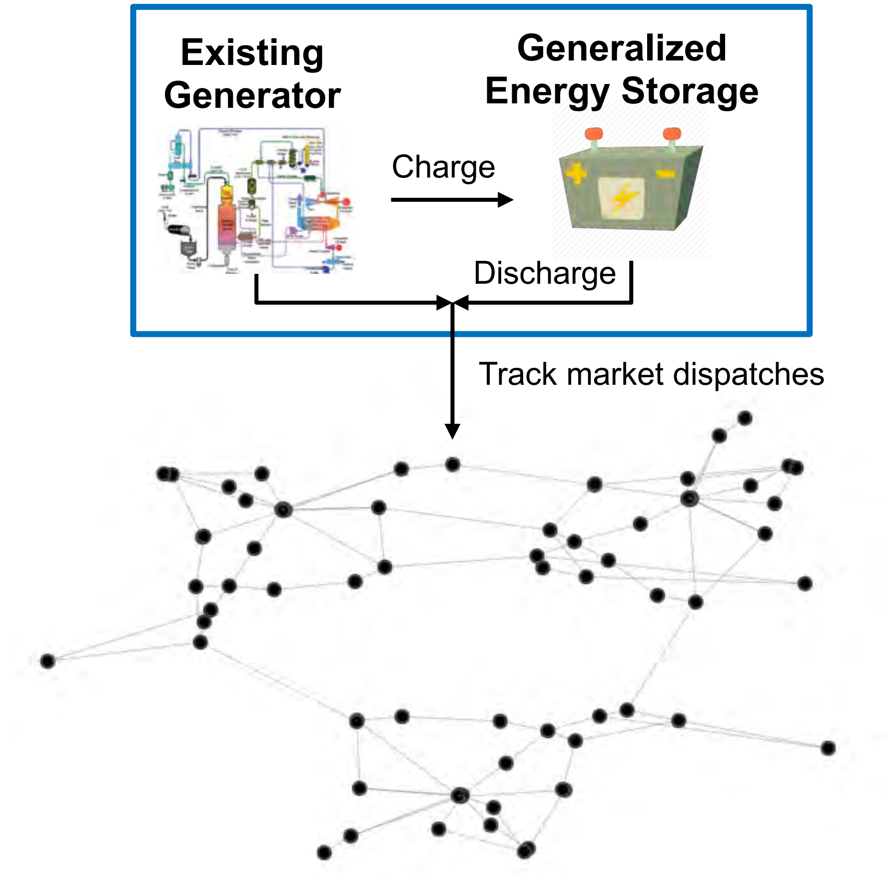
Case Study 2: Benefits of Integrated Energy Systems





RTS-GMLC Test System

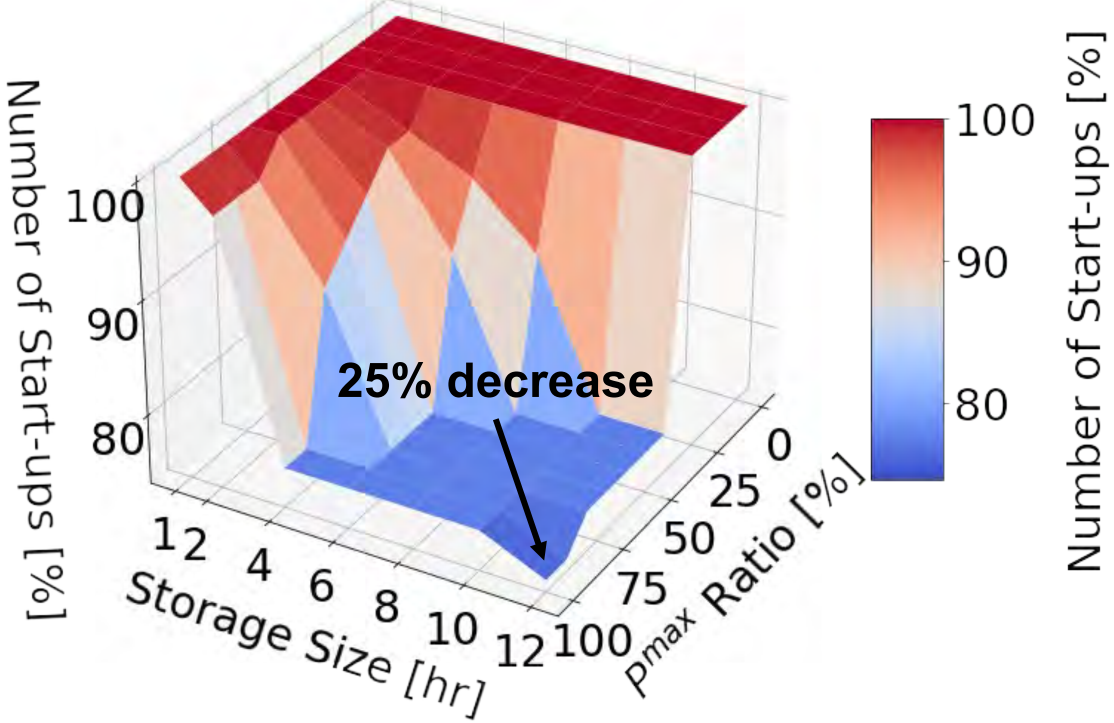
PRESCIENT

Case Study Setup:

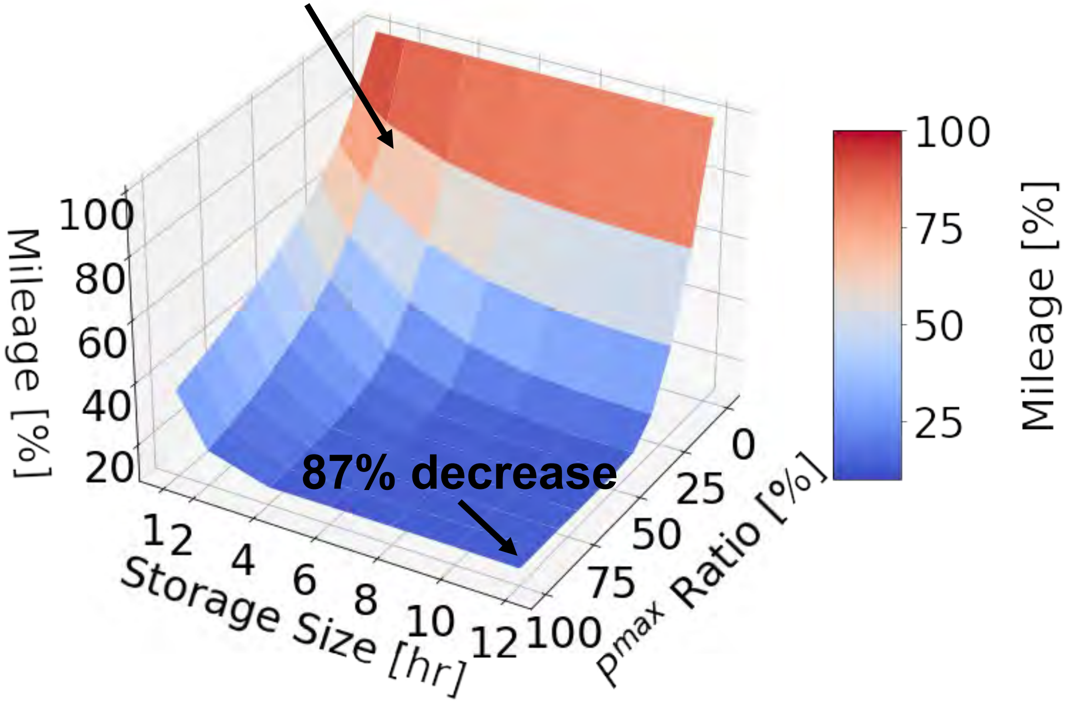
1. Augment thermal generators in RTS-GMLC test system with onsite storage systems.
2. Using static bids to get dispatch signals from Prescient.
3. Explore benefit of hybrid system by tracking dynamic dispatch signals
4. Simulation dates: 01/02/2020 – 12/29/2020

Leveraging energy storage in IES…

Reduces the number of start-ups



Reduces the ramping mileage



Significance: IES with storage can decrease the need to dynamical operate CO_2 capture systems, thereby reducing costs, simplifying designs, and mitigating control challenges.

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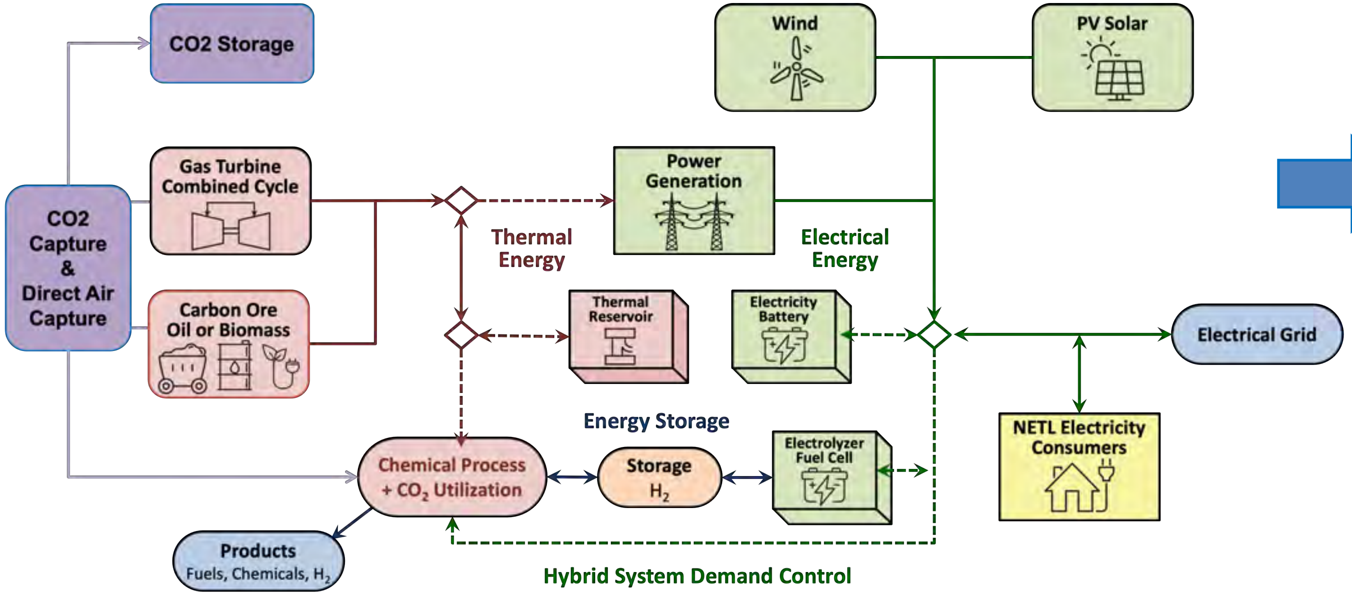
Holistic Analysis of Integrated Energy Systems (IES)

IESs provide **greater operational flexibility** by optimally coordinating material flows and energy conversions, **multiple value streams**

Multiple inputs and technologies:

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



Multiple outputs and markets:

Electricity energy
Ancillary services
H_2
Chemicals
Heating
Cooling

Process-centric Analysis:
- Which technologies are the best investment?
- How to size and operate (energy) storage?
- Which markets to participate in? How?

Grid-centric Analysis:
- How can IES improve grid reliability/resiliency/flexibility?
- How does adoption of IES impact market signals for conventional generators?
- Which market rules/structures fully leverage IES?

IDAES Institute for the Design of Advanced Energy Systems

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

Design & Optimization Infrastructure for Tightly Coupled Hybrid Systems

GRID MODERNIZATION LABORATORY CONSORTIUM U.S. Department of Energy

DISPATCHES

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

NATIONAL ENERGY TECHNOLOGY LABORATORY

NREL Transforming ENERGY

Sandia National Laboratories

BERKELEY LAB

INL Idaho National Laboratory

UNIVERSITY OF NOTRE DAME

Value Proposition

- Conceptual design of novel hybrid systems in a way that enables rigorous exploration of the design space
- Values the output of the hybrid system within the context of the grid and region it is deployed
- Detailed dynamic models coupled with nonlinear model predictive control based on market signals

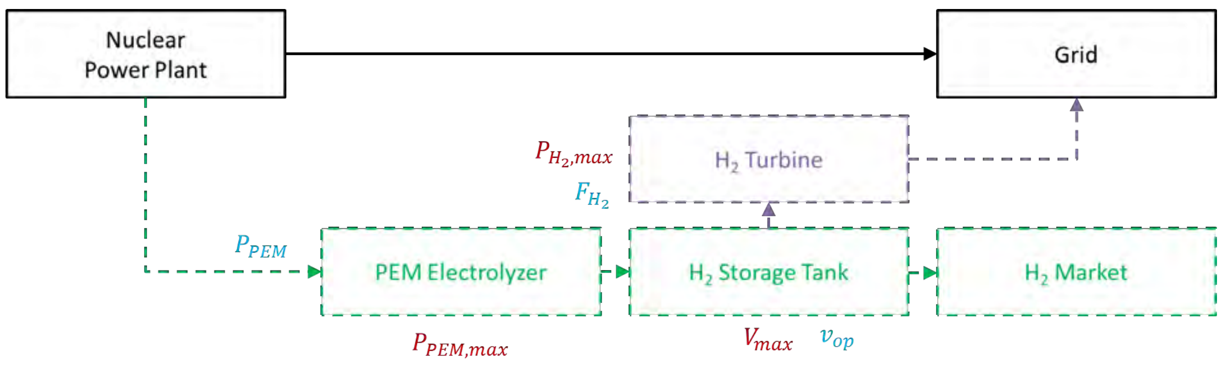
Project Objectives

- Open, multi-lab computational platform to support the design, optimization, and analysis of tightly coupled hybrid systems.
- Demonstrate and quantify the benefits of potential hybrid systems based on case studies
- Build on DOE investments in modeling and simulation capabilities to support a resilient, reliable, and cost-effective bulk power system.

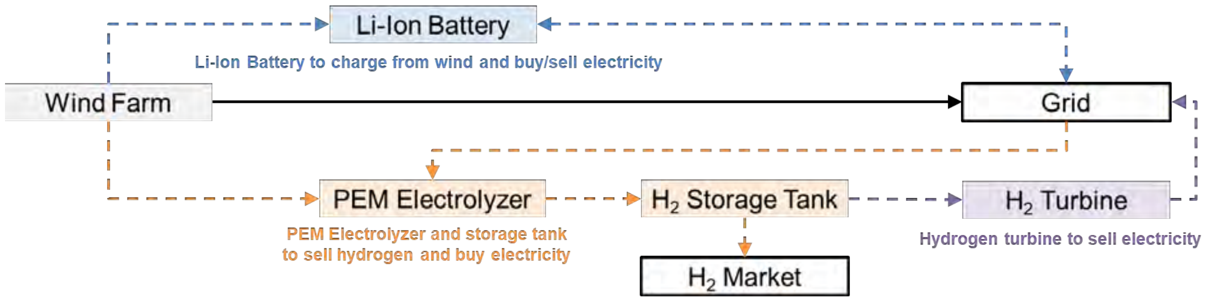
DISPATCHES Case Studies

GRID MODERNIZATION LABORATORY CONSORTIUM U.S. Department of Energy

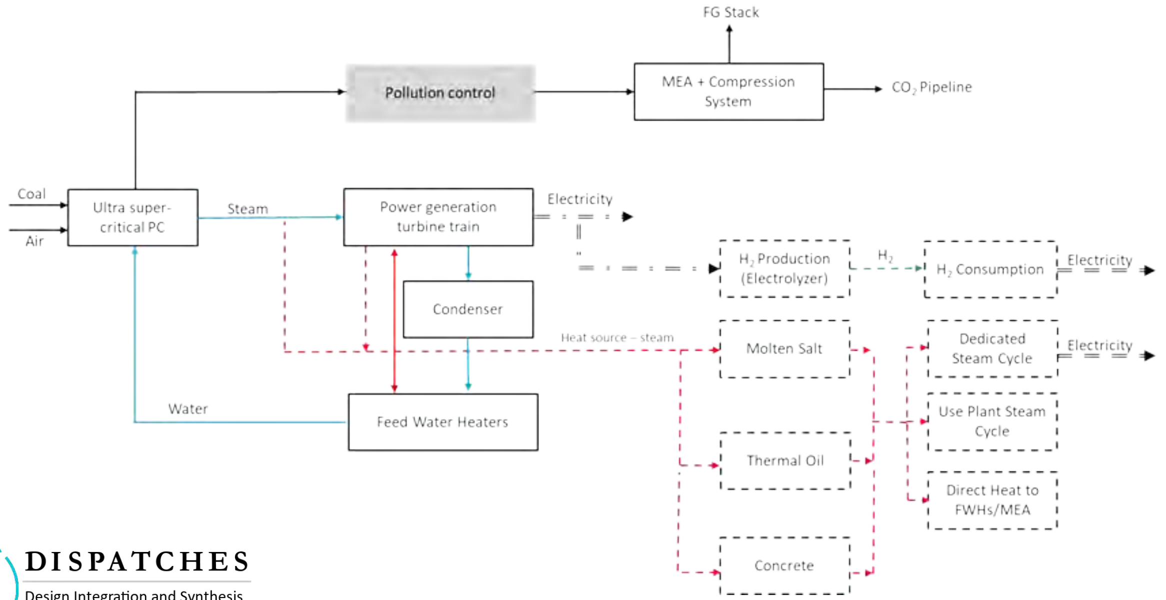
Nuclear Case



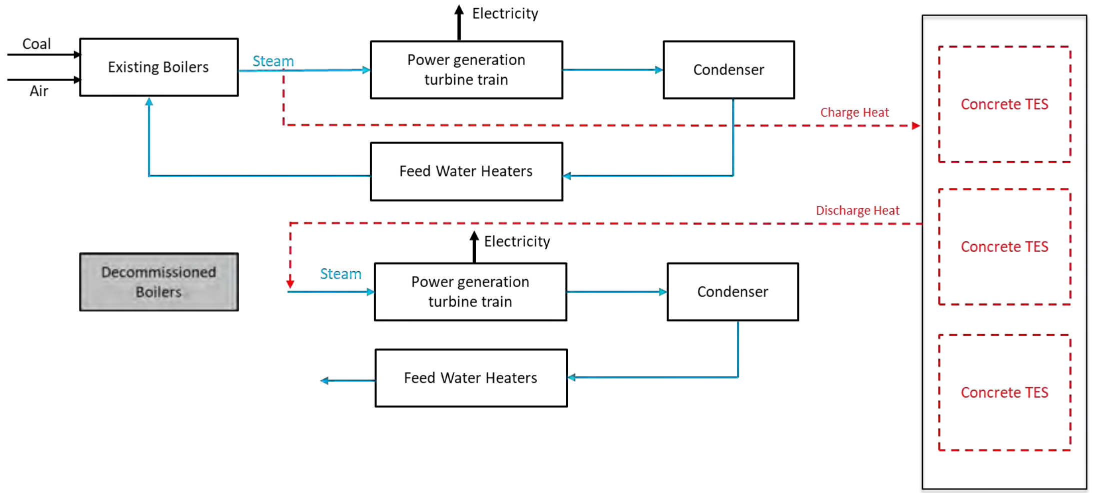
Renewables Case



Fossil Case (Greenfield)



Fossil Case (Retrofit)

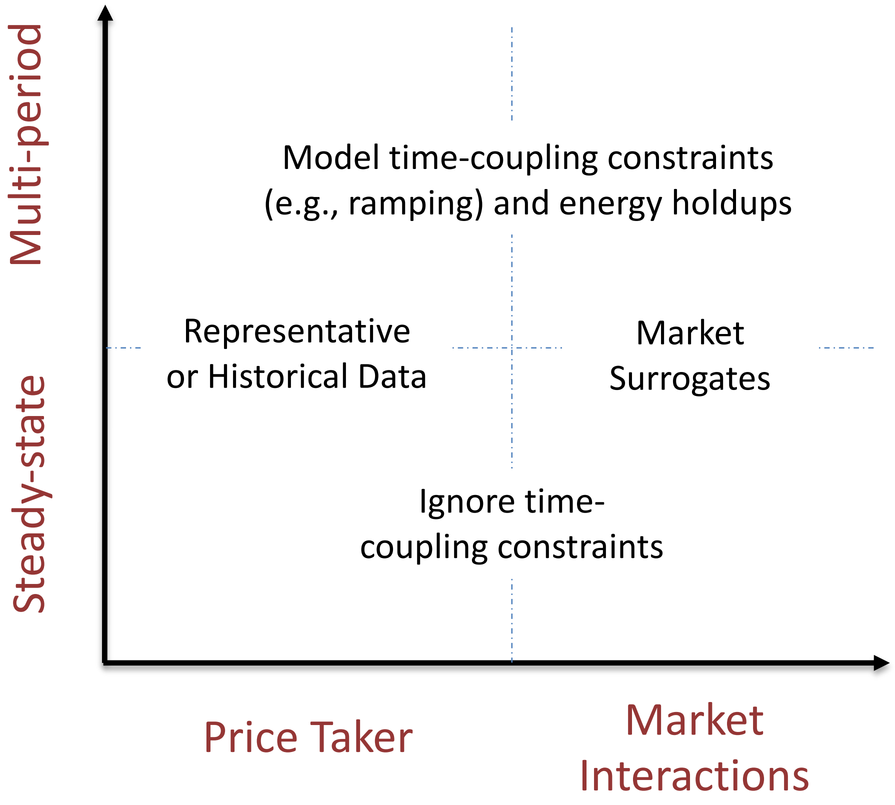


DISPATCHES
Design Integration and Synthesis Platform to Advance Tightly Coupled Hybrid Energy Systems

Multiscale Market-Based Optimization of IES

Design Optimization

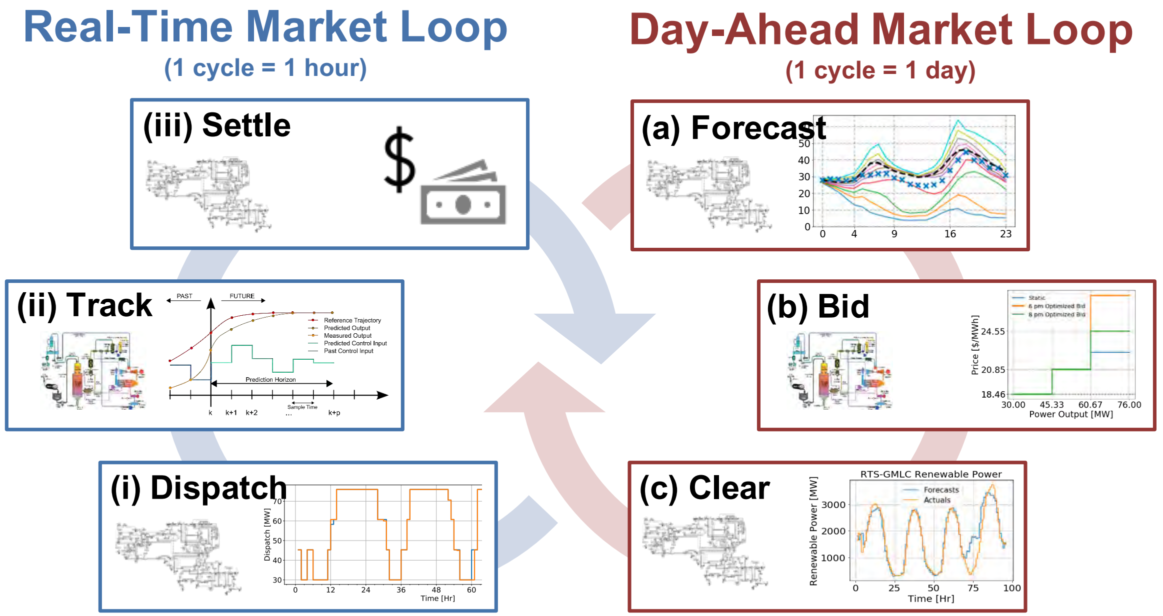
(Maximize Net Present Value)



Candidate IES designs (i.e., IDAES models) to evaluate

Multiscale Simulation

(Quantify Grid/IES Interactions)



Data to refine market representation (e.g., prices, surrogates)

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U.S. Department of Energy

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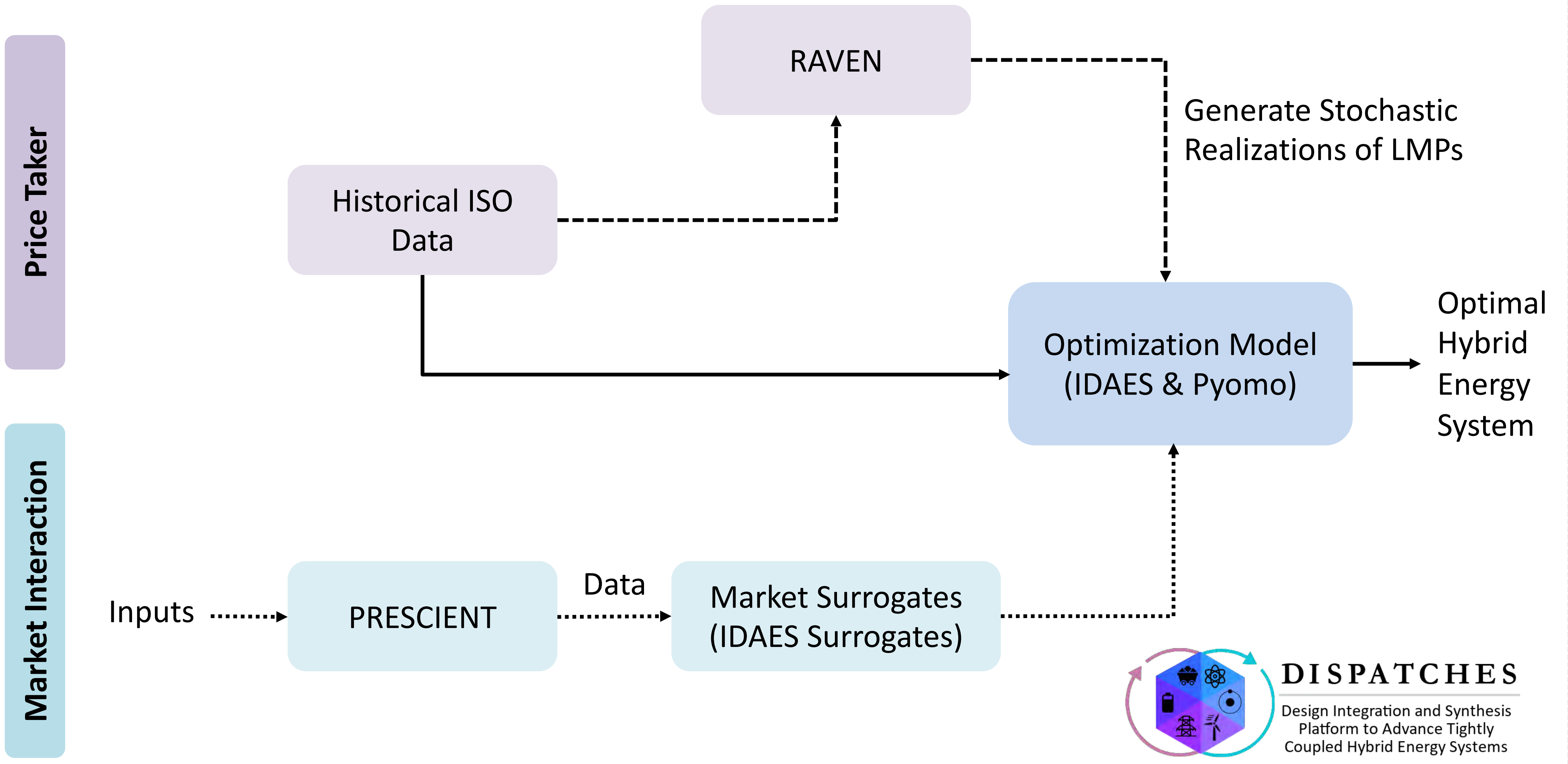
DISPATCHES Workflows



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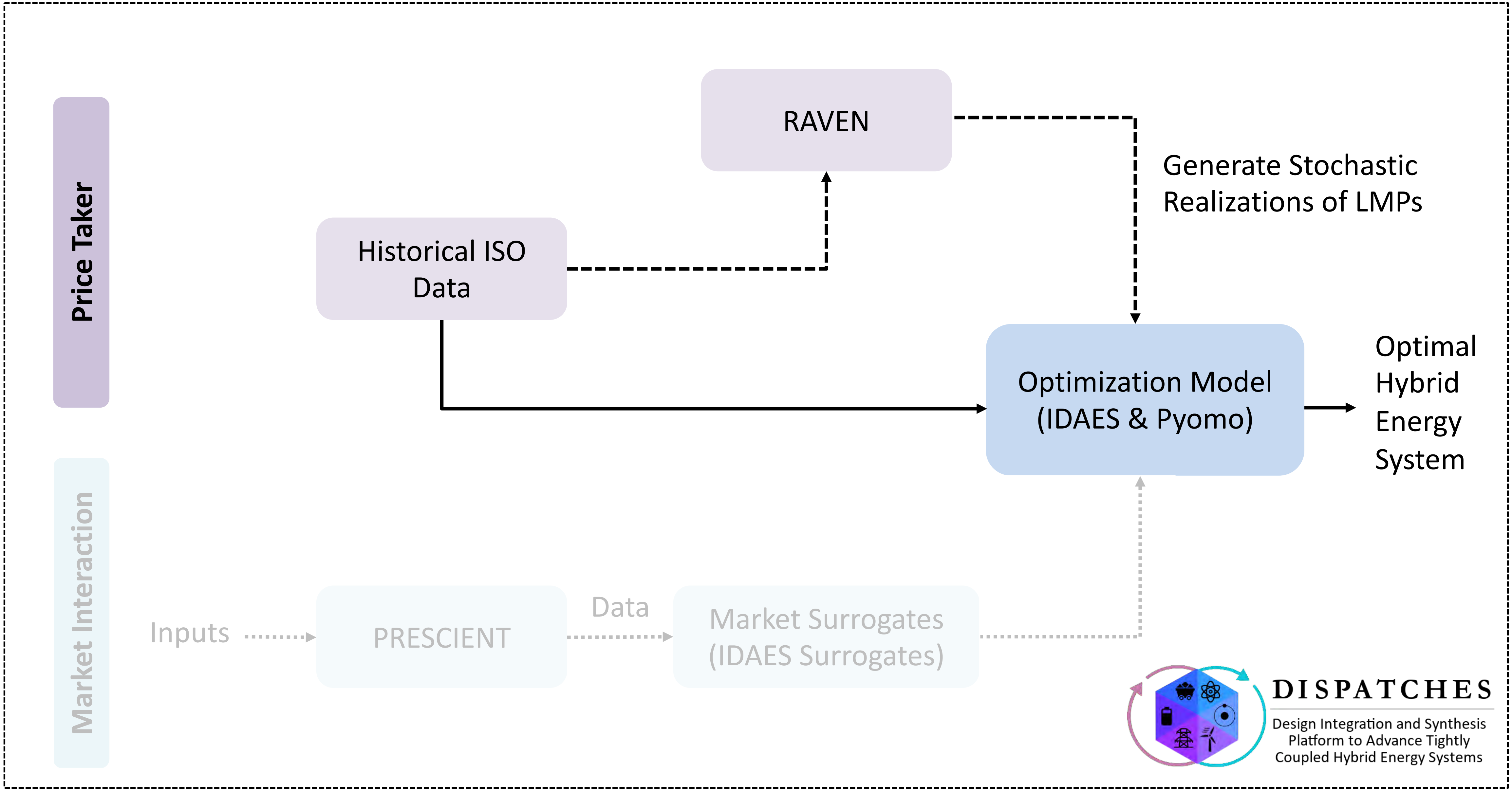
DISPATCHES Workflows – Price Taker



Multi-Period Price Taker (Self-Schedule)

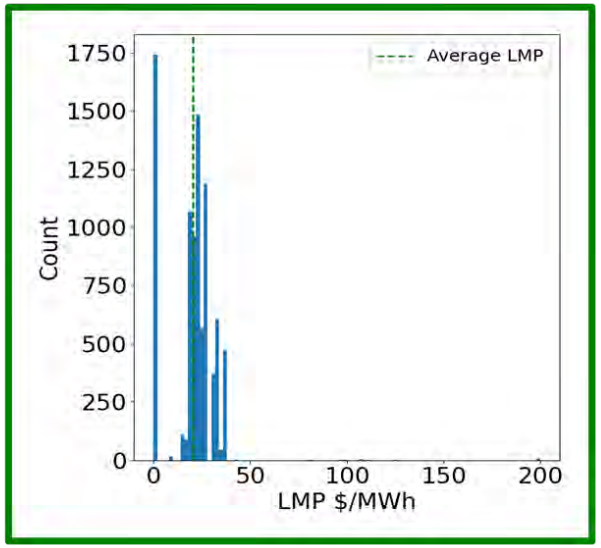
$$\max_{d,\boldsymbol{u},\boldsymbol{\delta}} \sum_{s\in S} \overbrace{\sum_{t\in T} w_s}^{\text{Weight / Frequency}} \Big[\overbrace{R(d,u_{s,t},\delta_{s,t},\pi_{s,t})}^{\text{Revenue}} - \overbrace{C(d,u_{s,t},\delta_{s,t})}^{\text{Cost (Operating + Capital)}}\Big]$$

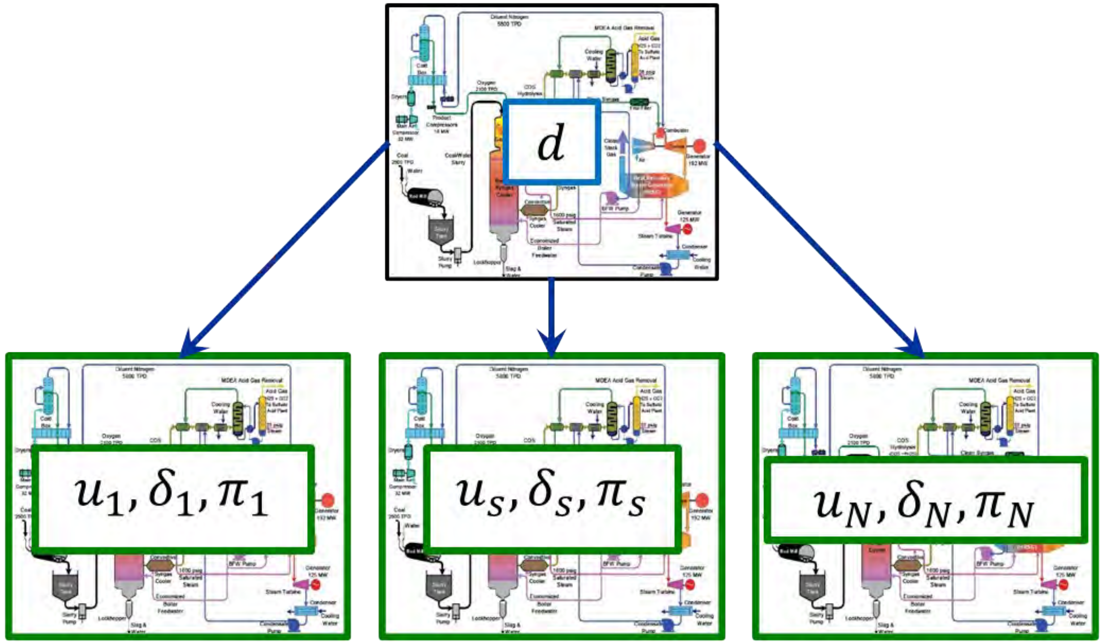
$$g(d,u_{s,t},\delta_{s,t}) = 0, \qquad \forall s \in S, t \in T$$

$$h(d,u_{s,t},\delta_{s,t},u_{s,t+1},\delta_{s,t+1}) = 0, \qquad \forall s \in S, t \in T$$

d	Design **decisions**
$\delta_{s,t}$	Power output **decision** for scenario
$u_{s,t}$	Operating **decisions** for scenario
$\pi_{s,t}$	Scenario price (**data**)
$R()$	Revenue: function of decisions and prices
$C()$	Cost: function of decisions

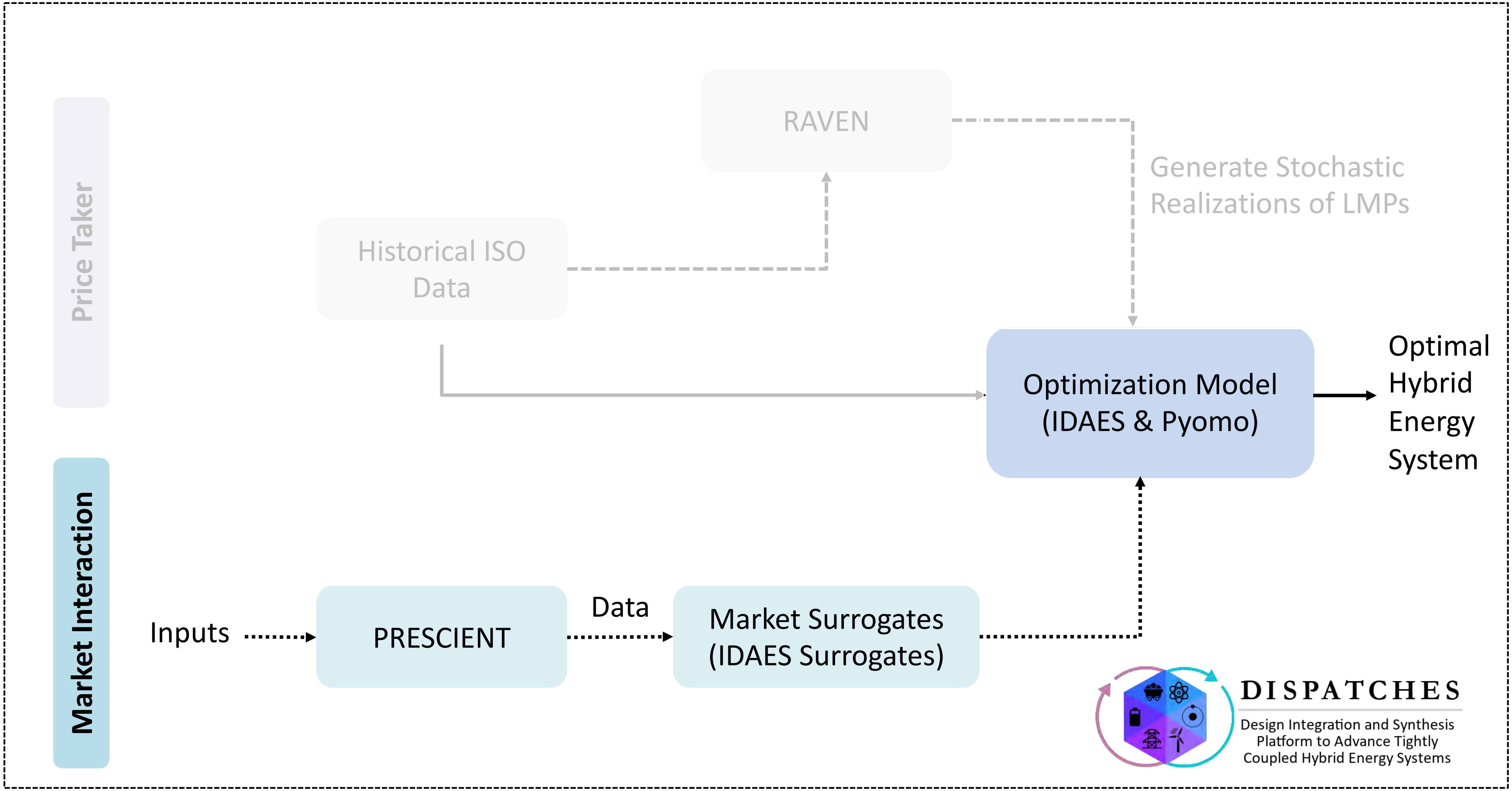
Simulated or Historical ISO Prices





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

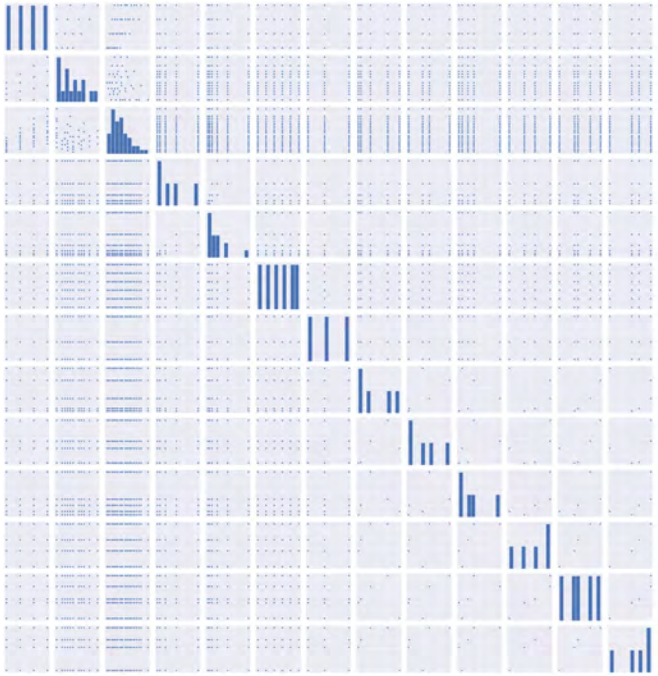
DISPATCHES Workflows



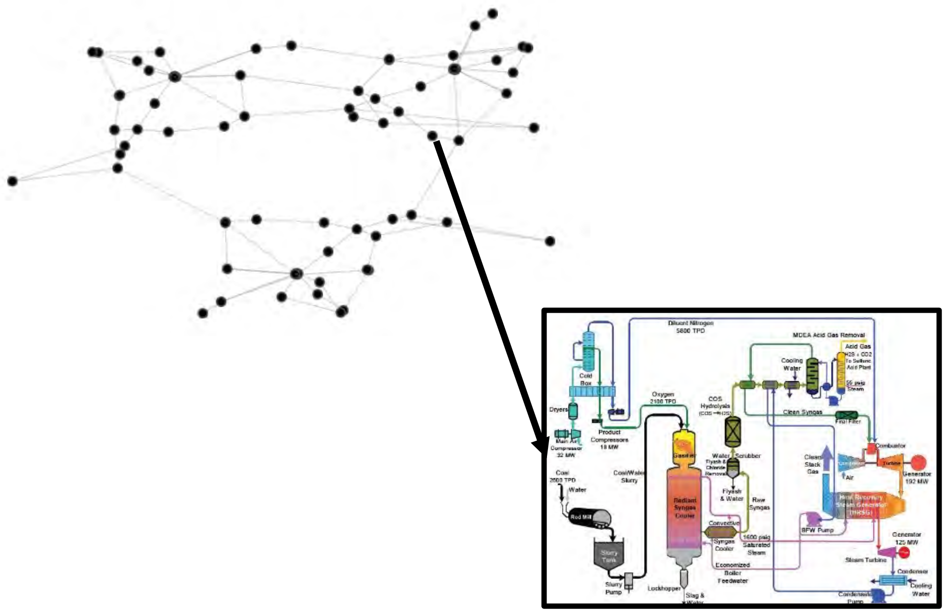
How would a new generator change market outcomes?

Simulation Design

	Market Inputs	7	No Load Cost [$/hr]
1	PMax [MW]	8	Start Time Hot [Hr]
2	PMin [MW]	9	Start Time Warm [Hr]
3	Ramp Rate [MW/hr]	10	Start Time Cold [Hr]
4	Min Up Time [Hr]	11	Start Cost Hot [$]
5	Min Down Time [Hr]	12	Start Cost Warm [$]
6	Marginal Cost [$/MWh]	13	Start Cost Cold [$]



Production Cost Modeling: RTS-GMLC Test System



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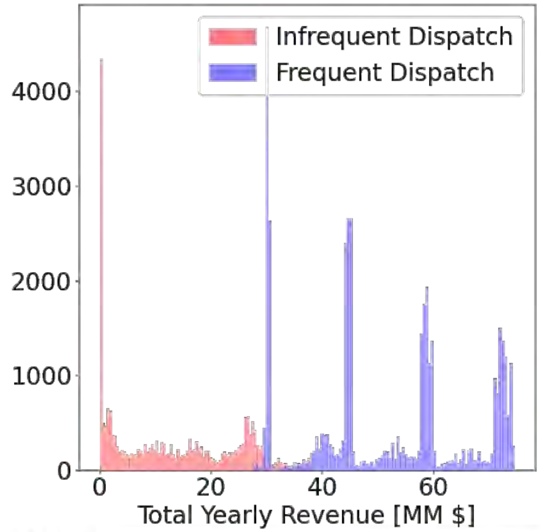
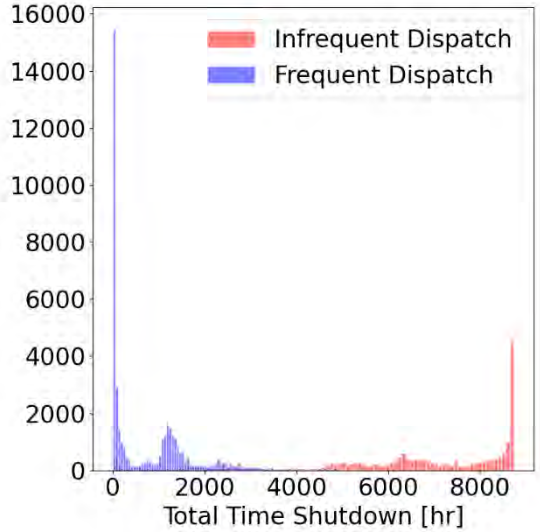
Revenue & Dispatch Results





64,800 1-year Prescient simulations (@ 3 hr each)

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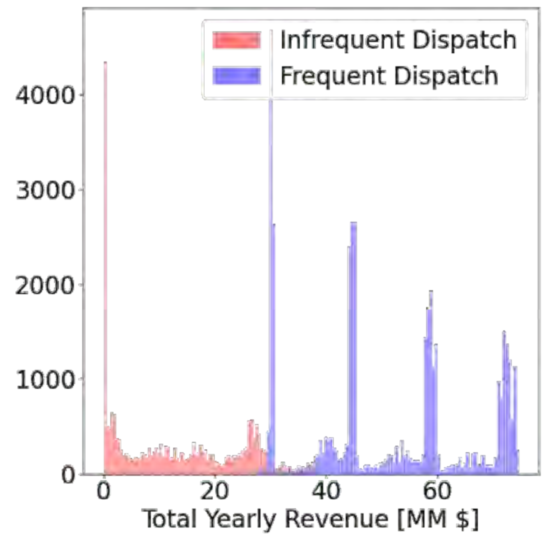
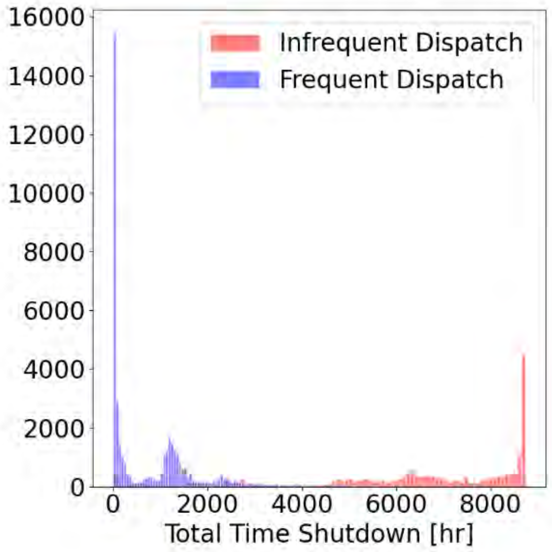
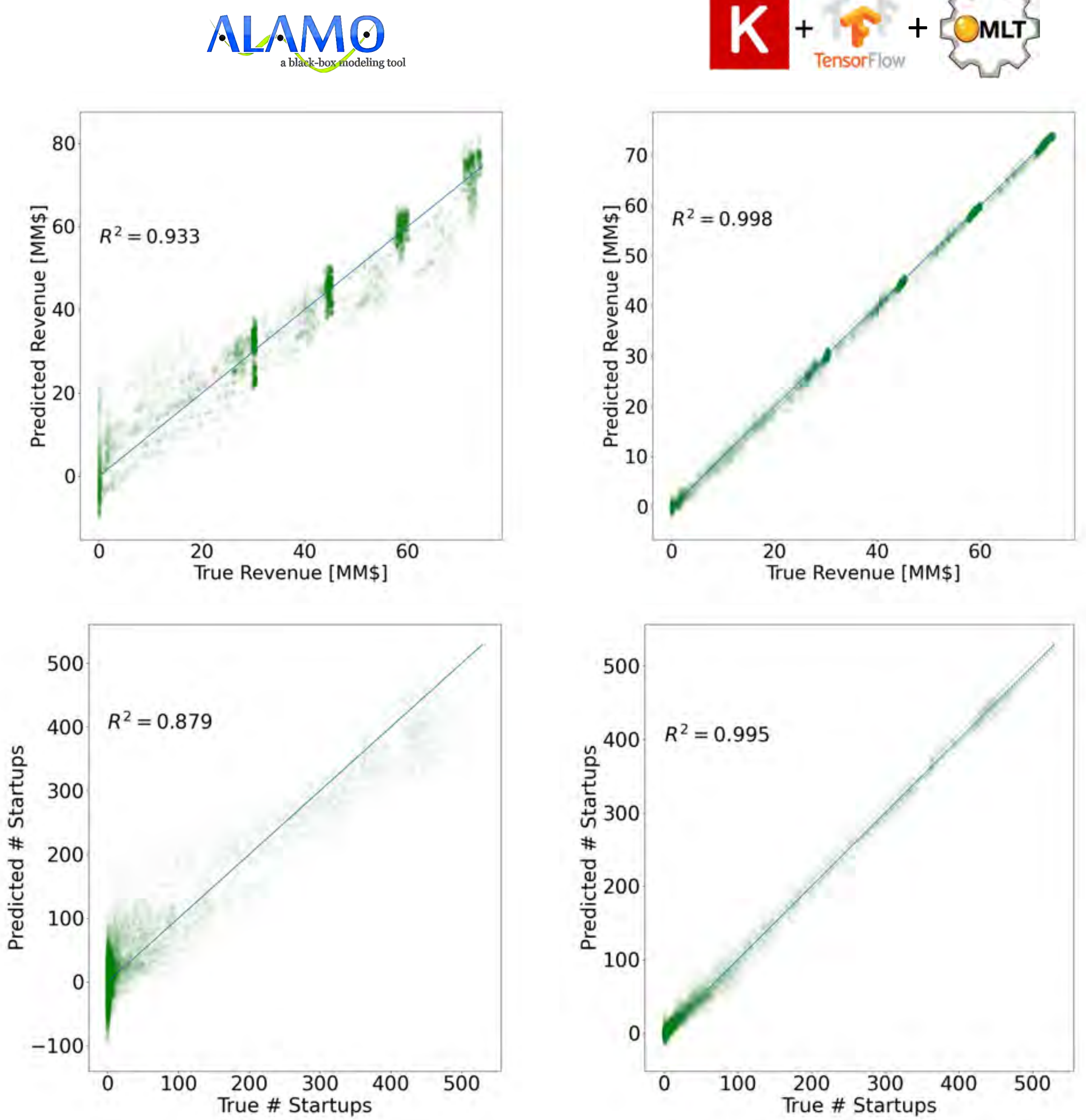
Surrogates Accurately Predict Market Outcomes





Fit Market Surrogates



Steady-State with Market Surrogates (Bid)

$$\max_{d,\boldsymbol{u},x} \overbrace{R(x)}^{\text{Revenue}} - \sum_{s \in S} \overbrace{w_s(x)[C(d, u_s, \delta_s)]}^{\text{Cost (Operating + Capital)}}$$

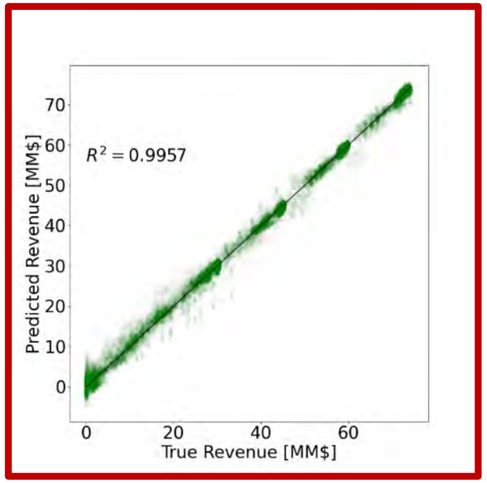
$$g(d, u_s, \delta_s) = 0, \qquad \forall s \in S \quad \text{Process Model}$$

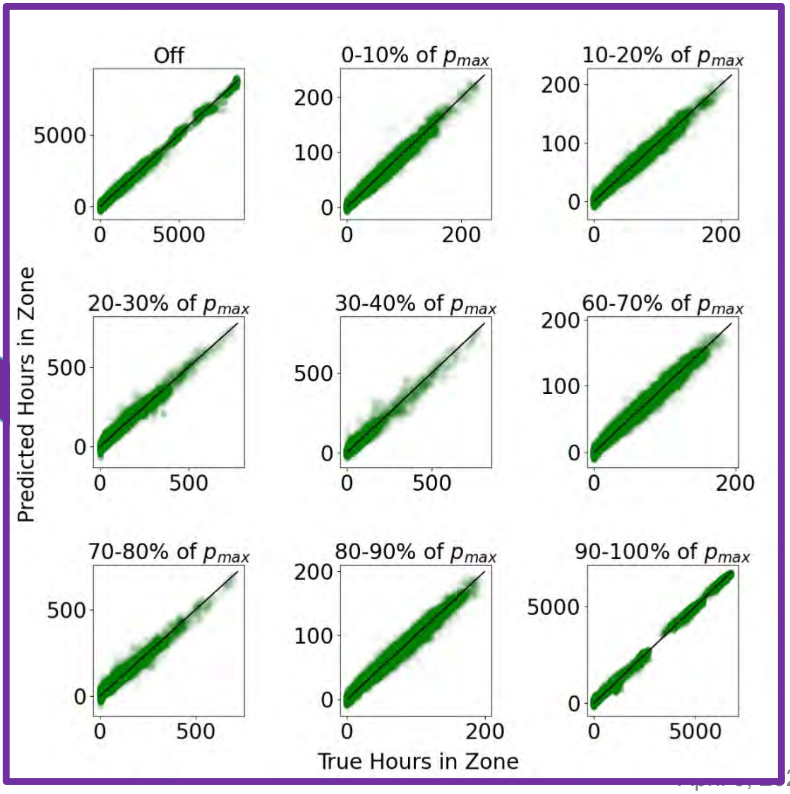
$$h(d, x) = 0 \quad \text{“Bid Rules”}$$

$$R(x) = f_{rev}(x) \quad \text{Revenue Surrogate}$$

$$w_s(x) = f_s(x), \qquad \forall s \in S \quad \text{Dispatch Surrogates}$$

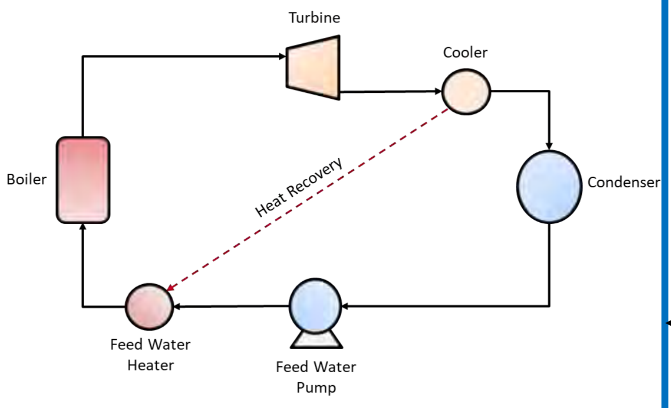
d	Design **decisions**
δ_s	Power output **data** for scenario
u_s	Operating **decisions** for scenario
x	Market Inputs (bid **decisions**)
$R()$	Revenue: function of market inputs
$C()$	Cost: function of decisions
w_s	Scenario weight: function of market inputs





Example: Optimal Design of Rankine Cycle for RTS-GMLC

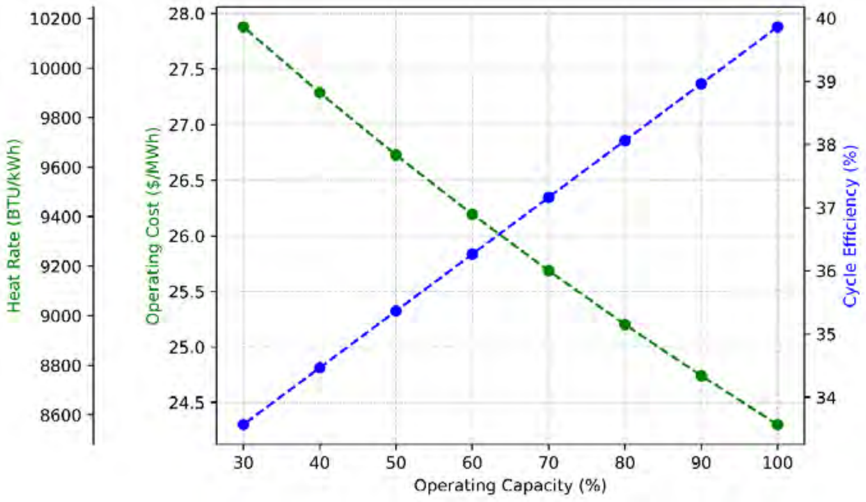
Steam Generator

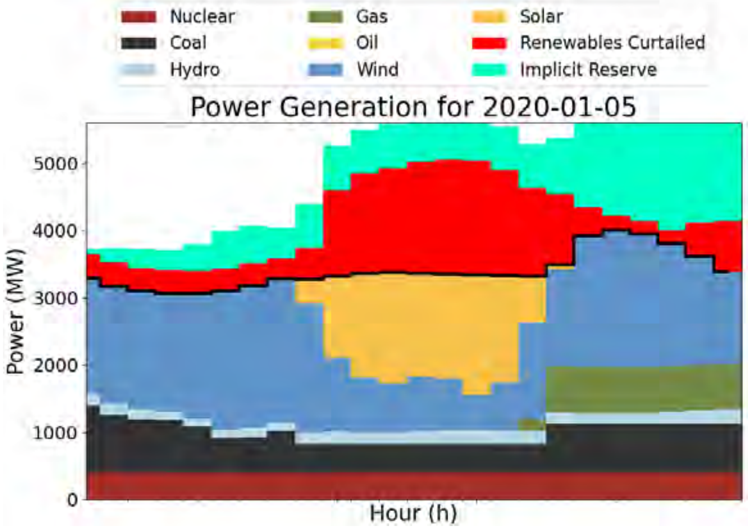


Power δ

Price π

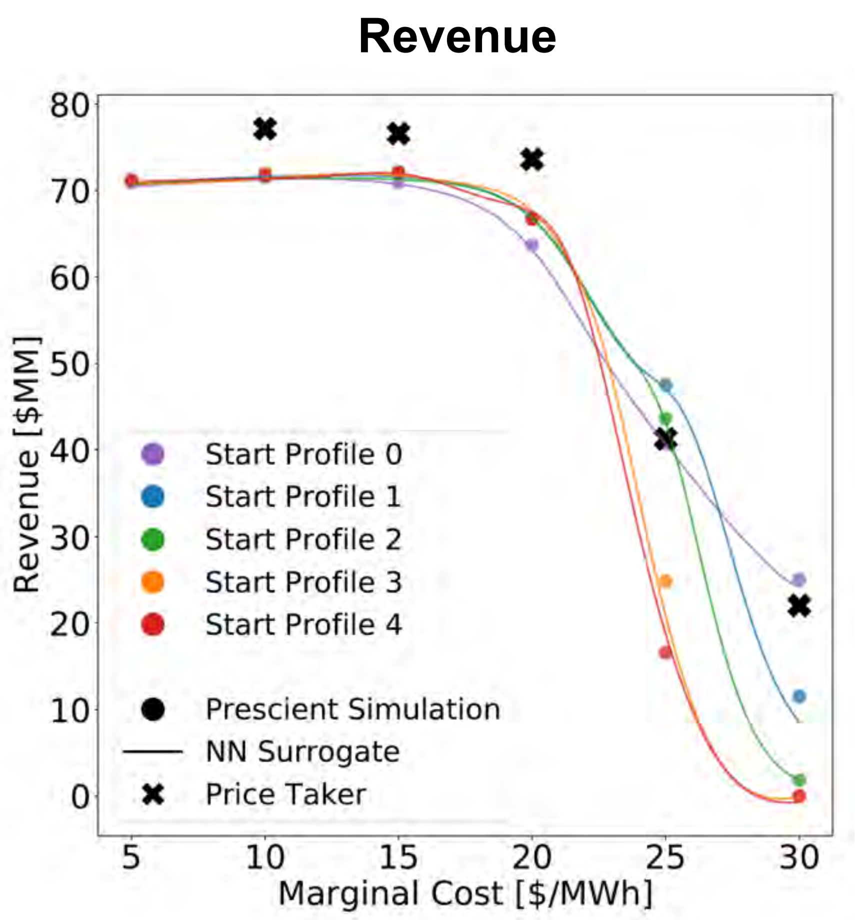
Energy Market

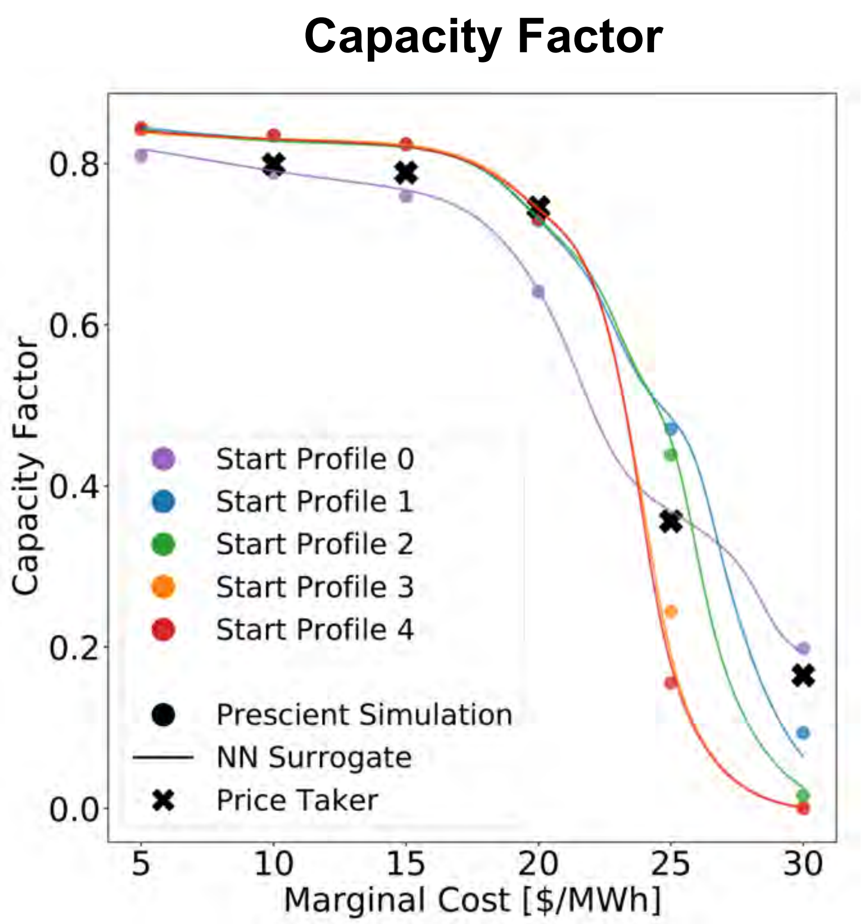




Price Taker vs. Market Surrogates (P_{max} = 433.5 MW)

GRID MODERNIZATION LABORATORY CONSORTIUM
U.S. Department of Energy





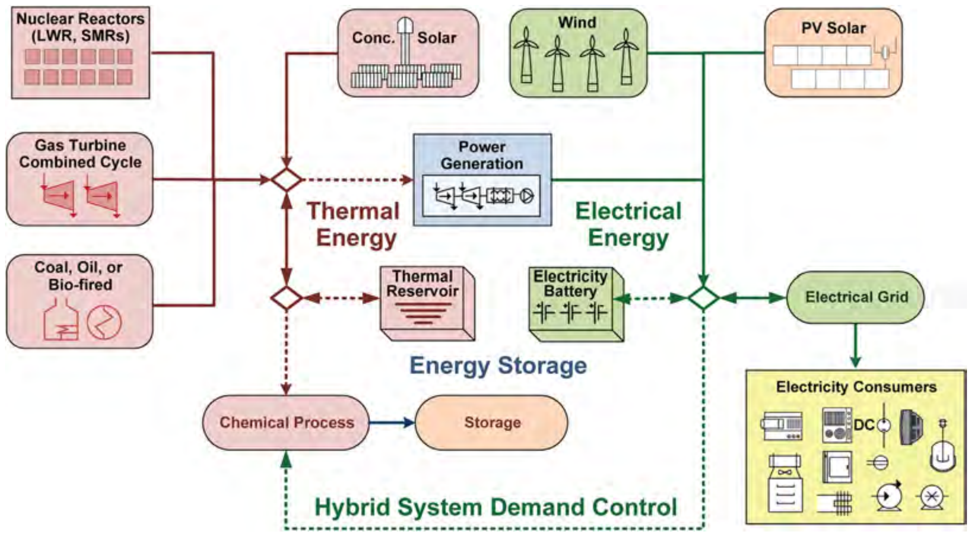
DISPATCHES
Design Integration and Synthesis Platform to Advance Tightly Coupled Hybrid Energy Systems

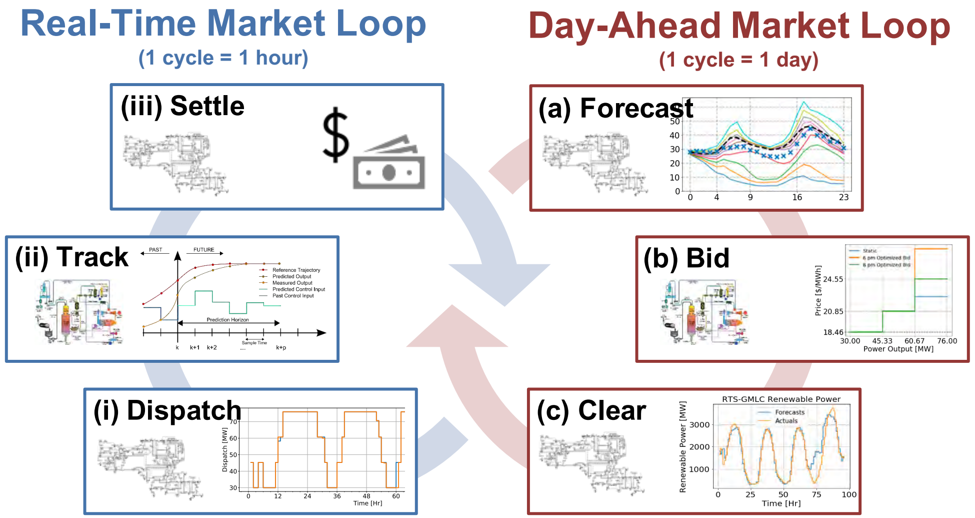
Take Away Messages

Integrated Energy Systems (IES) provide **dynamic flexibility**

Modeling and data-driven **co-optimization** of IES design, operations, and control

Multiscale simulation + **machine learning** embeds IES-market interactions into optimization





Further Reading: dowlinglab.nd.edu/publications

Multiscale & Multiproduct Markets
Dowling, Kumar, Zavala (2017), *Applied Energy*

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Concentrated Solar Thermal
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Forecasting & Market Uncertainty
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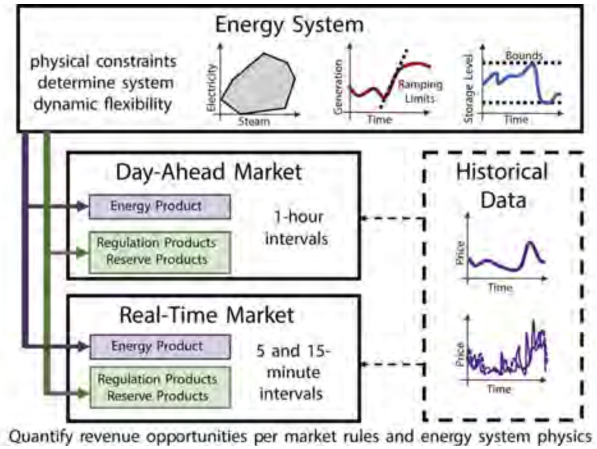
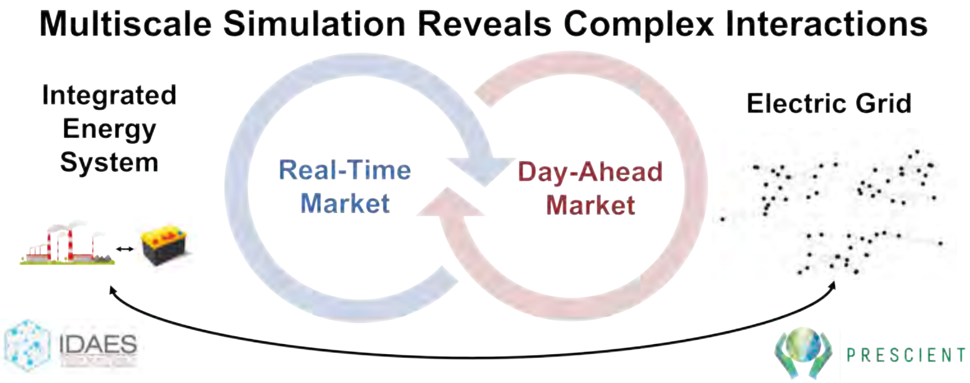
Gao, Knueven, Miller, Siirola, Dowling. (2022) *Applied Energy*





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