SAND2019-0421PE

Optimizing grid energy storage systems: From open-source tools to real-time adaptive control

David Copp, 8811

January 16, 2019

8800 Brown Bag

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

Outline

- **Solving grid challenges with energy storage**
  - Drivers of grid modernization
  - How can energy storage help?
- **Sandia's energy storage program**
- **Analytics and controls thrust**
  - Analysis, optimization, and control of energy storage
  - QuESt open-source software suite
  - Optimal, adaptive, real-time dispatch

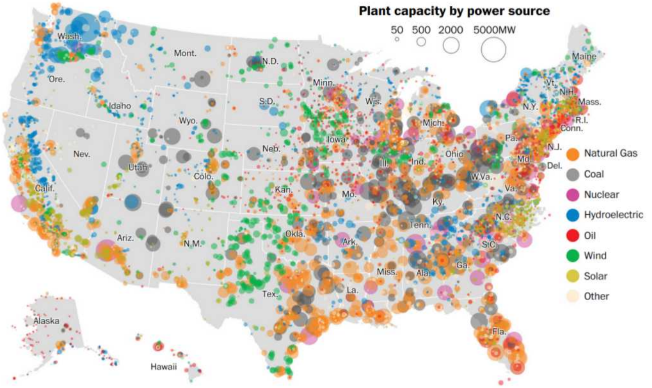
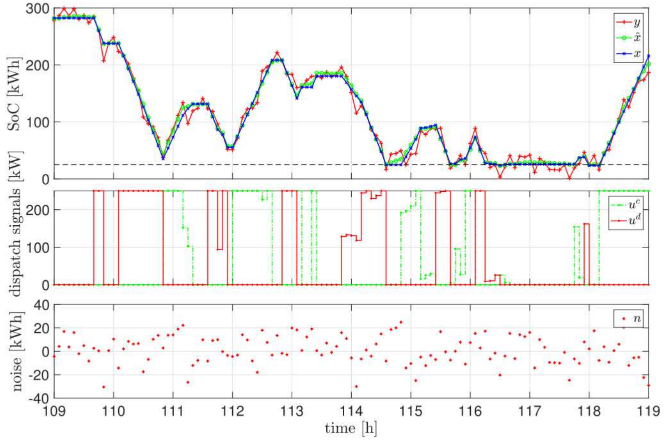
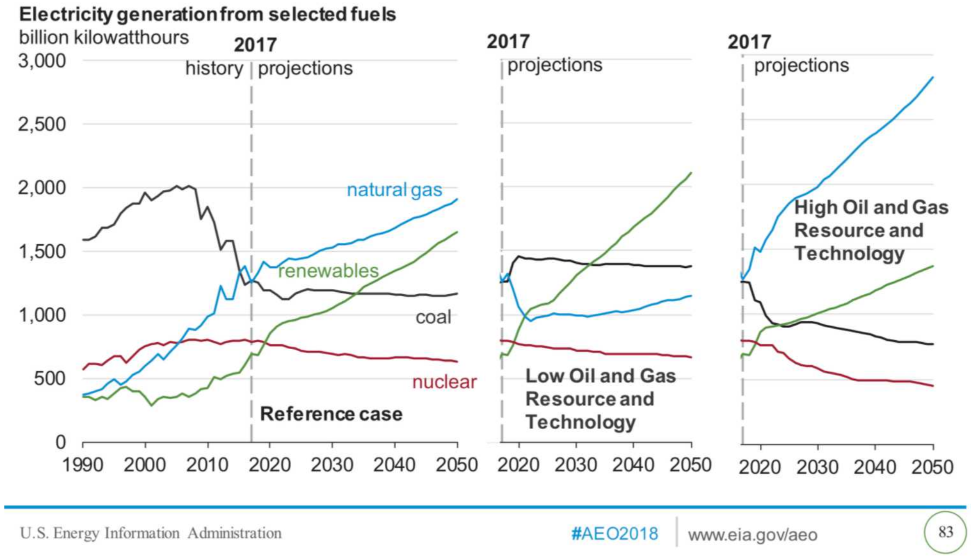
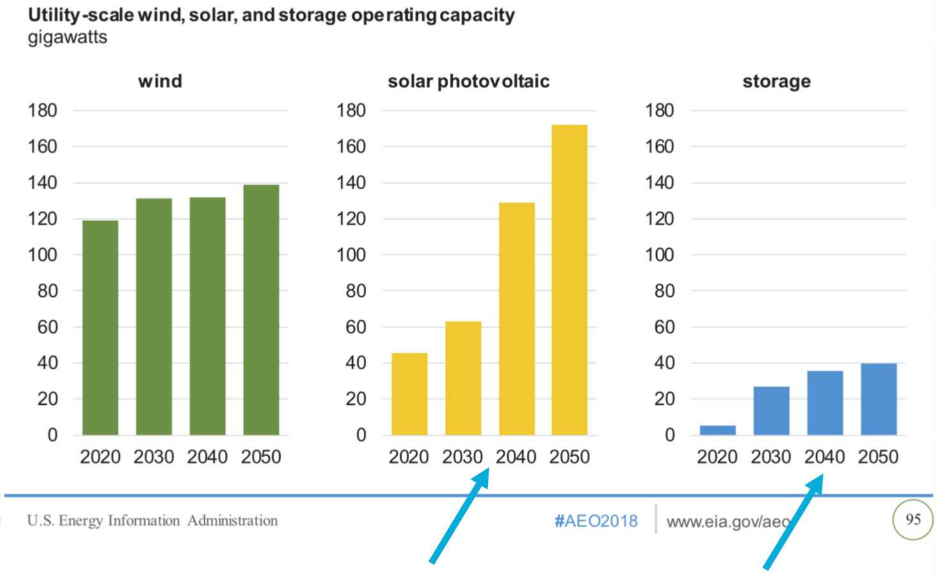


Image credit: Washington Post



Energy Storage Capacity Projected to Increase





400% increase 800% increase
from 2020 to 2050

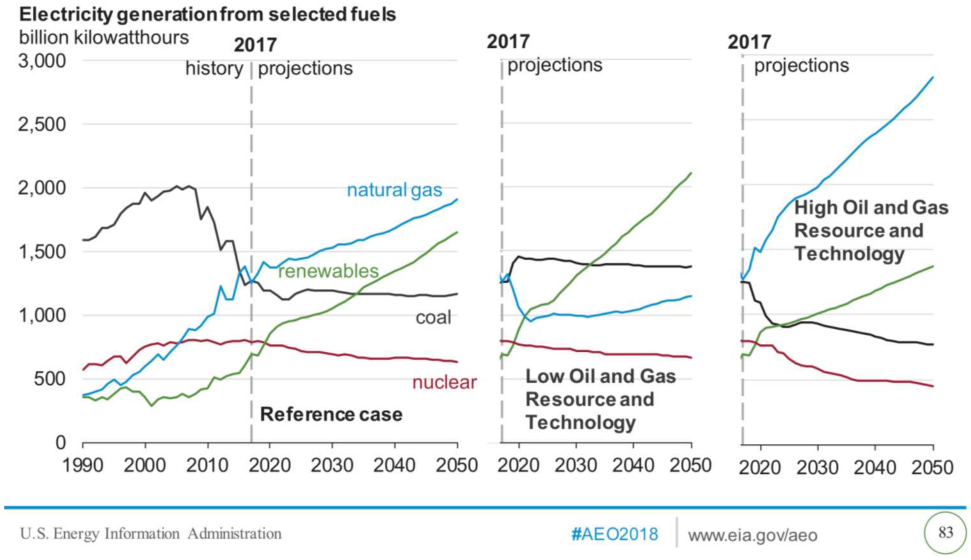
Drivers for Grid Modernization

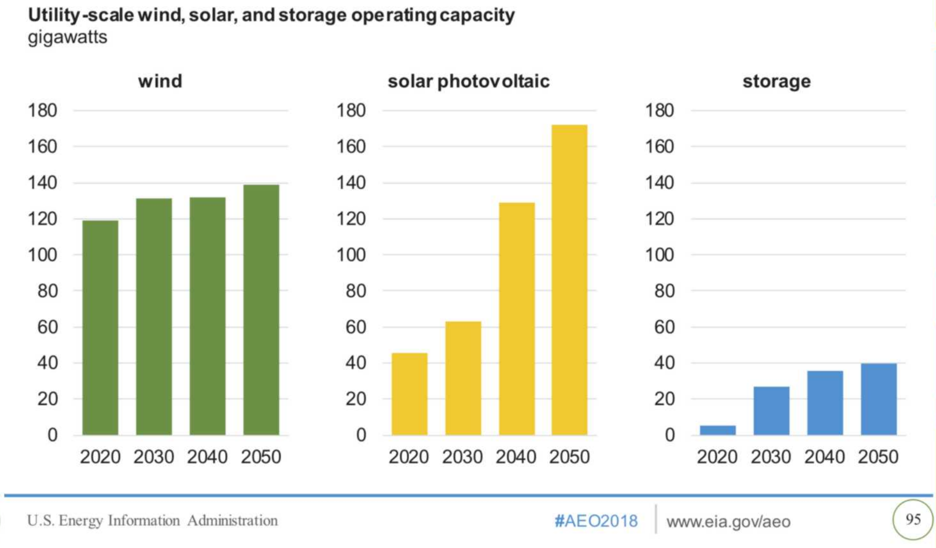
- Economic – aging power system exacts substantial costs due to outages and inefficient technologies
- Environmental – increased frequency and severity of weather events
- Security – cyber and physical
- Competitiveness – global competition in energy sector

Energy Storage Can:

- Reduce T&D upgrade costs
- Mitigate losses from outages
- Improve resilience
- Enable new technologies, growth

Energy Storage Capacity Projected to Increase





Power applications

- Frequency regulation
- Voltage support
- Small signal stability
- Frequency droop
- Synthetic inertia
- Renewable capacity firming

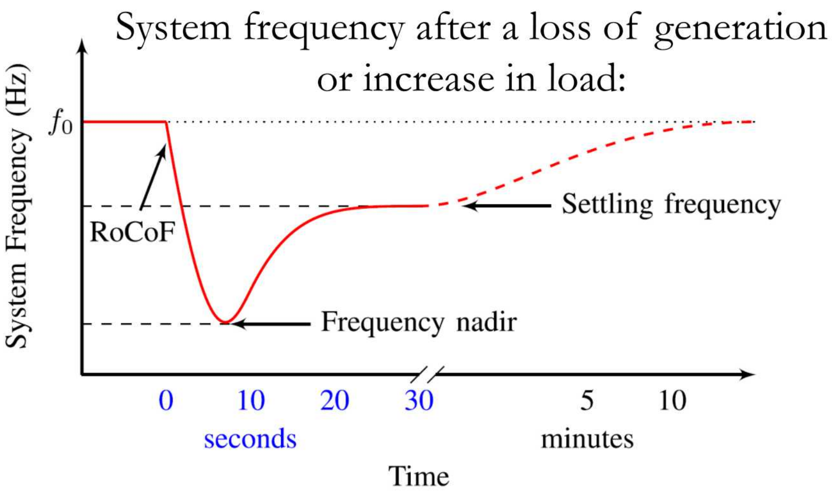
Energy applications

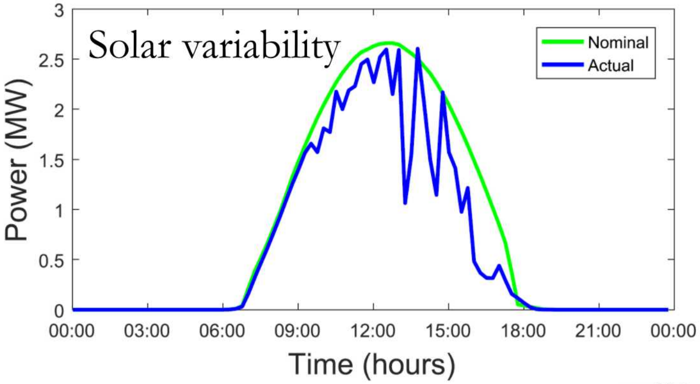
- Arbitrage
- Transmission and distribution upgrade deferral
- Customer demand charge or time-of-use charge reduction
- Grid resiliency
- Renewable energy time shift

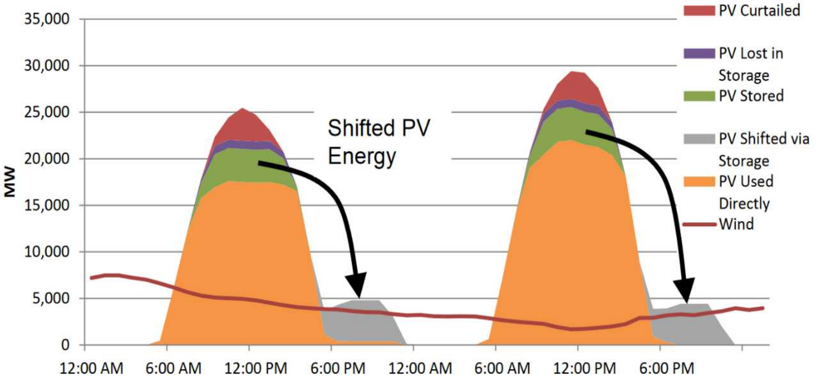
Energy Storage Applications

Image credit: AP

Image credit: mathworks.com







Energy Storage Applications

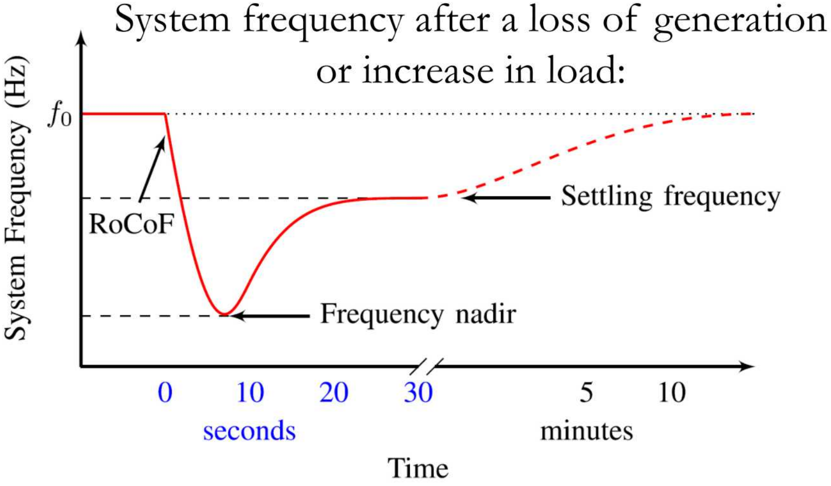
Frequency Droop + Synthetic Inertia

Image credit: AP

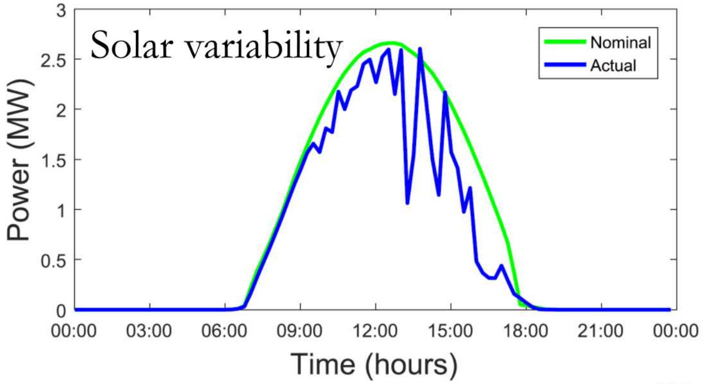
Renewable Capacity Firming

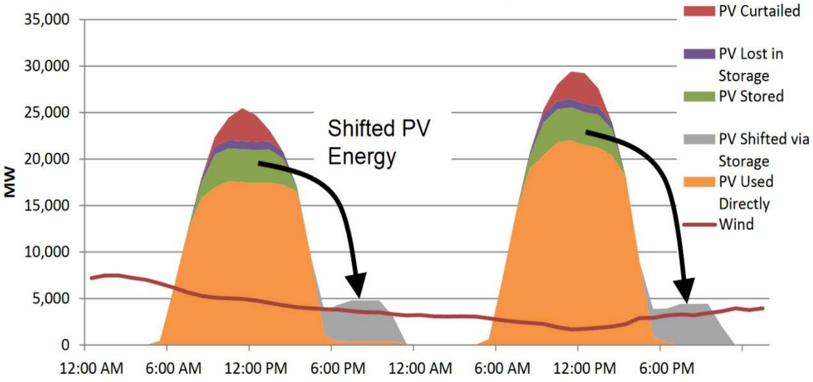
Renewable energy time shift

Image credit: mathworks.com



System frequency after a loss of generation or increase in load:





Outline

- **Solving grid challenges with energy storage**
  - Drivers of grid modernization
  - How can energy storage help?

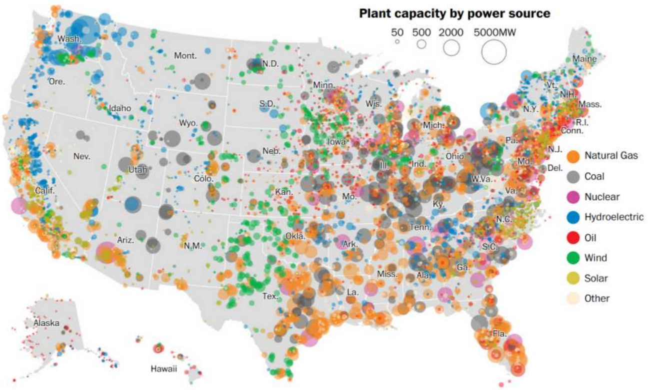


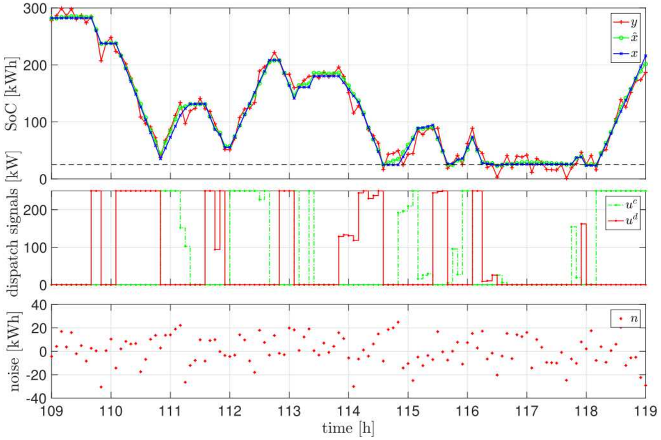
Image credit: Washington Post

- **Sandia's energy storage program**

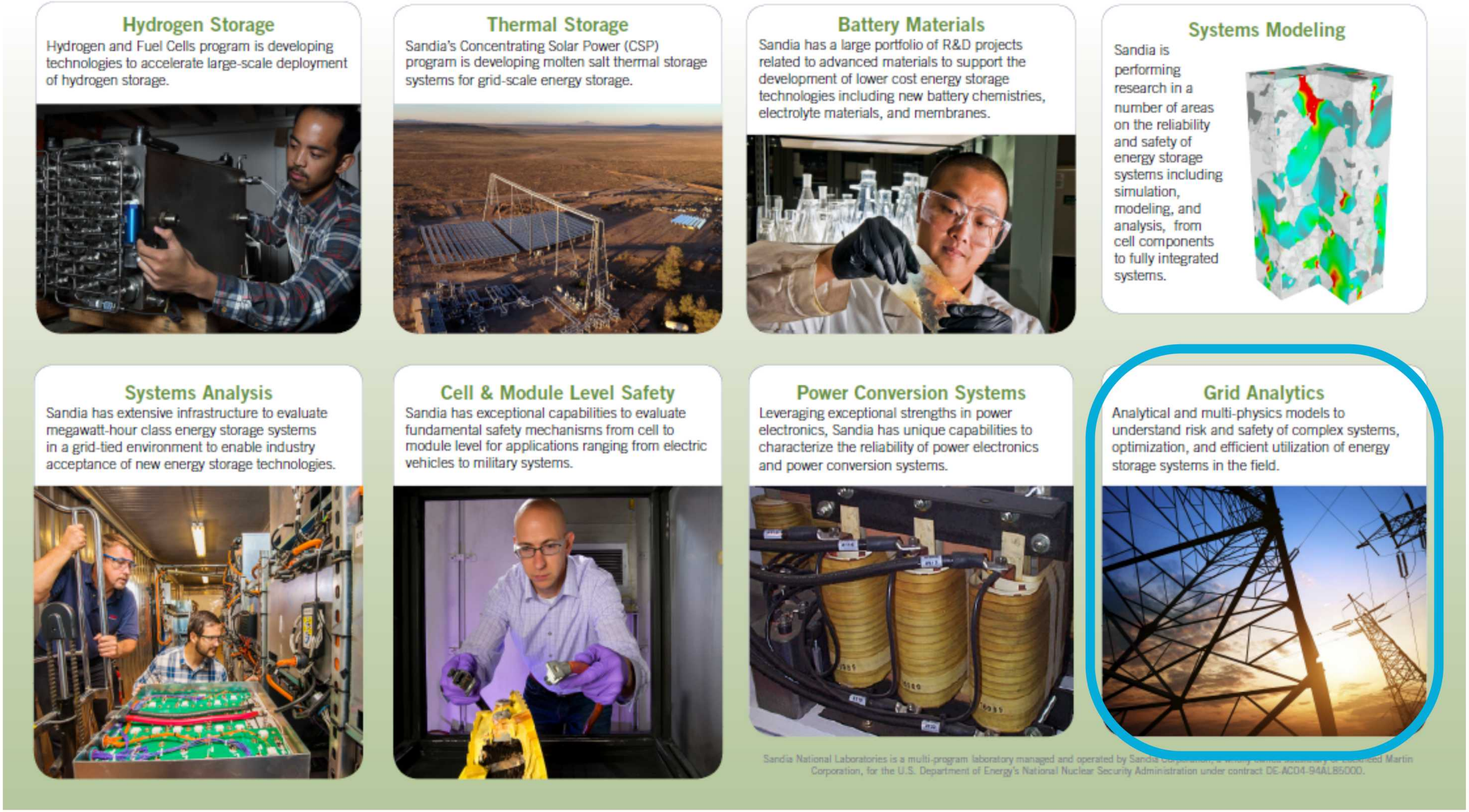
- **Analytics and controls thrust**
  - Analysis, optimization, and control of energy storage

  - QuESt open-source software suite

  - Optimal, adaptive, real-time dispatch



Energy Storage is a Major Crosscut



Hydrogen Storage
Hydrogen and Fuel Cells program is developing technologies to accelerate large-scale deployment of hydrogen storage.

Thermal Storage
Sandia's Concentrating Solar Power (CSP) program is developing molten salt thermal storage systems for grid-scale energy storage.

Battery Materials
Sandia has a large portfolio of R&D projects related to advanced materials to support the development of lower cost energy storage technologies including new battery chemistries, electrolyte materials, and membranes.

Systems Modeling
Sandia is performing research in a number of areas on the reliability and safety of energy storage systems including simulation, modeling, and analysis, from cell components to fully integrated systems.

Systems Analysis
Sandia has extensive infrastructure to evaluate megawatt-hour class energy storage systems in a grid-tied environment to enable industry acceptance of new energy storage technologies.

Cell & Module Level Safety
Sandia has exceptional capabilities to evaluate fundamental safety mechanisms from cell to module level for applications ranging from electric vehicles to military systems.

Power Conversion Systems
Leveraging exceptional strengths in power electronics, Sandia has unique capabilities to characterize the reliability of power electronics and power conversion systems.

Grid Analytics
Analytical and multi-physics models to understand risk and safety of complex systems, optimization, and efficient utilization of energy storage systems in the field.

Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

Wide ranging R&D covering energy storage technologies with applications in the grid, transportation, and stationary storage

Overview of Sandia Energy Storage Program

- **Materials Research –** Advancing new battery chemistries through technology development and commercialization.
- **Power Electronics –** Optimization at the interface between power electronics and electrochemistry. Power electronics including high voltage devices (SiC, GaN), high voltage passives and magnetics.
- **Energy Storage Safety –** Cell and module level safety test and analysis. Engineered safety of large systems. Predictive models for ES safety. Storage safety standards and protocols.
- **Energy Storage Analytics and Controls –** Analytics and controls for integration of utility class storage systems. Software tools for optimal use of energy storage across the electricity infrastructure. Standards development.
- **Energy Storage Project Development –** Support for demonstration projects.
- **Industry Outreach –** Outreach to utilities, regulators, and the industry.

Multidisciplinary R&D program collaborating across Sandia
1353, 1816, 1874, 2546, 8762, 8813, 8824

Outward looking with significant external collaboration with industry and academia.

University Partners

CUNY Energy Institute
Davidson College
Northeastern University
Stony Brook University
University of Kentucky
University of Washington
UC Irvine
University of Alaska Fairbanks
University Texas at Austin
New Mexico State University

Ohio State University
University Texas Arlington
New Mexico Tech
University New Mexico
Washington University at S. L.
Michigan State University
University of Utah
South Dakota State University
Clemson University
Southern Methodist University

$2.2M in funding to universities

Industry/Utility Partners

GeneSic Semiconductor
Creare
InnoCit
Mainstream Engineering
Powdermet
Urban Electric Power
Helix Power Corporation
Eugene Water and Electric Board
Cordova Electric Cooperative
Strategen
Mustang Prairie Energy
ANZA Electric
PNM Resources

WattJoule
UniEnergy Technologies
Sterling Municipal Light Department
Public Service of New Mexico
National Rural Electric Cooperative Association
Hawaii Electric Light
Green Mountain Power
Electric Power Board of Chattanooga
Electric Power Research Institute
Ecoult Battery
Demand Energy
Burlington Electric Department
NELHA

Outline

- **Solving grid challenges with energy storage**
  - Drivers of grid modernization
  - How can energy storage help?

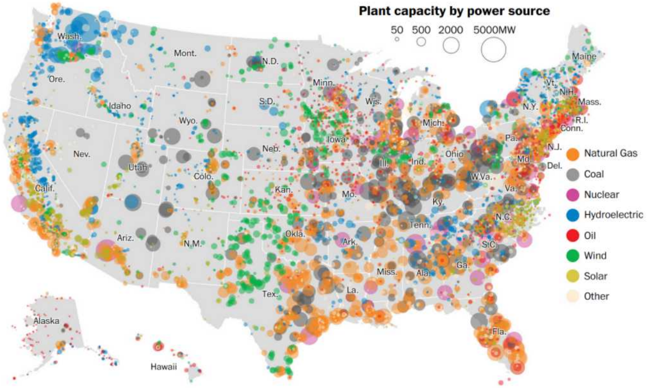


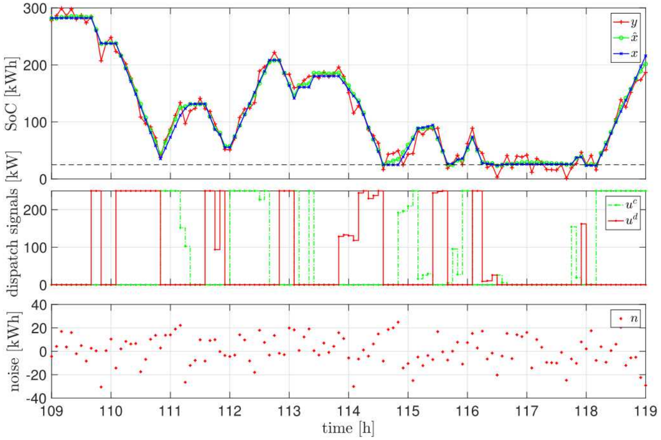
Image credit: Washington Post

- **Sandia's energy storage program**

- **Analytics and controls thrust**
  - Analysis, optimization, and control of energy storage

  - QuESt open-source software suite

  - Optimal, adaptive, real-time dispatch



Quest Energy Storage Software Suite

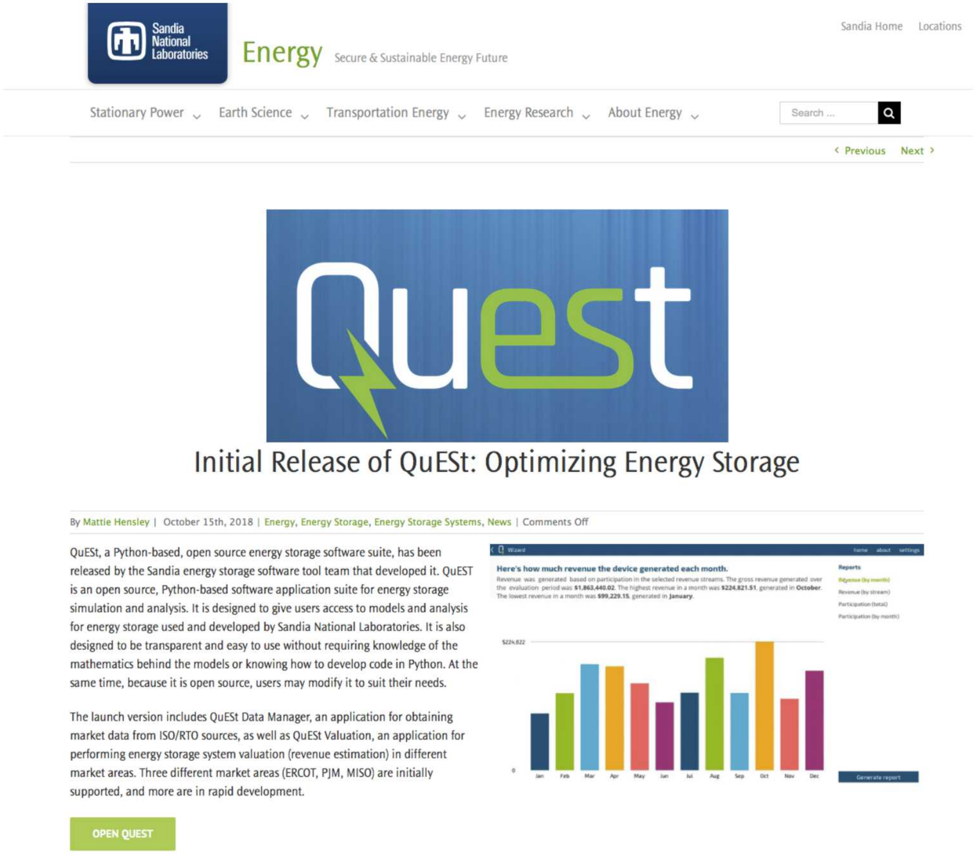
https://energy.sandia.gov/quest-optimizing-energy-storage/

- Open source, Python-based energy storage analysis software application suite.

- Developed as a graphical user interface for optimization and analysis capabilities of SNL's energy storage group.

- Initial development driven by Pyomo models for energy storage valuation in market areas.

- Now publicly available on GitHub
  - https://github.com/rconcep/snl-quest



Initial Release of QuESt: Optimizing Energy Storage

By Mattie Hensley | October 15th, 2018 | Energy, Energy Storage, Energy Storage Systems, News | Comments Off

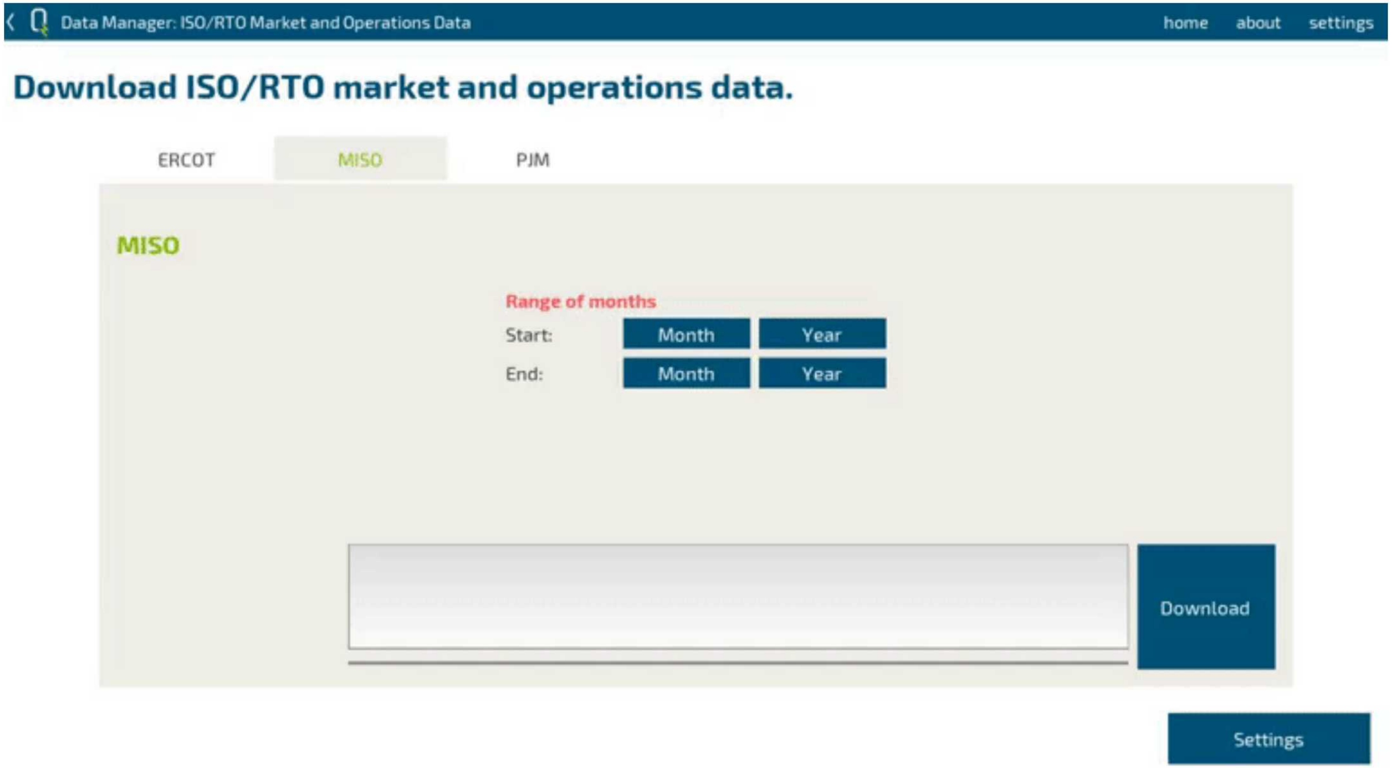
QuESt, a Python-based, open source energy storage software suite, has been released by the Sandia energy storage software tool team that developed it. QuEST is an open source, Python-based software application suite for energy storage simulation and analysis. It is designed to give users access to models and analysis for energy storage used and developed by Sandia National Laboratories. It is also designed to be transparent and easy to use without requiring knowledge of the mathematics behind the models or knowing how to develop code in Python. At the same time, because it is open source, users may modify it to suit their needs.

The launch version includes QuESt Data Manager, an application for obtaining market data from ISO/RTO sources, as well as QuESt Valuation, an application for performing energy storage system valuation (revenue estimation) in different market areas. Three different market areas (ERCOT, PJM, MISO) are initially supported, and more are in rapid development.

Here's how much revenue the device generated each month.

Revenue was generated based on participation in the selected revenue streams. The gross revenue generated over the evaluation period was **$1,863,440.02**. The highest revenue in a month was **$224,821.51**, generated in **October**. The lowest revenue in a month was **$99,229.15**, generated in **January**.

QuEST Data Manager



Download ISO/RTO market and operations data.

MISO

Range of months

Start: Month Year

End: Month Year

- Uses "web crawling" to search ISO/RTO website for download links
- Uses API provided by ISO/RTO to make queries
- Prepares a data bank for use in other applications, e.g., QuESt Valuation
  - Downloads and extracts compressed archives
  - Formats API query results
  - Names files and creates directory structure to keep track of what's been downloaded

Valuation: Energy Arbitrage Example

Formulate and solve linear program.

Data: day ahead Locational Marginal Price (LMP), ESS capacity, ESS power rating

Variables: charge and discharge schedules

(QuESt also currently supports participating in frequency regulation)

LMP

Power discharged

Power charged

$$\max_{u_k^d, u_k^c} \quad \sum_k \lambda_k \left(u_k^d - u_k^c\right)$$

Revenue

$$\text{subject to} \quad x_{k+1} = \eta_s x_k + \eta_c u_k^c \tau - \frac{1}{\eta_d} u_k^d \tau$$

Linear dynamics

$$0 \leq x_k \leq \bar{x}$$

SoC bounds

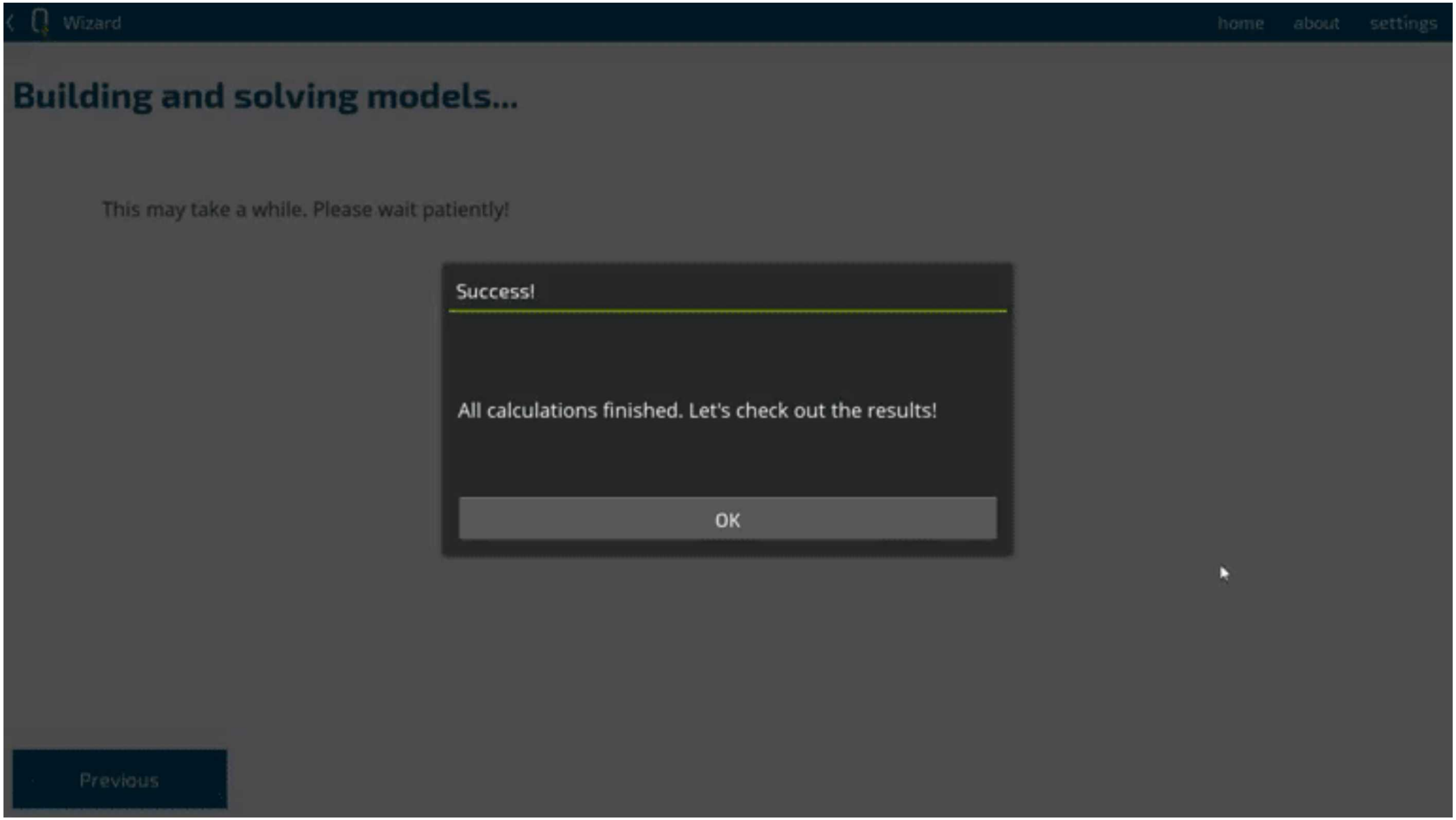
$$0 \leq u_k^c \leq \bar{u}$$

$$0 \leq u_k^d \leq \bar{u}$$

Charge/discharge bounds

QuESt Valuation Wizard

Quest Valuation Wizard – view results



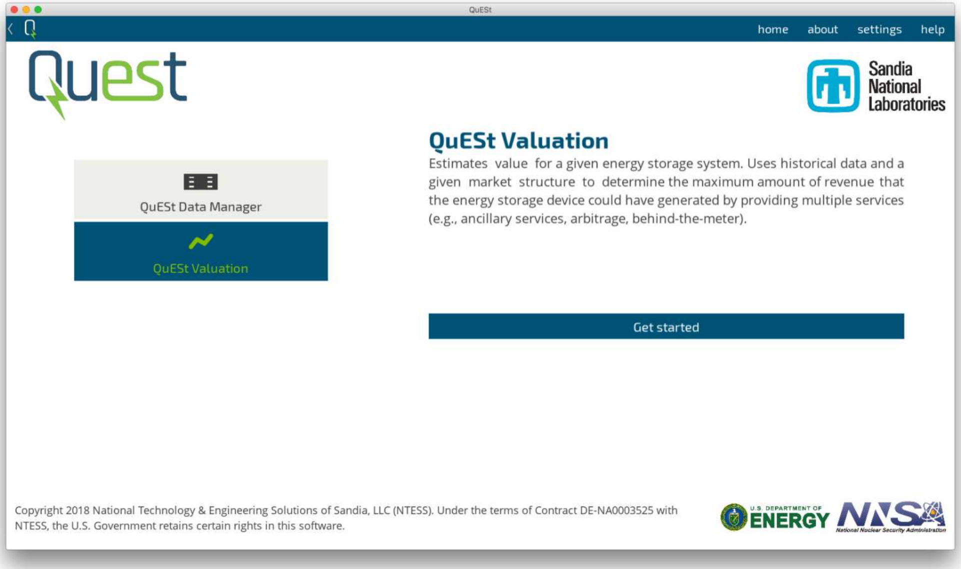
Building and solving models...

This may take a while. Please wait patiently!

Success!

All calculations finished. Let's check out the results!

Quest in the future



QuESt

home about settings help

Quest

Sandia National Laboratories

QuESt Data Manager

QuESt Valuation

QuESt Valuation

Estimates value for a given energy storage system. Uses historical data and a given market structure to determine the maximum amount of revenue that the energy storage device could have generated by providing multiple services (e.g., ancillary services, arbitrage, behind-the-meter).

Get started

U.S. DEPARTMENT OF ENERGY NNSA National Nuclear Security Administration

- Add support in QuESt Valuation/Data Manager for the remaining US markets.
- Additional energy storage models, such as degradation
- New applications
  - Behind-the-meter ES sizing and valuation
    - Solar + storage
  - Technology selection assistant
  - Data explorer for ES finance information (leverage global energy storage database)

Inquiries to:

Ricky Concepcion, 8813

rconcep@sandia.gov

Follow us on GitHub:

github.com/rconcep/snl-quest

Outline

- **Solving grid challenges with energy storage**
  - Drivers of grid modernization
  - How can energy storage help?
- **Sandia's energy storage program**
- **Analytics and controls thrust**
  - Analysis, optimization, and control of energy storage
  - QuESt open-source software suite
  - Optimal, adaptive, real-time dispatch

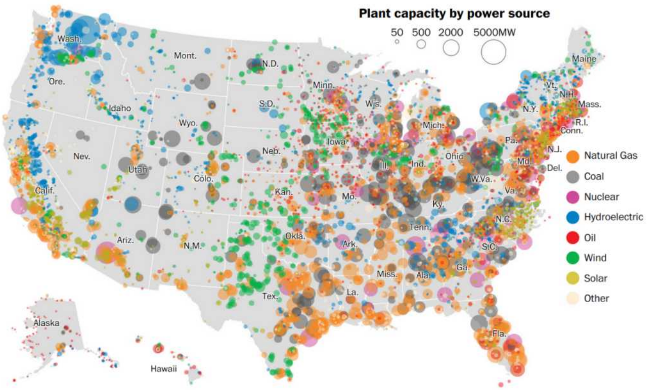
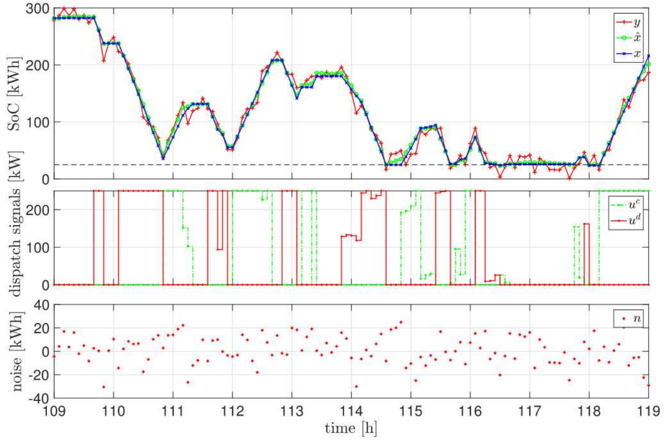
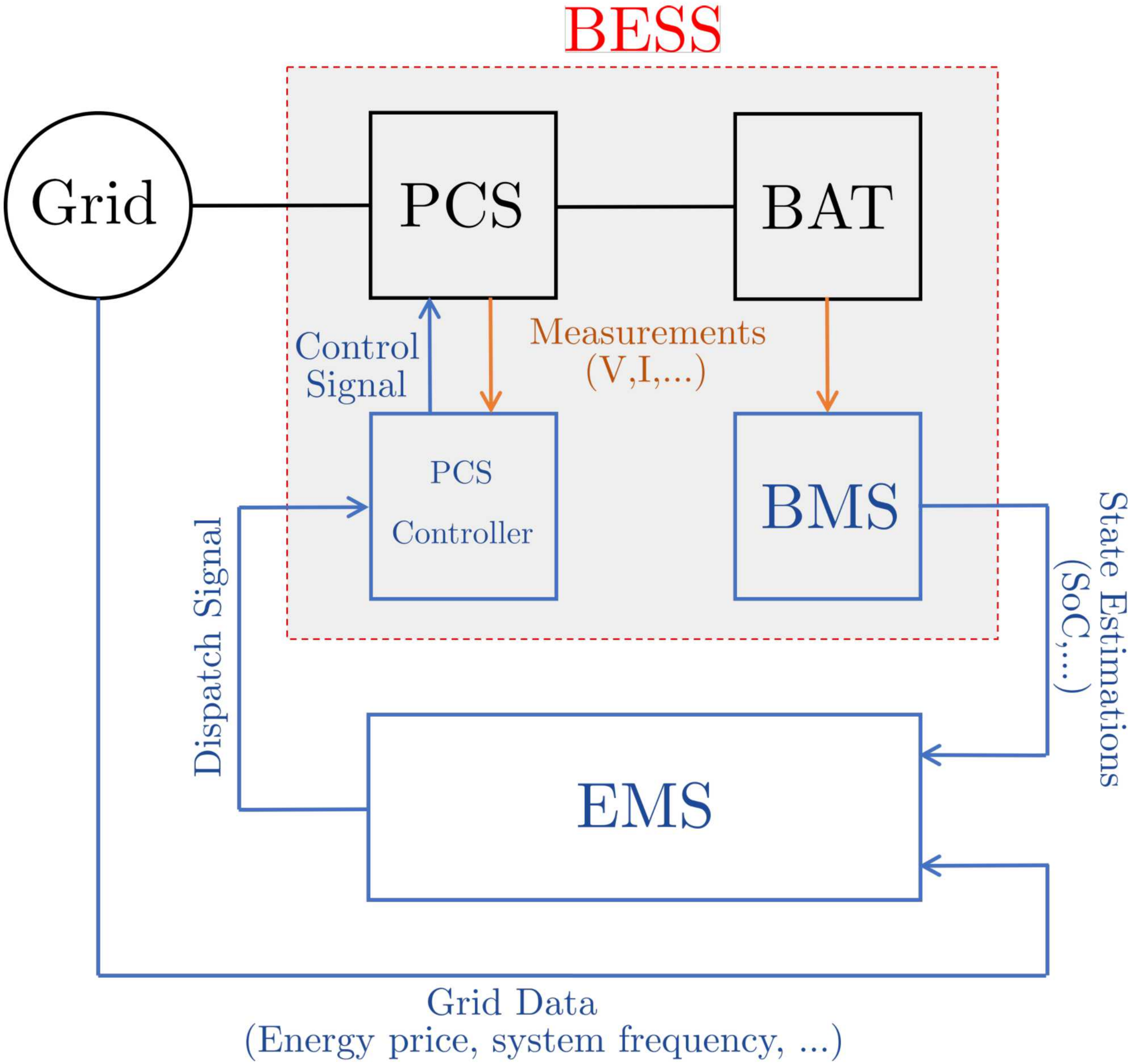


Image credit: Washington Post



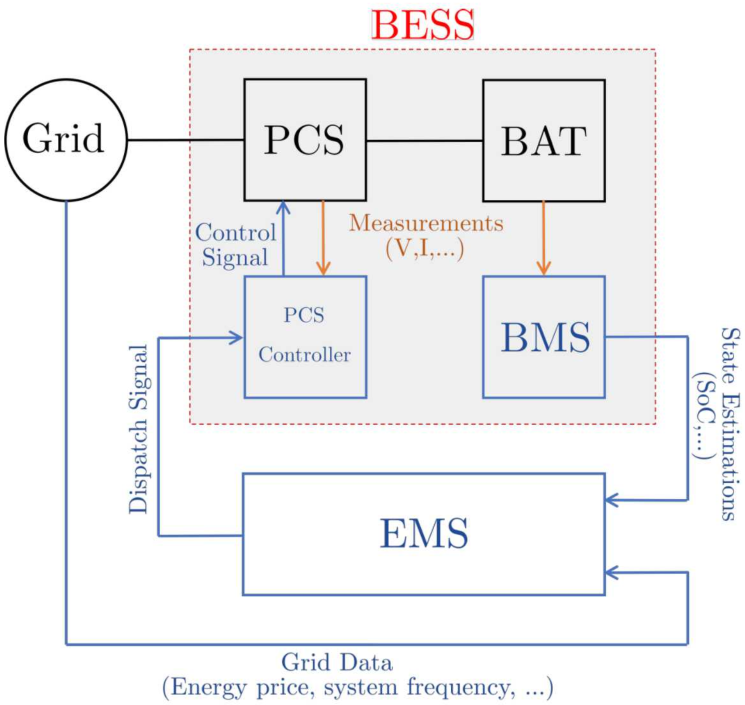
Battery Energy Storage System (BESS)



System/Process

Estimation & Control

Challenges



1) Often not yet cost effective or optimally utilized. Need:
   a) Optimal deployment and operation in existing environment
   b) New market design to accommodate and compensate new resource capabilities
   c) Modeling, analysis, testing
      i. Models range from cells to systems:
         - Often too complicated (computationally intractable)
         - Or too simple (reasonable for analysis but not realistic enough for control)
         - Safety

Energy flow models for Energy Management System (EMS):

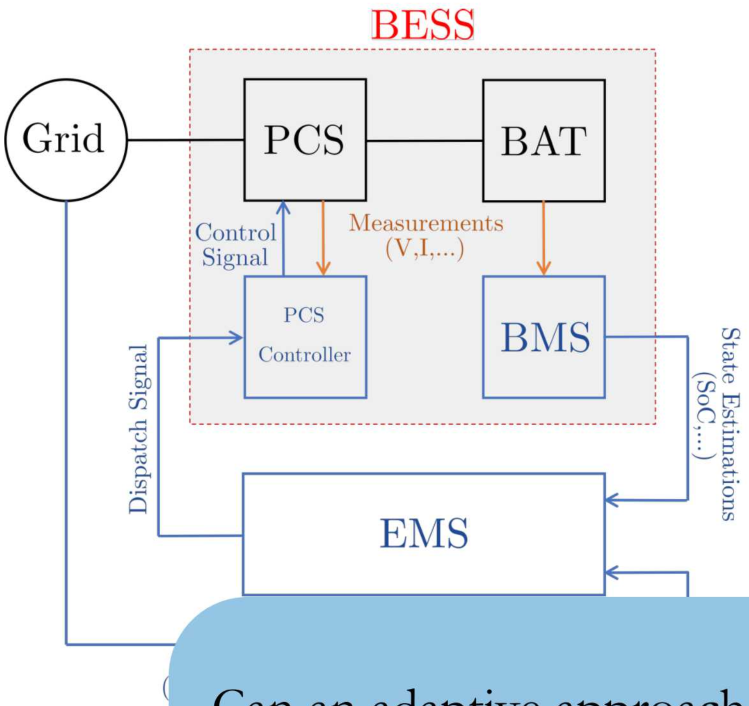
$$x_{k+1} = \eta_s x_k + f_k^c(x_k, u_k^c, \ldots)\tau - f_k^d(x_k, u_k^d, \ldots)\tau$$

Nonlinear dynamics

$$x_{k+1} = \eta_s x_k + \eta_c u_k^c \tau - \frac{1}{\eta_d} u_k^d \tau$$

Linear dynamics

Challenges



1) Often not yet cost effective or optimally utilized. Need:
   a) Optimal deployment and operation in existing environment
   b) New market design to accommodate and compensate new resource capabilities
   c) Modeling, analysis, testing
      i. Models range from cells to systems:
         - Often too complicated (computationally intractable)
         - Or too simple (reasonable for analysis but not

Can an adaptive approach effectively capture the nonlinear dynamics and maintain computational tractability?

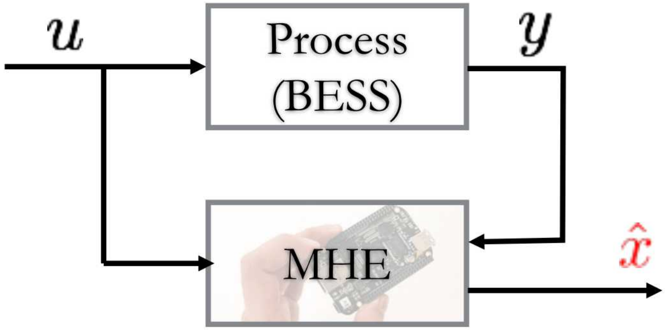
Energ

$$x_{k+1} = \eta_s x_k + f_k^c(x_k, u_k^c, \ldots)\tau - f_k^d(x_k, u_k^d, \ldots)\tau$$ Nonlinear dynamics

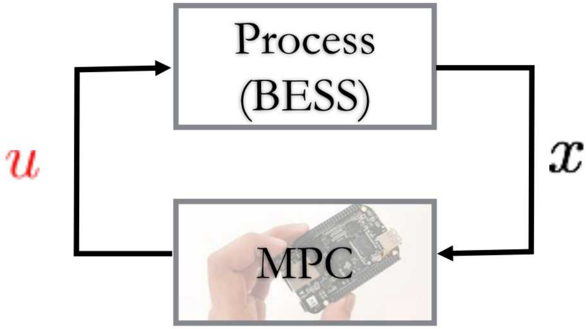
$$x_{k+1} = \eta_s x_k + \eta_c u_k^c \tau - \frac{1}{\eta_d} u_k^d \tau$$ Linear dynamics

Online Optimization in Feedback Control

Moving Horizon Estimation (MHE)

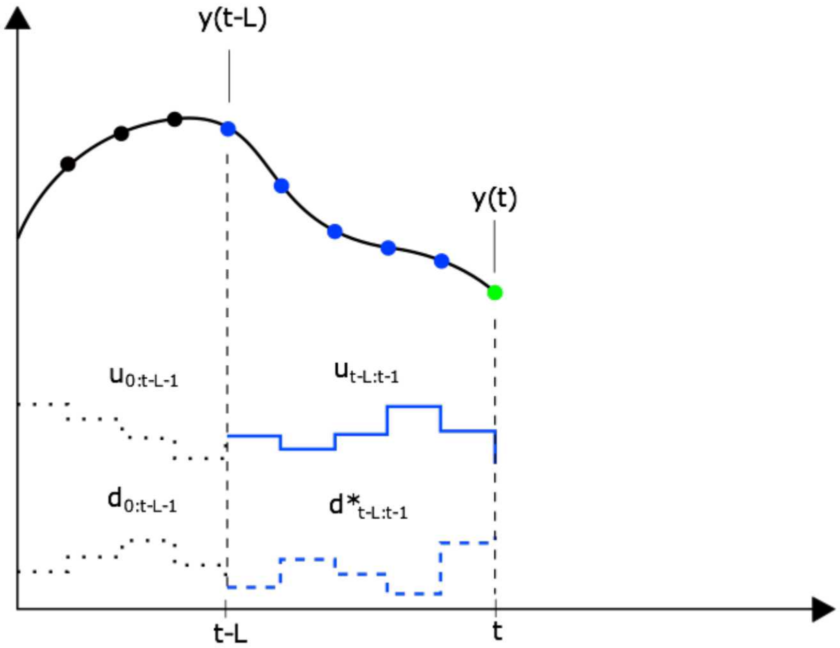


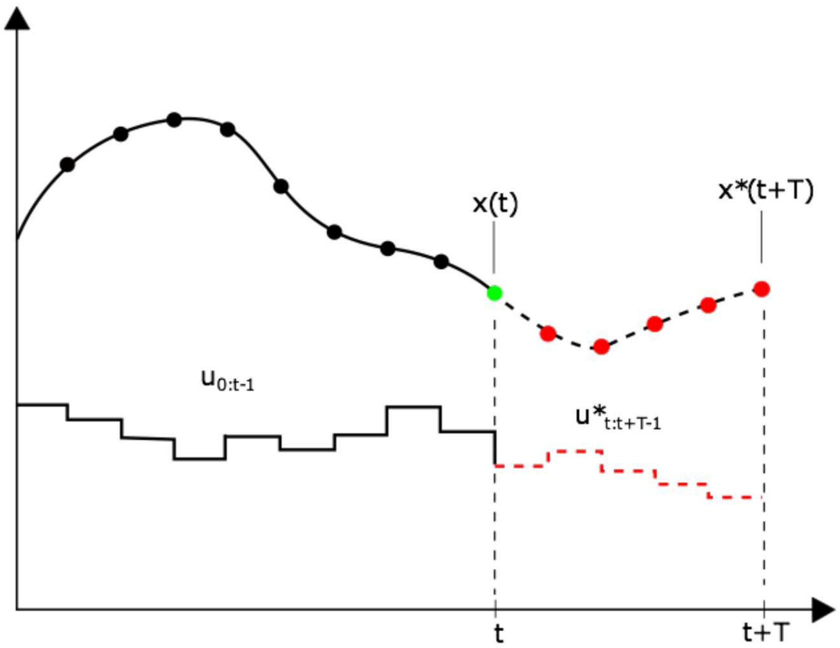
Model Predictive Control (MPC)



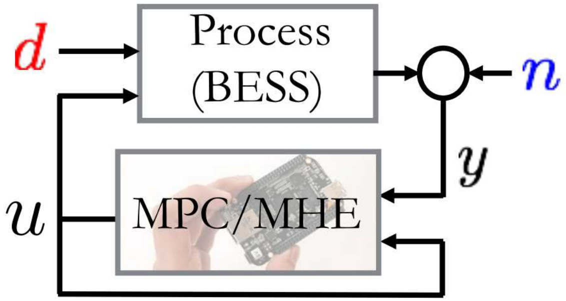
Finite-horizon online optimization problems that handle:

- nonlinear dynamics
- constraints
- sophisticated noise/disturbance models (MHE)



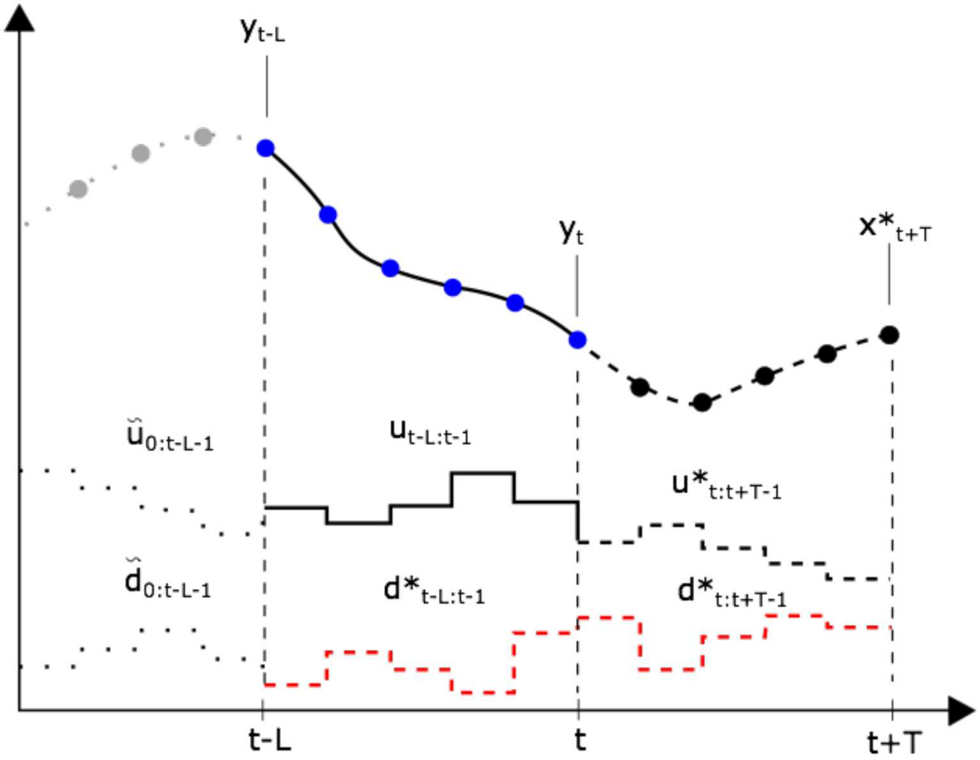


Combined MPC + MHE

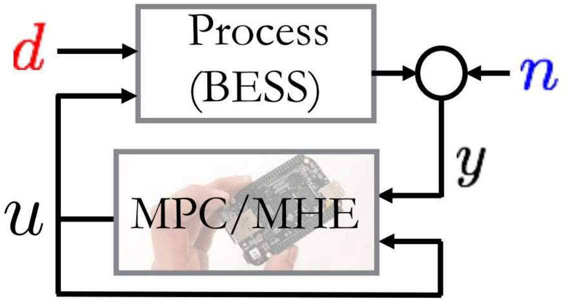


process dynamics:

$$x_{t+1} = f(x_t, u_t, d_t)$$
$$y_t = g(x_t) + n_t$$



Combined MPC + MHE



process dynamics:

$$x_{t+1} = f(x_t, u_t, d_t)$$
$$y_t = g(x_t) + n_t$$

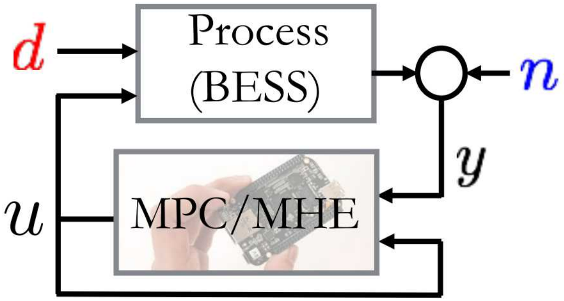
Why combine MPC + MHE in a single optimization?

1. [Theory] Enables stability analysis of the closed-loop.
2. [Practice] Resulting controller protects system against potentially optimistic/naïve state estimates

Is it too conservative?

Not necessarily, since one can control conservativeness by penalizing unlikely disturbances/noise.

MPC/MHE Theory and References

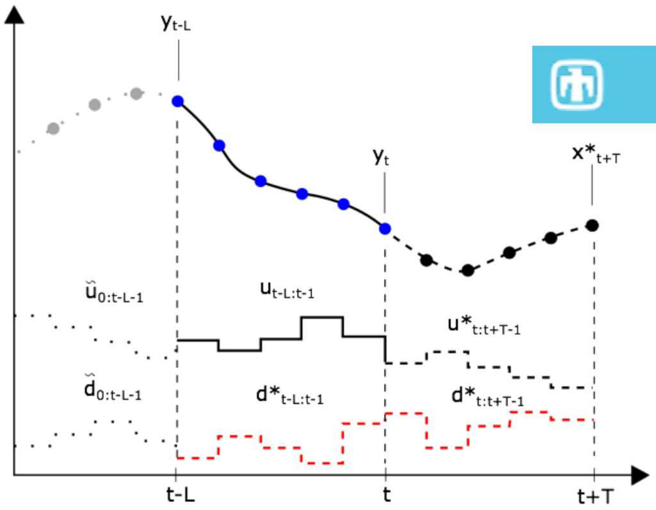


process dynamics:

$$x_{t+1} = f(x_t, u_t, d_t)$$
$$y_t = g(x_t) + n_t$$

Stability Theory	Controllability Observability Saddle-point solution → closed-loop stability
Numerical Optimization	primal-dual-like interior-point method
Applications	online parameter estimation, artificial pancreas, UAV coordination
References	Copp, Hespanha, ***Automatica***, 2017. Copp, Gondhalekar, Hespanha, ***OCAM***, 2017. Copp, Hespanha, ***Control of Complex Systems***, 2016. Copp, Hespanha, ***ACC***, 2016. Quintero, Copp, Hespanha, **ACC**, 2015. Copp, Hespanha, ***CDC***, 2014.

Adaptive MPC/MHE



Past control inputs

Past measurements

Future control inputs

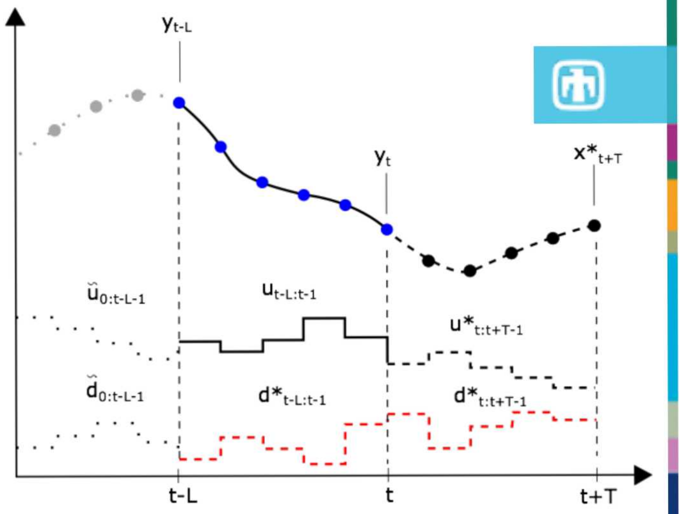
State estimates/predictions

Estimated efficiencies

$$\min_{\hat{\mathbf{u}}} \max_{\underline{\hat{\eta}_c, \hat{\eta}_d}, \hat{\mathbf{x}}} \quad J_k(\hat{\mathbf{x}}, \mathbf{u}, \hat{\mathbf{u}}, \mathbf{y}, \hat{\eta}_c, \hat{\eta}_d)$$

Copp, Nguyen, Byrne. **Submitted**, 2018.

Adaptive MPC/MHE



State estimates/predictions

Past control inputs

Future control inputs

Past measurements

Estimated efficiencies

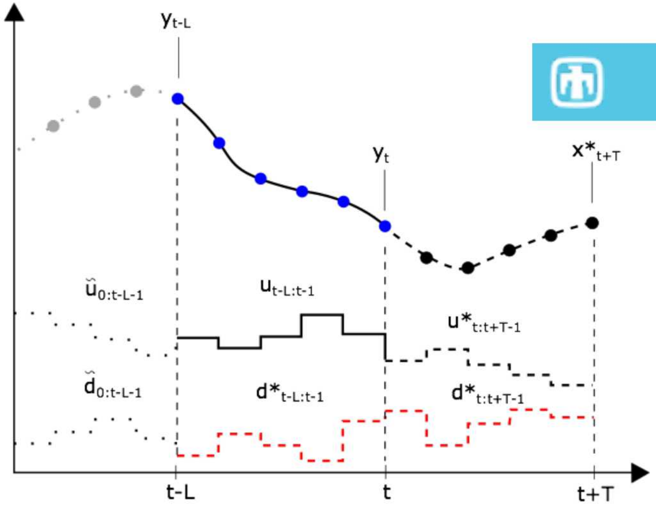
$$\min_{\hat{\mathbf{u}}} \max_{\hat{\eta}_c, \hat{\eta}_d, \hat{\mathbf{x}}} \quad J_k(\hat{\mathbf{x}}, \mathbf{u}, \hat{\mathbf{u}}, \mathbf{y}, \hat{\eta}_c, \hat{\eta}_d)$$

$$\text{subject to} \quad \hat{u}_k \leq \bar{u}$$

ESS power rating

Copp, Nguyen, Byrne. **Submitted**, 2018.

Adaptive MPC/MHE



State estimates/predictions

Past control inputs

Future control inputs

Past measurements

Estimated efficiencies

$$\min_{\hat{\mathbf{u}}} \ \max_{\hat{\eta}_c,\hat{\eta}_d,\hat{\mathbf{x}}} \quad J_k(\hat{\mathbf{x}}, \mathbf{u}, \hat{\mathbf{u}}, \mathbf{y}, \hat{\eta}_c, \hat{\eta}_d)$$

$$\text{subject to} \quad \hat{u}_k \leq \bar{u}$$

ESS power rating

$$0 \leq \hat{x}_k + \hat{\eta}_c \hat{u}_k \tau - \frac{1}{\eta_d} \hat{u}^d_k \tau \leq \bar{x}$$

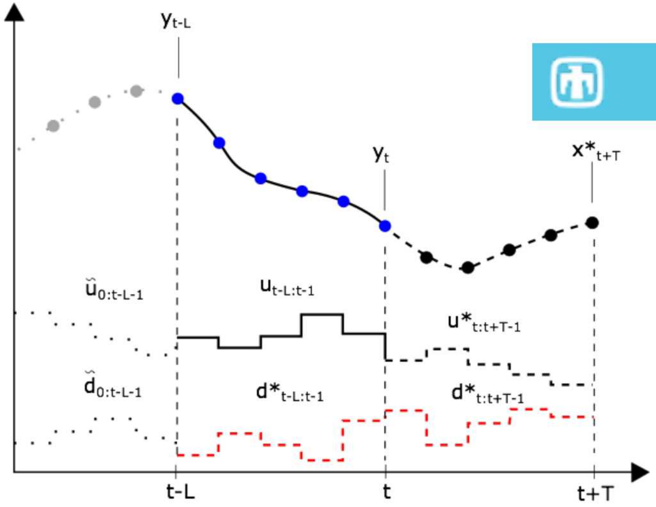
$$\delta \bar{x} \leq \hat{x}_k + \hat{\eta}_c \hat{u}_k \tau - \frac{1}{\eta_d} \hat{u}^d_k \tau \leq \bar{x} - \delta \bar{x}$$

ESS linear dynamics

Desired fraction of unused SoE

Copp, Nguyen, Byrne. **Submitted**, 2018.

Adaptive MPC/MHE



State estimates/predictions

Past control inputs

Future control inputs

Past measurements

Estimated efficiencies

$$\min_{\hat{\mathbf{u}}} \max_{\hat{\eta}_c, \hat{\eta}_d, \hat{\mathbf{x}}} \quad J_k(\hat{\mathbf{x}}, \mathbf{u}, \hat{\mathbf{u}}, \mathbf{y}, \hat{\eta}_c, \hat{\eta}_d)$$

$$\text{subject to} \quad \hat{u}_k \leq \bar{u}$$

ESS power rating

$$0 \leq \hat{x}_k + \hat{\eta}_c \hat{u}_k \tau - \frac{1}{\eta_d} \hat{u}_k^d \tau \leq \bar{x}$$

$$\delta \bar{x} \leq \hat{x}_k + \hat{\eta}_c \hat{u}_k \tau - \frac{1}{\eta_d} \hat{u}_k^d \tau \leq \bar{x} - \delta \bar{x}$$

ESS linear dynamics

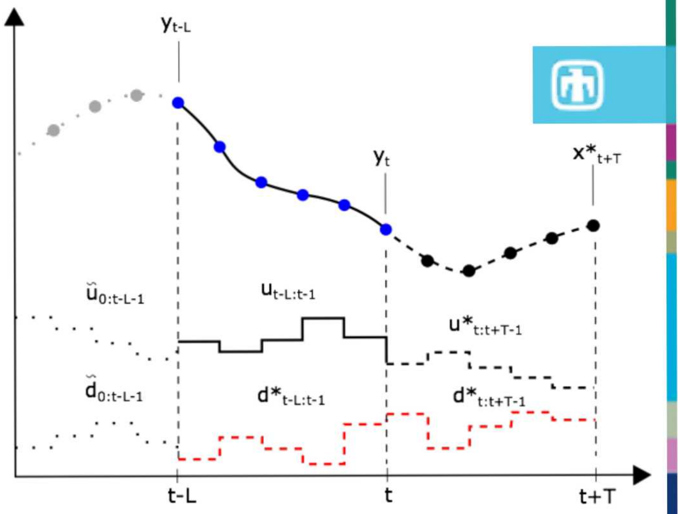
Desired fraction of unused SoE

$$\hat{x}_k = y_k - \hat{n}_k$$

Output equation

Copp, Nguyen, Byrne. **Submitted**, 2018.

Adaptive MPC/MHE



State estimates/predictions

Past control inputs

Future control inputs

Past measurements

Estimated efficiencies

$$\min_{\hat{\mathbf{u}}} \max_{\hat{\eta}_c,\hat{\eta}_d,\hat{\mathbf{x}}} \quad J_k(\hat{\mathbf{x}}, \mathbf{u}, \hat{\mathbf{u}}, \mathbf{y}, \hat{\eta}_c, \hat{\eta}_d)$$

$$\text{subject to} \quad \hat{u}_k \leq \bar{u}$$

ESS power rating

$$0 \leq \hat{x}_k + \hat{\eta}_c \hat{u}_k \tau - \frac{1}{\eta_d} \hat{u}_k^d \tau \leq \bar{x}$$

$$\delta\bar{x} \leq \hat{x}_k + \hat{\eta}_c \hat{u}_k \tau - \frac{1}{\eta_d} \hat{u}_k^d \tau \leq \bar{x} - \delta\bar{x}$$

Desired fraction of unused SoE

ESS linear dynamics

$$\hat{x}_k = y_k - \hat{n}_k$$

Output equation

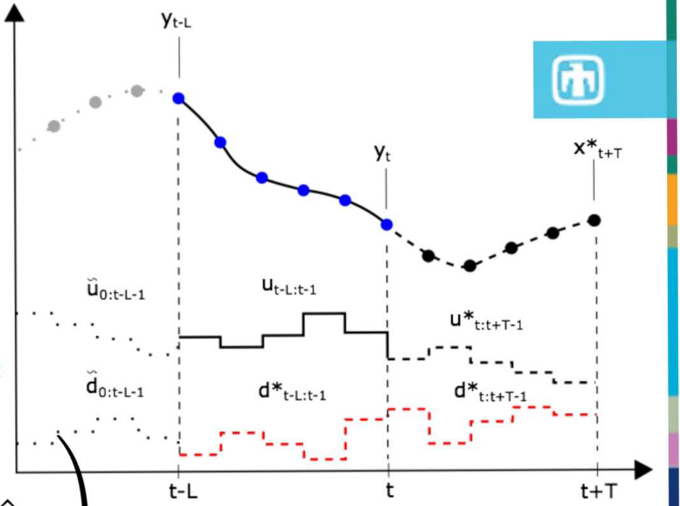
$$\eta_c^{\min} \leq \hat{\eta}_c \leq \eta_c^{\max}$$

$$\eta_f^{\min} \leq \hat{\eta}_d \leq \eta_d^{\max}$$

Bounds on efficiencies

Copp, Nguyen, Byrne. **Submitted**, 2018.

Example: Energy Arbitrage



Real-time energy price

Power charge

Power discharge

Time step

Weight*Noise

$$\min_{\hat{\mathbf{u}}} \max_{\hat{\eta}_c,\hat{\eta}_d,\hat{\mathbf{x}}} \left(\underbrace{\sum_{k=t}^{t+T-\tau} \lambda_k(\hat{u}_k^c - \hat{u}_k^d)\tau}_{\text{arbitrage}} - \underbrace{\sum_{k=t-L}^{t} w\hat{n}_k}_{\text{estimation}} \right)$$

$$\text{subject to} \quad \hat{u}_k \le \bar{u}$$

ESS power rating

$$0 \le \hat{x}_k + \hat{\eta}_c\hat{u}_k\tau - \frac{1}{\eta_d}\hat{u}_k^d\tau \le \bar{x}$$

$$\delta\bar{x} \le \hat{x}_k + \hat{\eta}_c\hat{u}_k\tau - \frac{1}{\eta_d}\hat{u}_k^d\tau \le \bar{x} - \delta\bar{x}$$

Desired fraction of unused SoE

ESS linear dynamics

$$\hat{x}_k = y_k - \hat{n}_k$$

Output equation

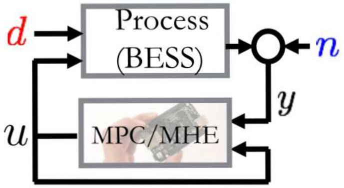
$$\eta_c^{\min} \le \hat{\eta}_c \le \eta_c^{\max}$$

$$\eta_f^{\min} \le \hat{\eta}_d \le \eta_d^{\max}$$

Bounds on efficiencies

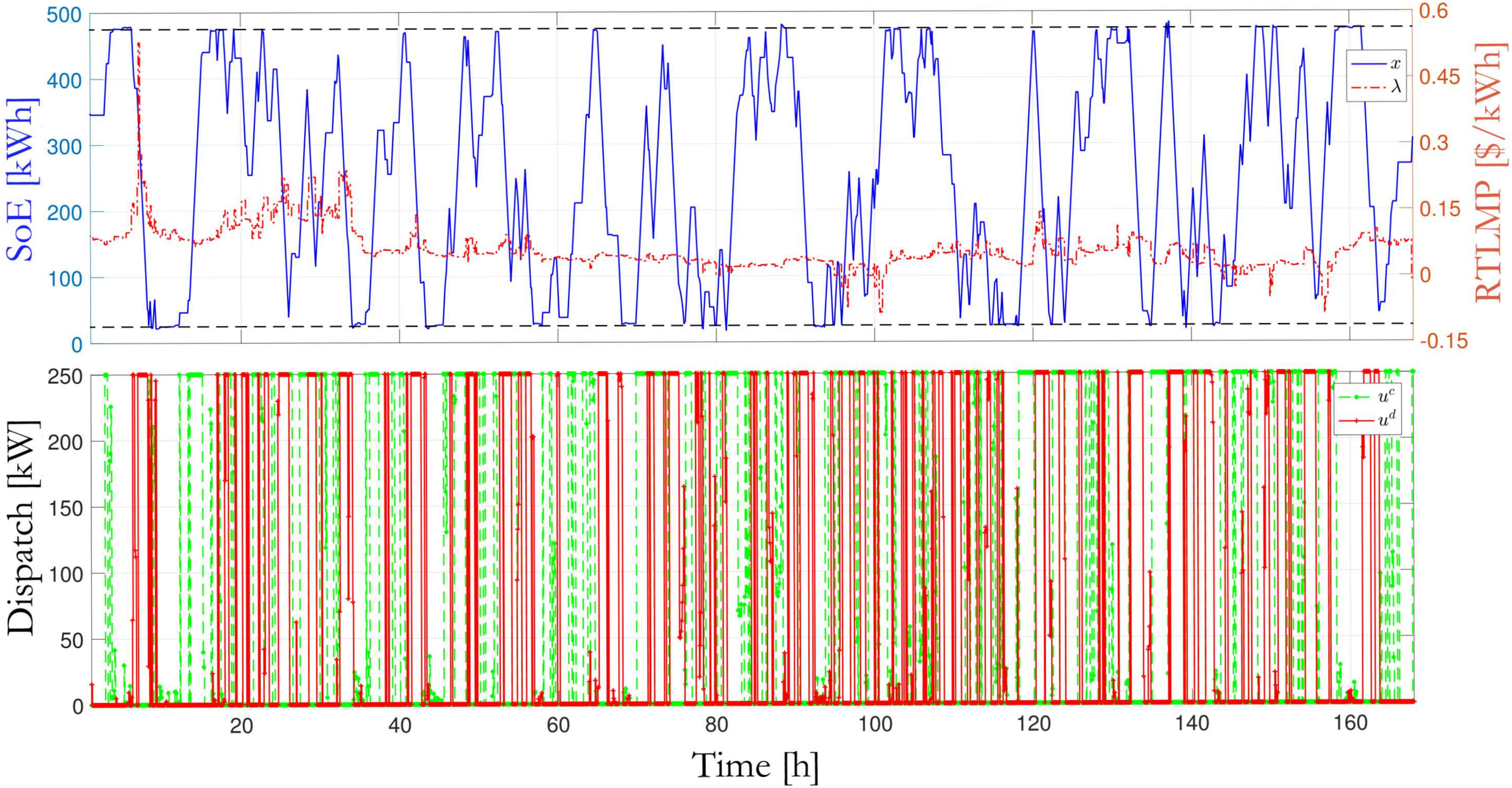
Copp, Nguyen, Byrne. **Submitted**, 2018.

Adaptive MPC: Results for January 18-24, 2018



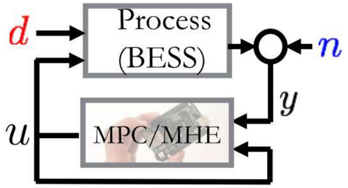
Process: Nonlinear Li-ion BESS model

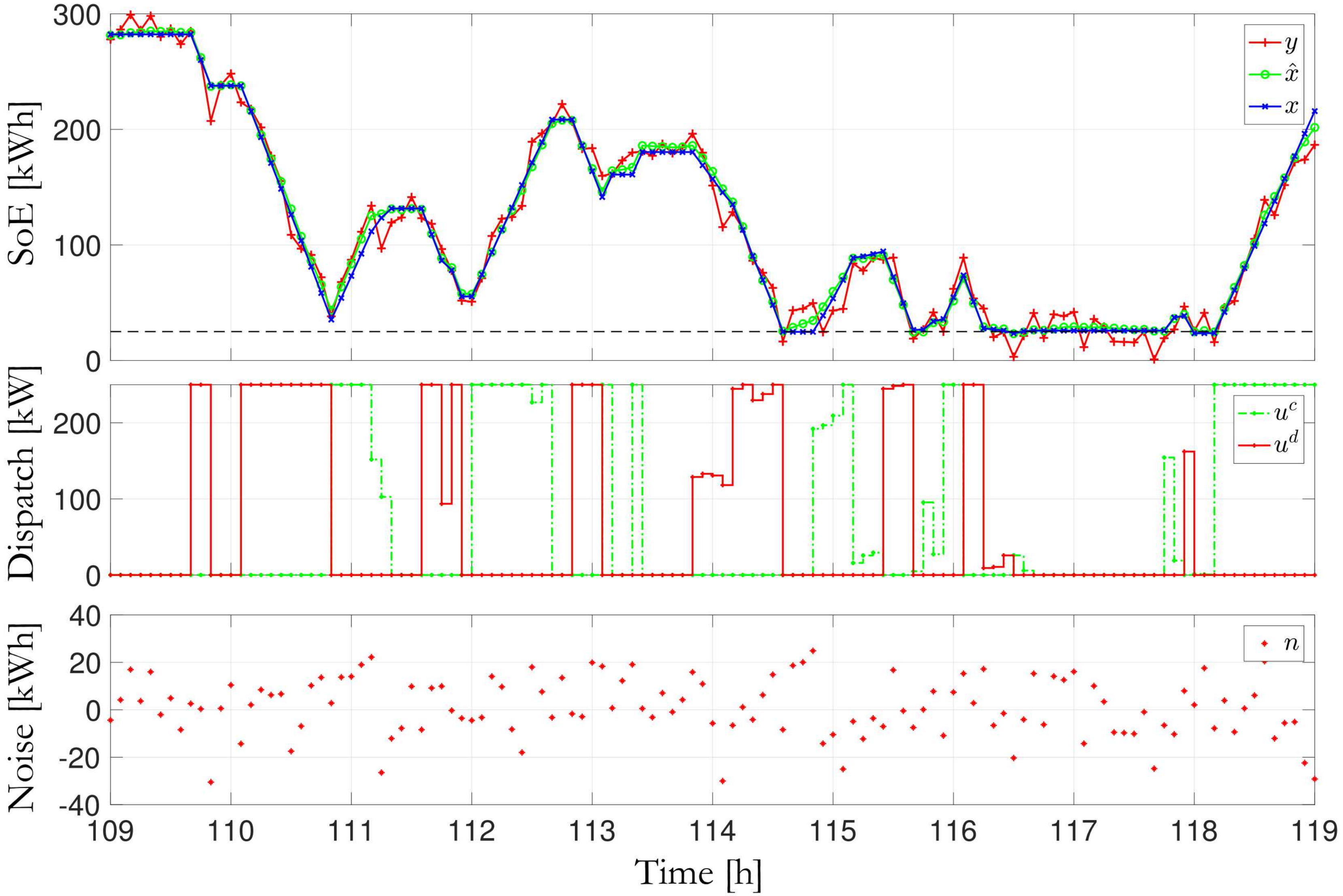
Predictive model: adaptive linear energy flow



Copp, Nguyen, Byrne. **Submitted**, 2018.

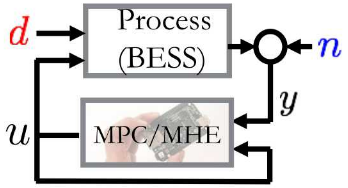
Adaptive MPC: Results for January 18-24, 2018

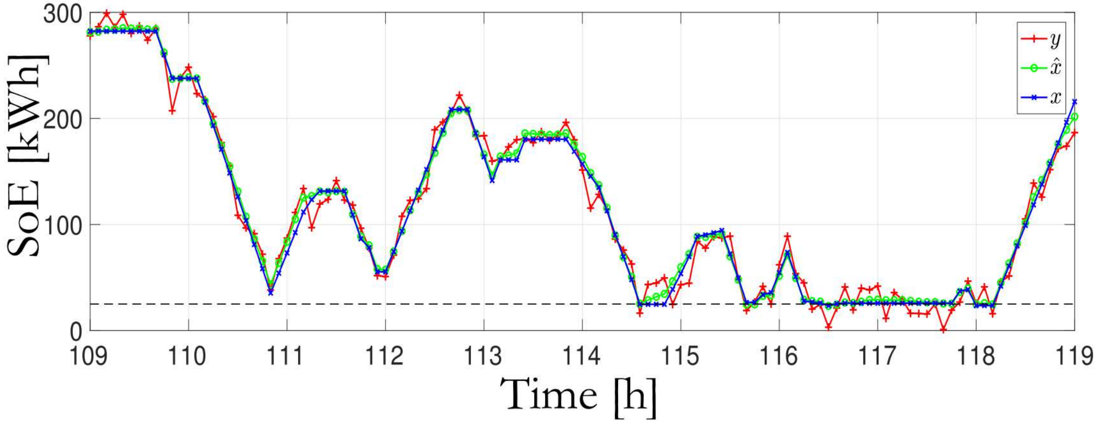


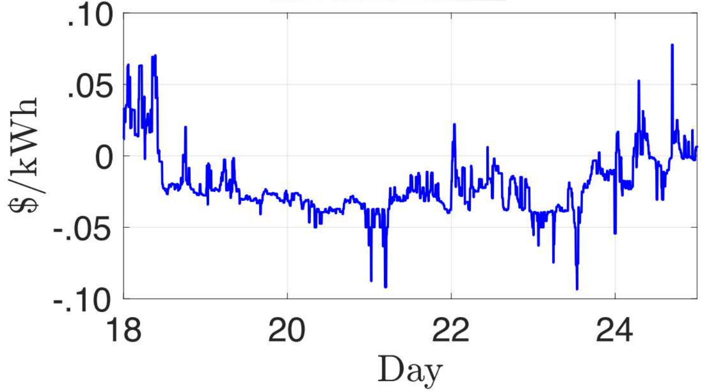


Copp, Nguyen, Byrne. **Submitted**, 2018.

Results Comparison







Using 5-minute real-time energy prices from East Cambridge node in ISO New England...

Results for January 18-24, 2018.

Case	Revenue	RMSE of $\hat{x}$	Constraint violation ϵ
Adaptive	\$439.30	3.63	36.87
$\eta_c = \eta_d = 0.90$	\$437.78	13.44	168.14
$\eta_c = \eta_d = 0.91$	\$441.73	11.36	150.92
$\eta_c = \eta_d = 0.92$	\$443.49	6.52	101.34
$\eta_c = \eta_d = 0.93$	\$442.85	5.96	130.50

Advantages:
1) Significantly improved state estimation
2) Significantly less constraint violation

Copp, Nguyen, Byrne. **Submitted**, 2018.

Acknowledgements

Funding provided by US DOE Energy Storage Program managed by Dr. Imre Gyuk of the DOE Office of Electricity Delivery and Energy Reliability.

U.S. DEPARTMENT OF
ENERGY

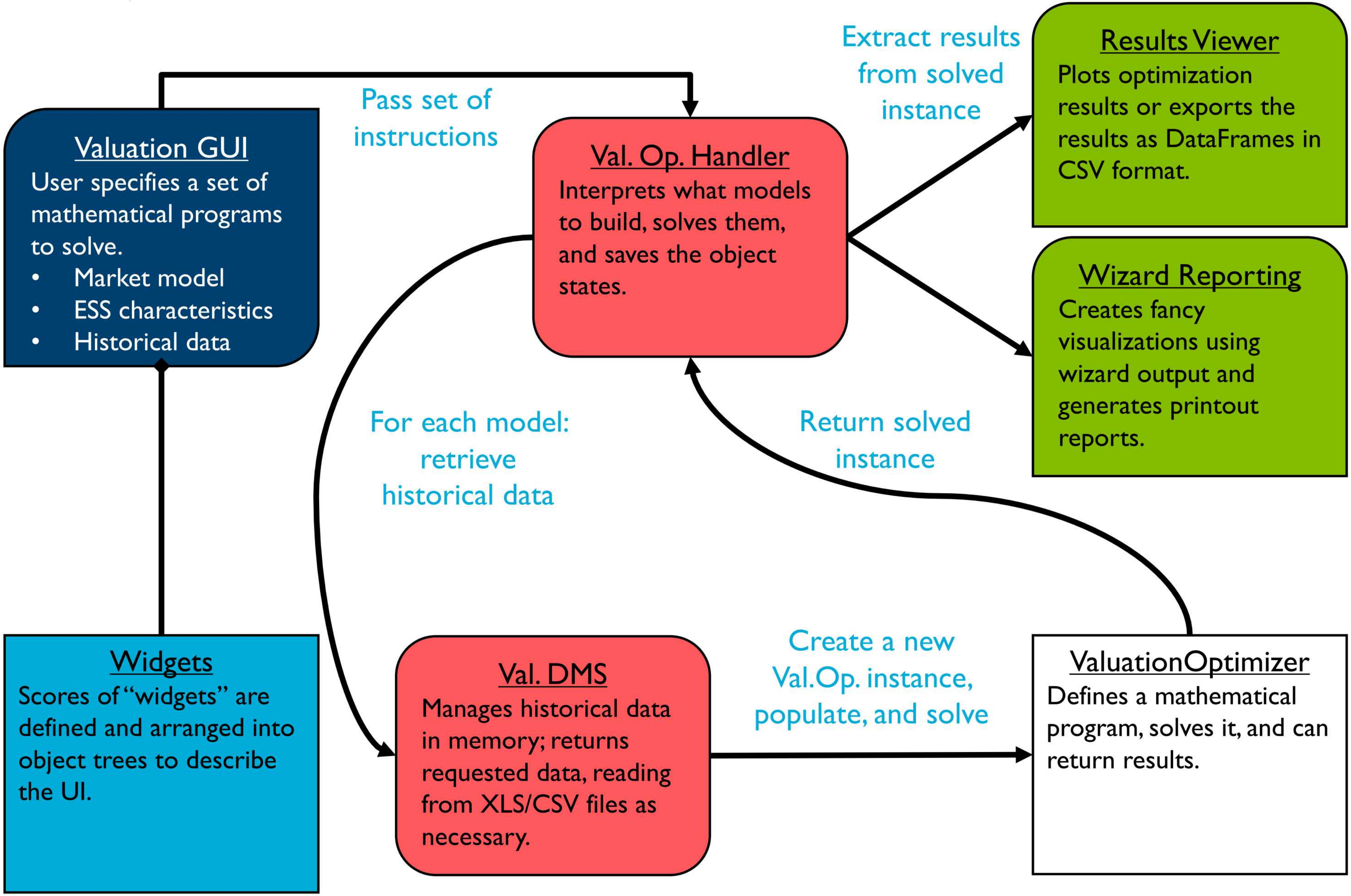
Colleagues:
Tu Nguyen
Felipe Wilches-Bernal
Ricky Concepcion
David Schoenwald
Ray Byrne
Babu Chalamala

dcopp@sandia.gov

Thank you.

Extra slides

Quest Valuation Software Architecture



Valuation GUI

User specifies a set of mathematical programs to solve.

- Market model
- ESS characteristics
- Historical data

Pass set of instructions

Val. Op. Handler

Interprets what models to build, solves them, and saves the object states.

Extract results from solved instance

Results Viewer

Plots optimization results or exports the results as DataFrames in CSV format.

Wizard Reporting

Creates fancy visualizations using wizard output and generates printout reports.

For each model: retrieve historical data

Return solved instance

Widgets

Scores of "widgets" are defined and arranged into object trees to describe the UI.

Val. DMS

Manages historical data in memory; returns requested data, reading from XLS/CSV files as necessary.

Create a new Val.Op. instance, populate, and solve

ValuationOptimizer

Defines a mathematical program, solves it, and can return results.

Energy Storage Analytics

Equitable Regulatory Environment Thrust Area

Goals: Lower barriers to widespread deployment of energy storage by identifying new and existing value streams, quantifying the impact of policy on deployment, and developing new control strategies

Objectives:

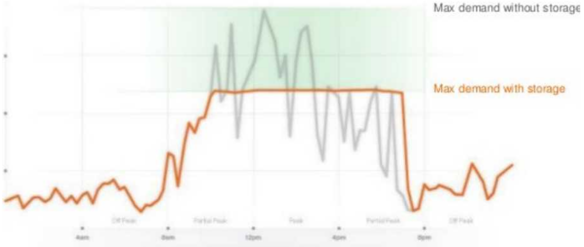
- Project case studies
- Tools for storage valuation
- Identify new value streams
- Control strategies to maximize revenue/grid benefit
- Assess policy impact on storage
- Develop policy recommendations

Energy Storage as Flexible Resource

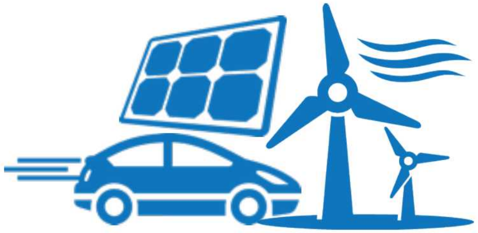
Grid-scale energy storage can enable significant cost savings to industry while improving infrastructure reliability and efficiency

Mitigate $79B/yr in commercial losses from outages

Reduce $2T in required T&D upgrades



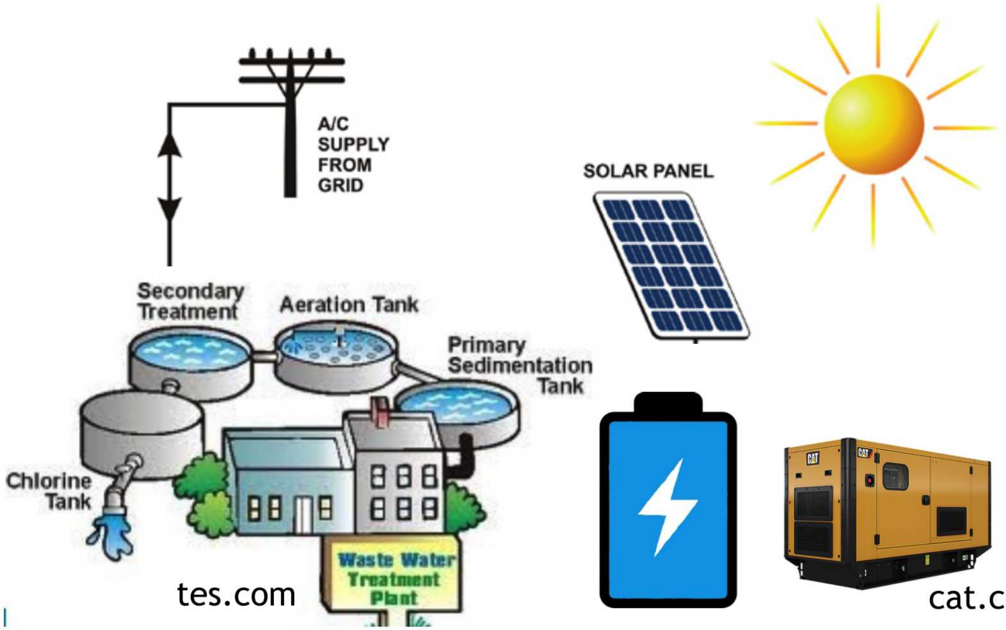
Reduce commercial and industrial electrical bills through demand charge management. 7.5 million U.S. customers are enrolled in dynamic pricing (EIA 2015)



Balance the variability of 825 GW of new renewable generation while improving grid reliability and efficiency.

U.S. DEPARTMENT OF ENERGY

Example: Optimal Sizing Behind-the-Meter Energy Storage

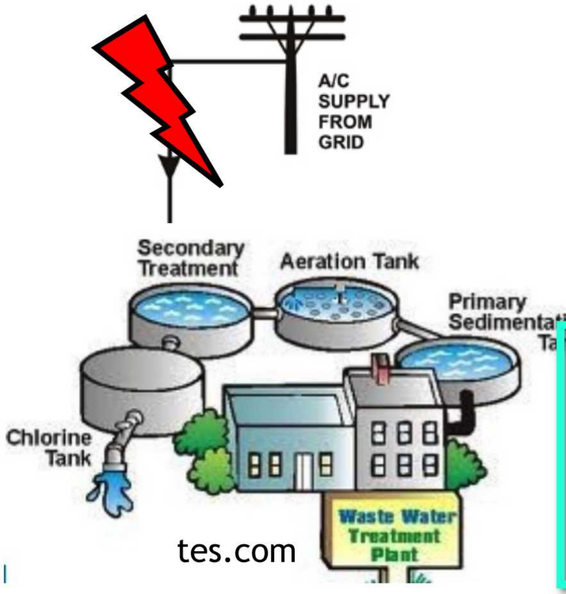


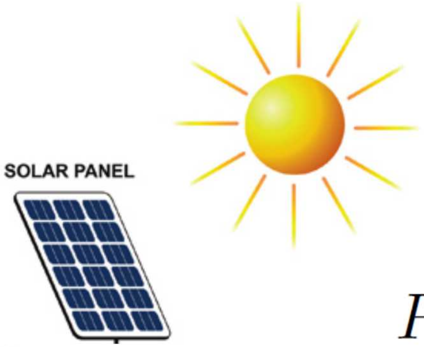
tes.com

cat.com

Copp, Nguyen, Byrne. **IEEE PESGM**, 2018.

Example: Optimal Sizing Behind-the-Meter Energy Storage





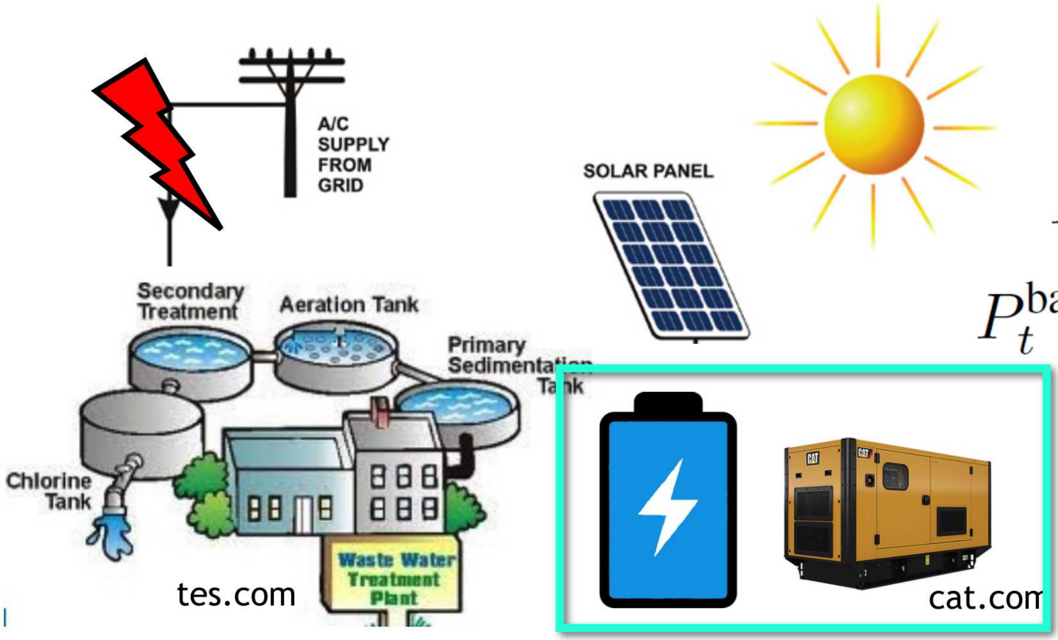
$$P_t^{\text{net}} = P_t^{\text{load}} - P_t^{\text{PV}}$$

$$P_t^{\text{balance}} = P_t^{\text{net}} + \underbrace{P_t^c - P_t^d - P_t^g}_{\text{Decision variables}}$$

minimize	energy from ES and generator to balance critical load
subject to	dynamics
	constraints

Copp, Nguyen, Byrne. **IEEE PESGM**, 2018.

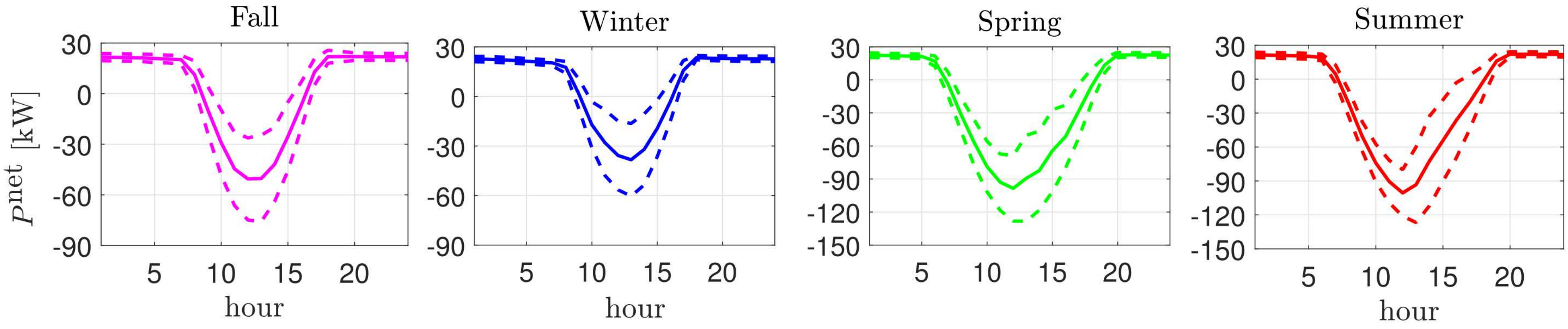
Example: Optimal Sizing Behind-the-Meter Energy Storage



$$P_t^{\text{net}} = P_t^{\text{load}} - P_t^{\text{PV}}$$

$$P_t^{\text{balance}} = P_t^{\text{net}} + \underbrace{P_t^c - P_t^d - P_t^g}_{\text{Decision variables}}$$

Stochastic optimization considering PV and load uncertainty.



Copp, Nguyen, Byrne. **IEEE PESGM**, 2018.

Stochastic Optimization

$$\min_{\mathbf{P}^c,\mathbf{P}^d,\mathbf{P}^g} \quad w_1\overline{S}_{\text{ESS}} + w_2\overline{S}_{\text{gen}} \qquad \forall t \in \mathcal{T}$$

Optimization horizon

subject to

$$\overline{S}_{\text{ESS}} \geq 0$$

ESS energy capacity

$$\sum_{t=1}^{T} P_t^g \leq \overline{S}_{\text{gen}}$$

Generator energy provided

$$P_t^c \geq 0$$

ESS charge

$$P_t^d \geq 0$$

ESS discharge

$$P_t^c + P_t^d \leq \overline{P}_{\text{ESS}}$$

ESS power rating

$$0 \leq P_t^g \leq \overline{P}_{\text{gen}}$$

Generator power rating

$$0 \leq \gamma_s S_t + \gamma_c P_t^c - P_t^d \leq \overline{S}_{\text{ESS}}$$

ESS SOC dynamics

$$\mathbb{P}\{P_t^{\text{net}} + P_t^c - P_t^d - P_t^g \leq 0\} \geq \alpha$$

Load balancing probabilistic constraint

Copp, Nguyen, Byrne. **IEEE PESGM**, 2018.

Stochastic Optimization

$$\min_{\mathbf{P}^c, \mathbf{P}^d, \mathbf{P}^g} \quad w_1 \overline{S}_{\text{ESS}} + w_2 \overline{S}_{\text{gen}} \qquad \forall t \in \mathcal{T}$$ Optimization horizon

subject to $\overline{S}_{\text{ESS}} \geq 0$ ESS energy capacity

If forecasts follow normal distributions…

→ probabilistic constraint can be formulated as a deterministic inequality constraint

Solve resulting Linear Program

$$0 \leq P_t^g \leq \overline{P}_{\text{gen}}$$ Generator power rating

$$0 \leq \gamma_s S_t + \gamma_c P_t^c - P_t^d \leq \overline{S}_{\text{ESS}}$$ ESS SOC dynamics

$$\mathbb{P}\{P_t^{\text{net}} + P_t^c - P_t^d - P_t^g \leq 0\} \geq \alpha$$ Load balancing probabilistic constraint

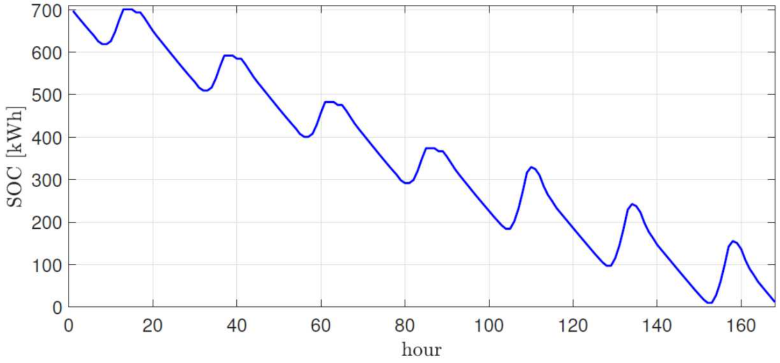
Copp, Nguyen, Byrne. **IEEE PESGM**, 2018.

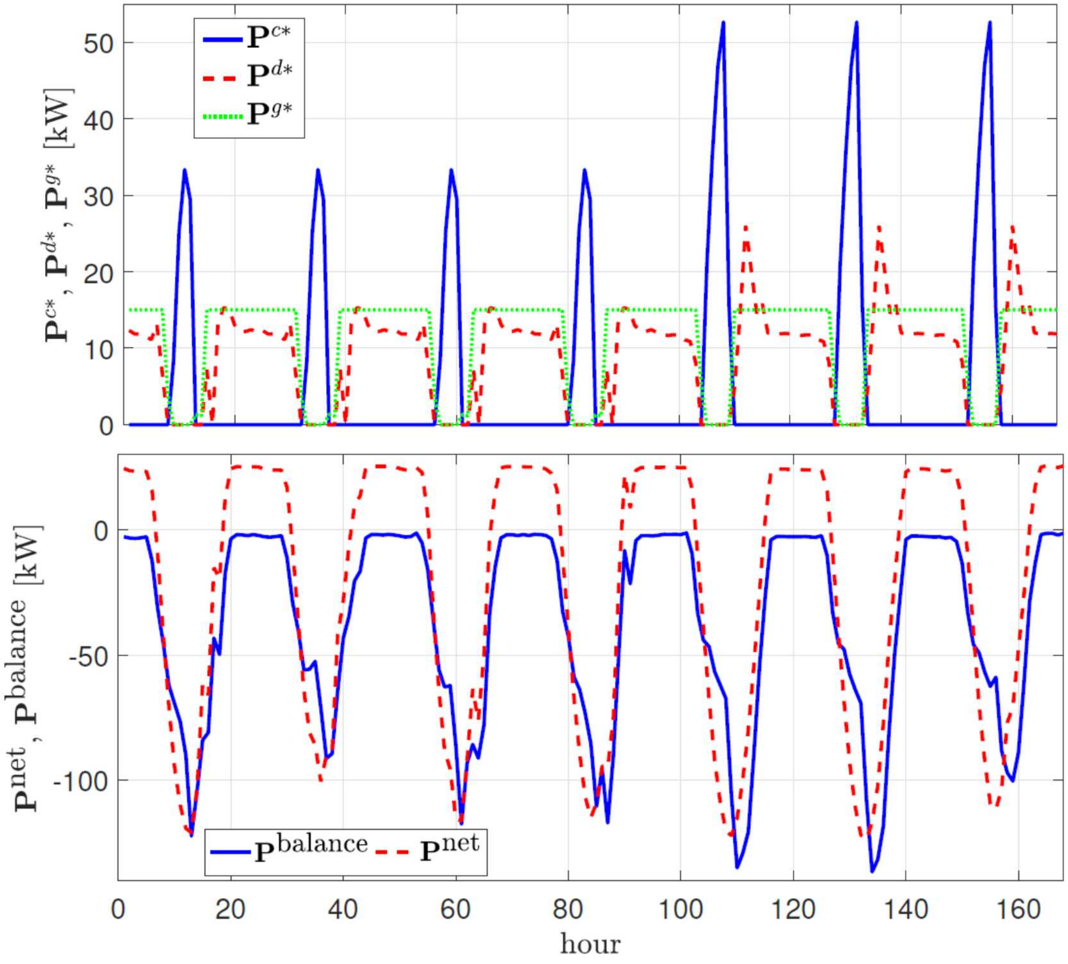
Results: Optimizing Behind-the-Meter Energy Storage

$$\min_{\mathbf{P}^c,\mathbf{P}^d,\mathbf{P}^g} \quad w_1\overline{S}_{\text{ESS}} + w_2\overline{S}_{\text{gen}}$$

May 28 – June 3, 2016

$\overline{S}^*_{\text{ESS}}$	871 kWh
$\overline{S}^*_{\text{gen}}$	1870 kWh





$$P_t^{\text{net}} = P_t^{\text{load}} - P_t^{\text{PV}}$$

$$P_t^{\text{balance}} = P_t^{\text{net}} + P_t^c - P_t^d - P_t^g$$

Copp, Nguyen, Byrne. **IEEE PESGM**, 2018.

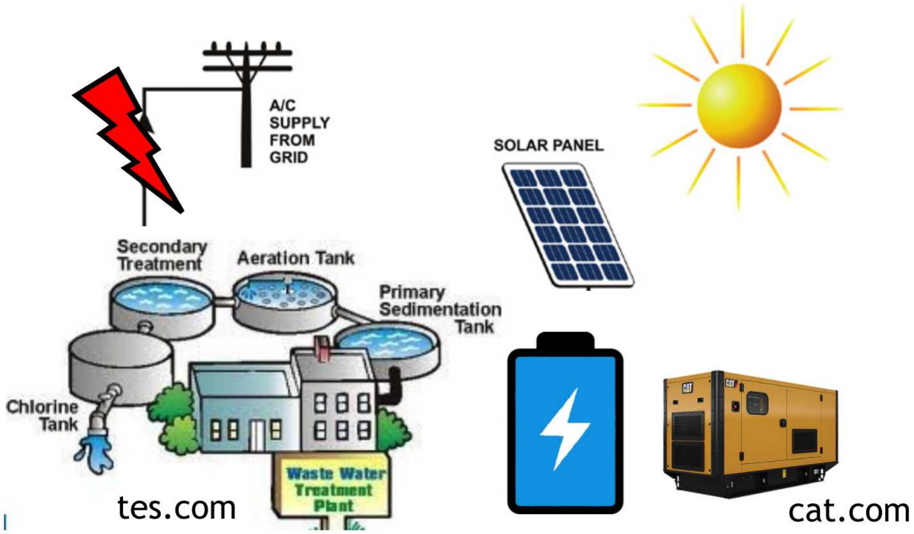
Parameters

Parameter	Description	Value	Units
h	Time step	1	hour
γ_{PV}	PV panel efficiency	0.15	-
γ_{conv}	PV conversion efficiency	0.90	-
γ_s	ESS storage efficiency	1.00	-
γ_c	ESS charging efficiency	0.85	-
A_{PV}	Total area of solar panels	1000	m^2
$\overline{P}_{\text{ESS}}$	ESS power rating	150	kW
$\overline{P}_{\text{gen}}$	Generator power rating	15	kW
S_0	Initial SOC	$0.8\overline{S}_{\text{ESS}}$	kWh
w_1	Weight on $\overline{S}_{\text{ESS}}$	1	-
w_2	Weight on $\overline{S}_{\text{gen}}$	1.1	-
T	Optimization horizon	168	hours
α	Desired fraction of time critical load is met	0.99	-

	May 28 - June 3	August 28 - September 3
$\overline{S}^*_{\text{ESS}}$	871 kWh	1276 kWh
$\overline{S}^*_{\text{gen}}$	1870 kWh	2092 kWh

Conclusion

- Proposed stochastic optimization for sizing and scheduling behind-the-meter energy storage.
- With normally distributed forecasting errors, probabilistic constraint can be reformulated as a linear inequality constraint, and optimization problem becomes a linear program.
- Case study: Reasonably-sized energy storage system, when optimally scheduled with the generator, successfully balanced critical load with *naive forecasts* of stochastic load and PV generation.
- Smaller energy storage may be used times of year when PV generation is higher relative to critical load, such as Spring and Summer.



tes.com

cat.com