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2018 Monthly Webinar Series, 2-3pm ET

February 13:
Mathematics of the Electric Grid

March 13:
Probability for People and Places

April 10:
Social and Biological Networks

May 8:
Mathematics of Redistricting

June 12:
Number Theory: The Riemann Hypothesis

July 10: *Topology*

August 14:
Algorithms for Threat Detection

September 11:
Mathematical Analysis

October 9: *Combinatorics*

November 13:
Why Machine Learning Works

December 11:
Mathematics of Epidemics

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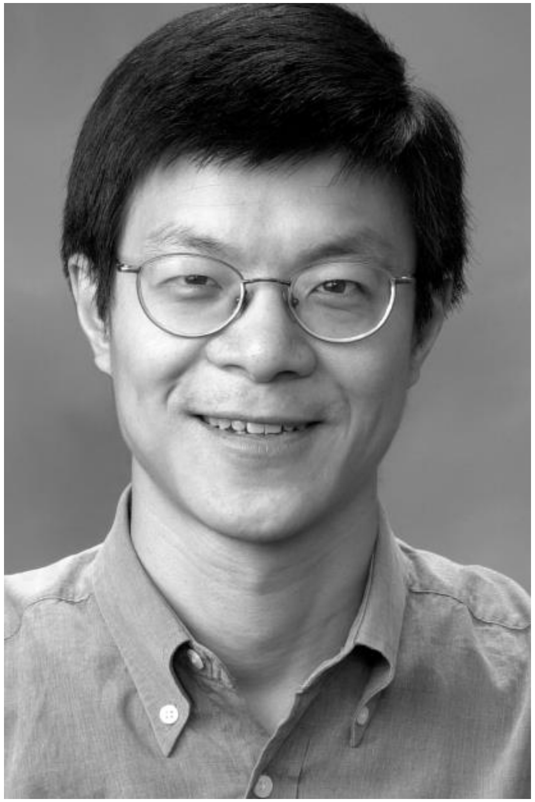
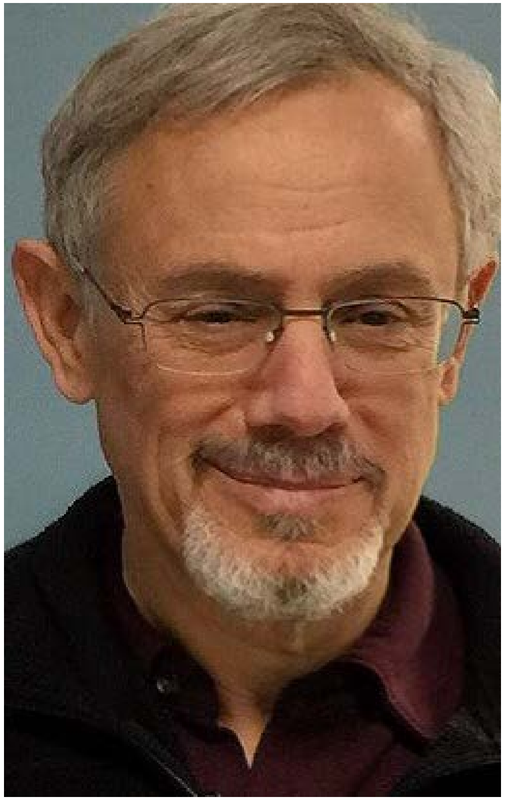
MATHEMATICAL FRONTIERS
Mathematics of the Electric Grid

Sean Meyn, University of Florida



Steven Low, Caltech



Mark Green, UCLA (moderator)

MATHEMATICAL FRONTIERS
Mathematics of the Electric Grid

Sean Meyn,
University of Florida

Professor and Robert C. Pittman Eminent Scholar Chair in the Department of Electrical and Computer Engineering

Networks of Power Today and Tomorrow

Networks of Power Today and Tomorrow

COGNITION & CONTROL IN COMPLEX SYSTEMS

Department of Electrical and Computer Engineering
University of Florida

Thanks to to our sponsors: NSF, Google, DOE, ARPA-E

See also:

National Academies Workshop: https://vimeo.com/album/3275353

NREL AEG Workshop: https://www.nrel.gov/grid/autonomous-energy.html

Simons Center Bootcamp:
https://simons.berkeley.edu/workshops/realtime2018-boot-camp

Networks of Power

Outline

1) Motivation
2) Network Today
3) Network Tomorrow: New Balancing Resources
4) Conclusions
5) References

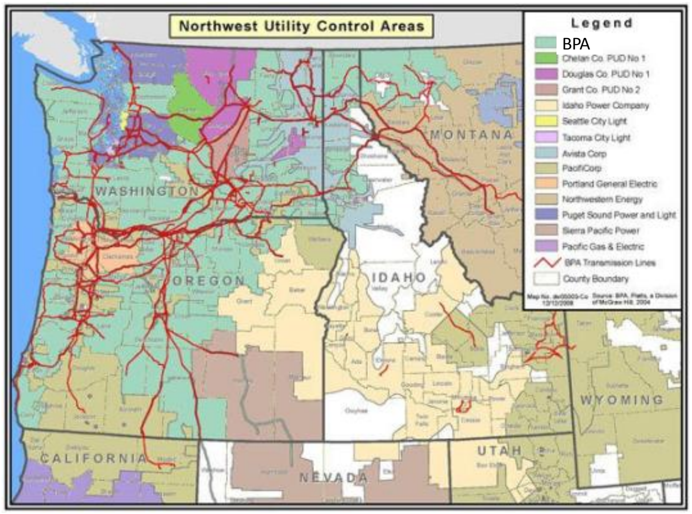
Motivation: Grid in Transition
What's the Big Deal?

- Revolution in energy and communication technologies
  ⇒revolutionary thinking about how to manage the power grid
- Solar and wind energy bring variability and uncertainty
  ⇒opportunities and challenges
- Research challenges in
  - networks, control & communication
  - creative modeling, such as PDE and mean-field models
  - statistics, optimization and "machine learning"
  - economics (new viewpoints are needed!)
  - and of course, all aspects of *power systems*

These lectures focus on large-scale systems questions, leaving out

- New technologies: power electronics, solar cells, electric storage
- Cyber-security
- Detection and response to cascading failures, …

Network Today: Balancing Energy, Frequency, and Phase View of the Balancing Authority



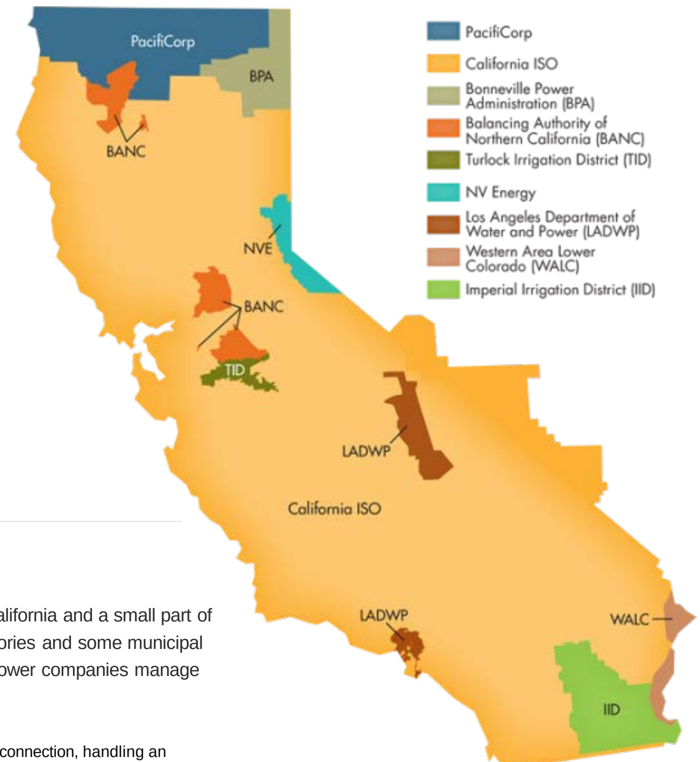
California ISO

Home > About Us > Our Business > The ISO grid

The ISO grid

The ISO manages the flow of electricity for about 80 percent of California and a small part of Nevada, which encompasses all of the investor-owned utility territories and some municipal utility service areas. There are some pockets where local public power companies manage their own transmission systems.

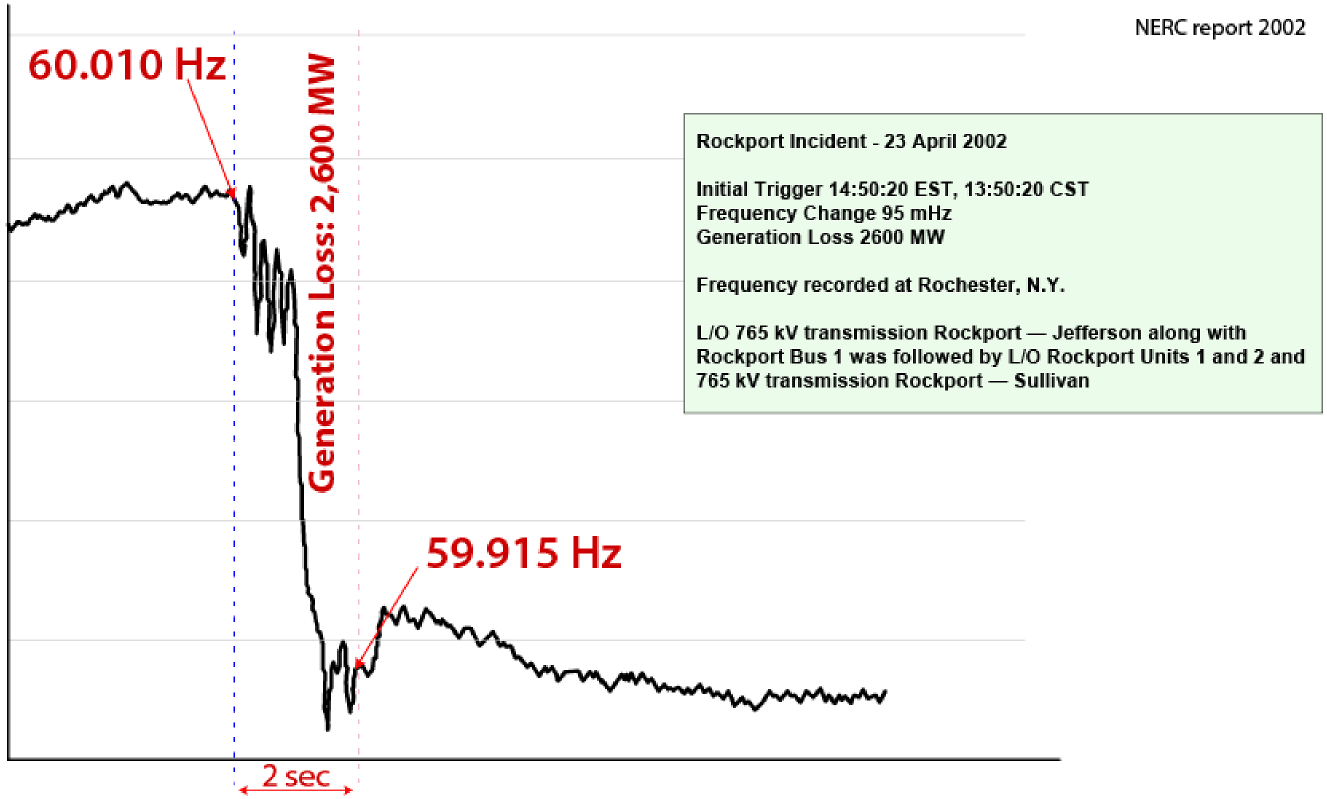
The ISO is the largest of about 38 balancing authorities in the western interconnection, handling an estimated 35 percent of the electric load in the West. A balancing authority is responsible for operating a transmission control area. It matches generation with load and maintains consistent electric frequency of the grid, even during extreme weather conditions or natural disasters.



Network Today: Balancing Energy, Frequency, and Phase View of the Balancing Authority

Balancing Frequency

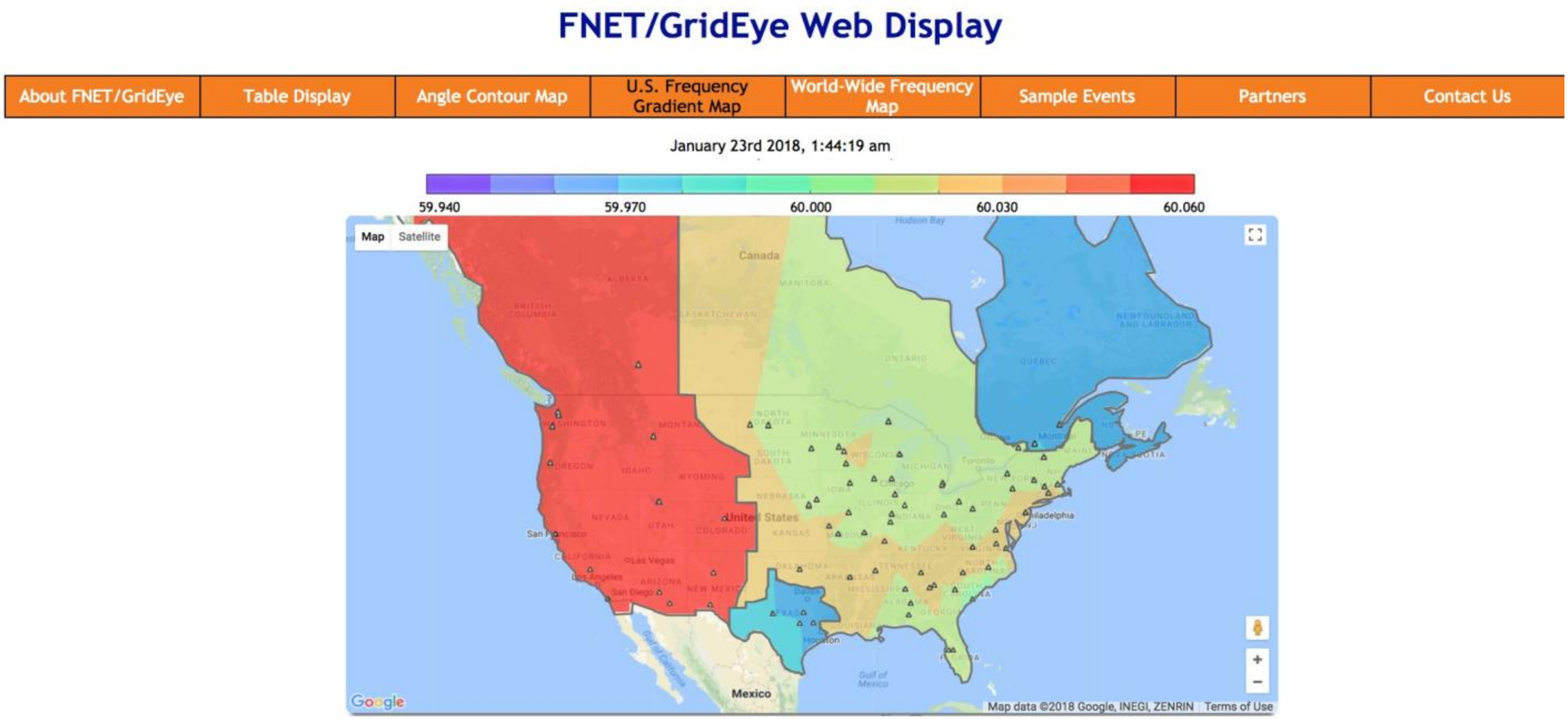
Frequency deviation of 0.1 Hz ⇒ Panic!



Breaker failure ⇒ transients ⇒ two generators tripped

Network Today: Balancing Energy, Frequency, and Phase View of the Balancing Authority *Balancing Frequency*

Frequency is continuous across interconnected regions



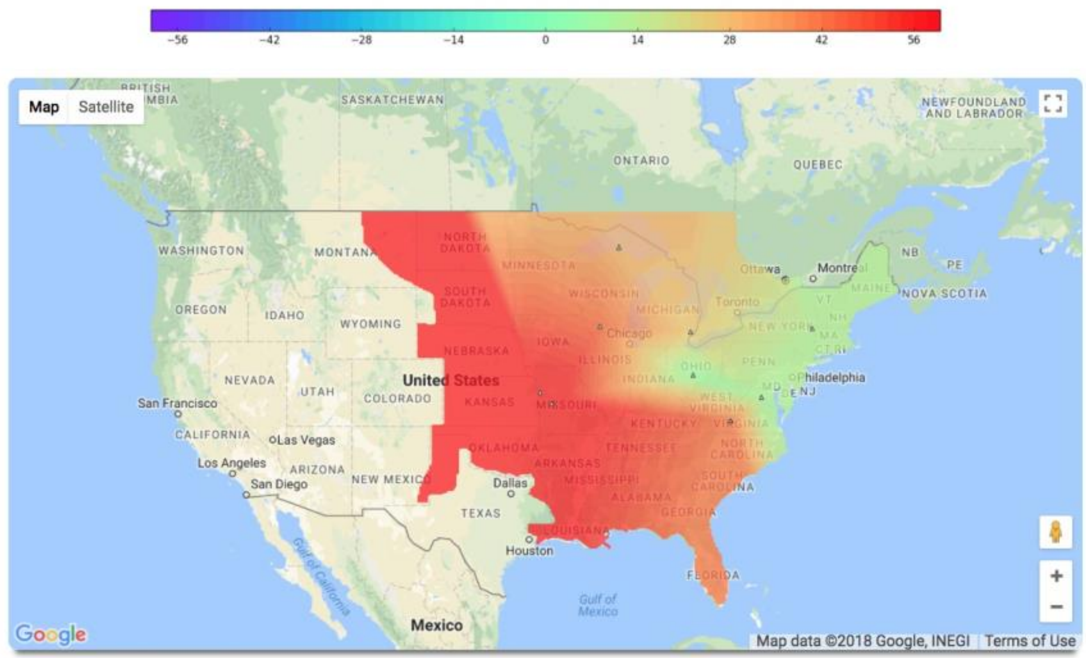
Network Today: Balancing Energy, Frequency, and Phase View of the Balancing Authority
Balancing Frequency

Phase angle is also continuous

FNET/GridEye Web Display

About FNET/GridEye	Table Display	Angle Contour Map	U.S. Frequency Gradient Map	World-Wide Frequency Map	Sample Events	Partners	Contact Us	Future Applications

January 23rd 2018, 1:44:19 am

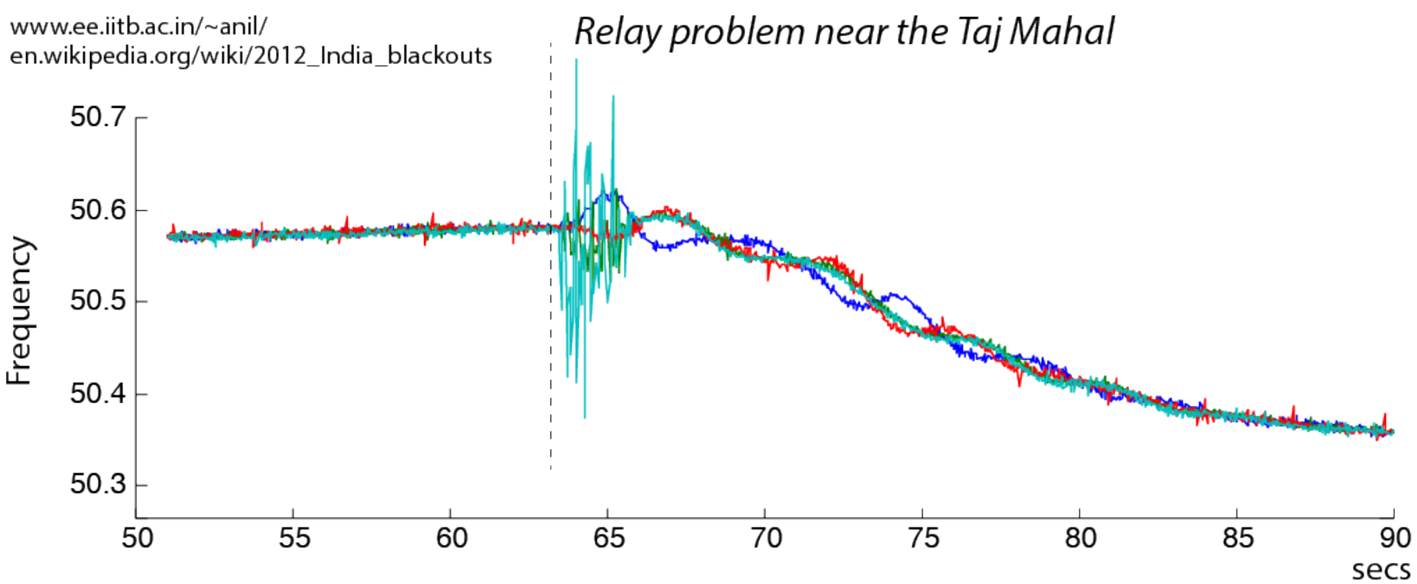


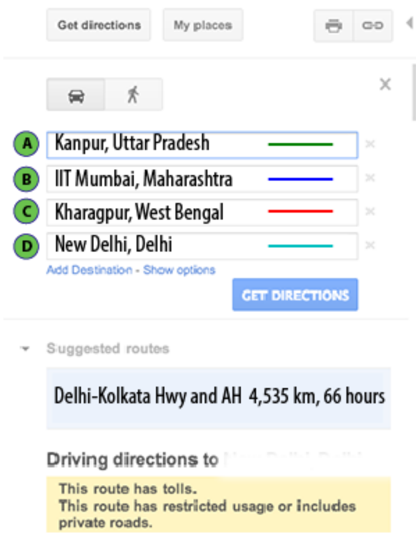
THE UNIVERSITY of TENNESSEE UT
OAK RIDGE National Laboratory

Network Today: Balancing Energy, Frequency, and Phase View of the Balancing Authority

Balancing Frequency

Frequency floats more freely in other regions of the globe

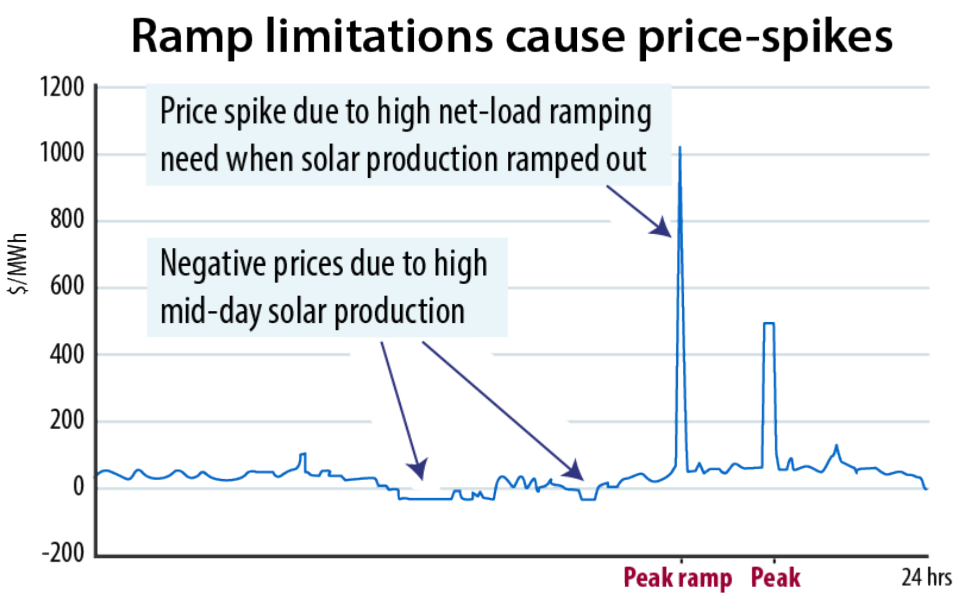


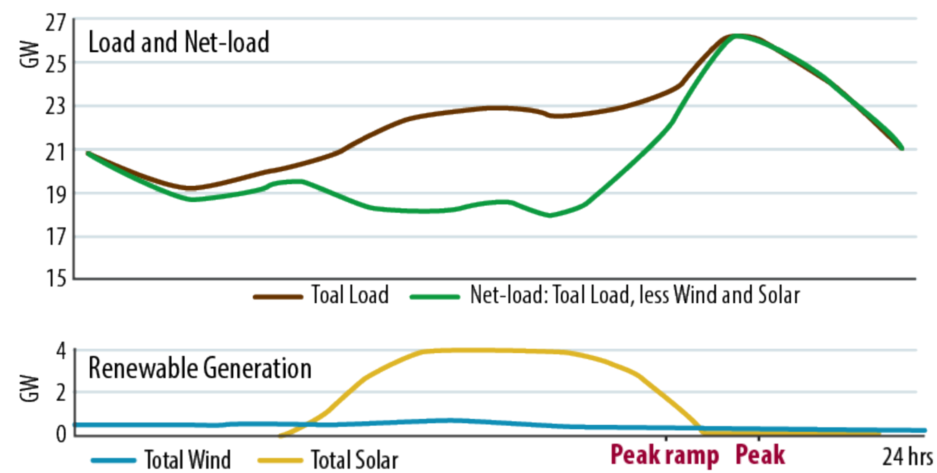


A disturbance in Agra appears to spread instantly to Mumbai and Calcutta.

Network Today: Balancing Energy, Frequency, and Phase View of the Balancing Authority
Ducks, Peaks, Ramps, Voltage, Power, Energy …

Dreaded Duck Curve in the South West





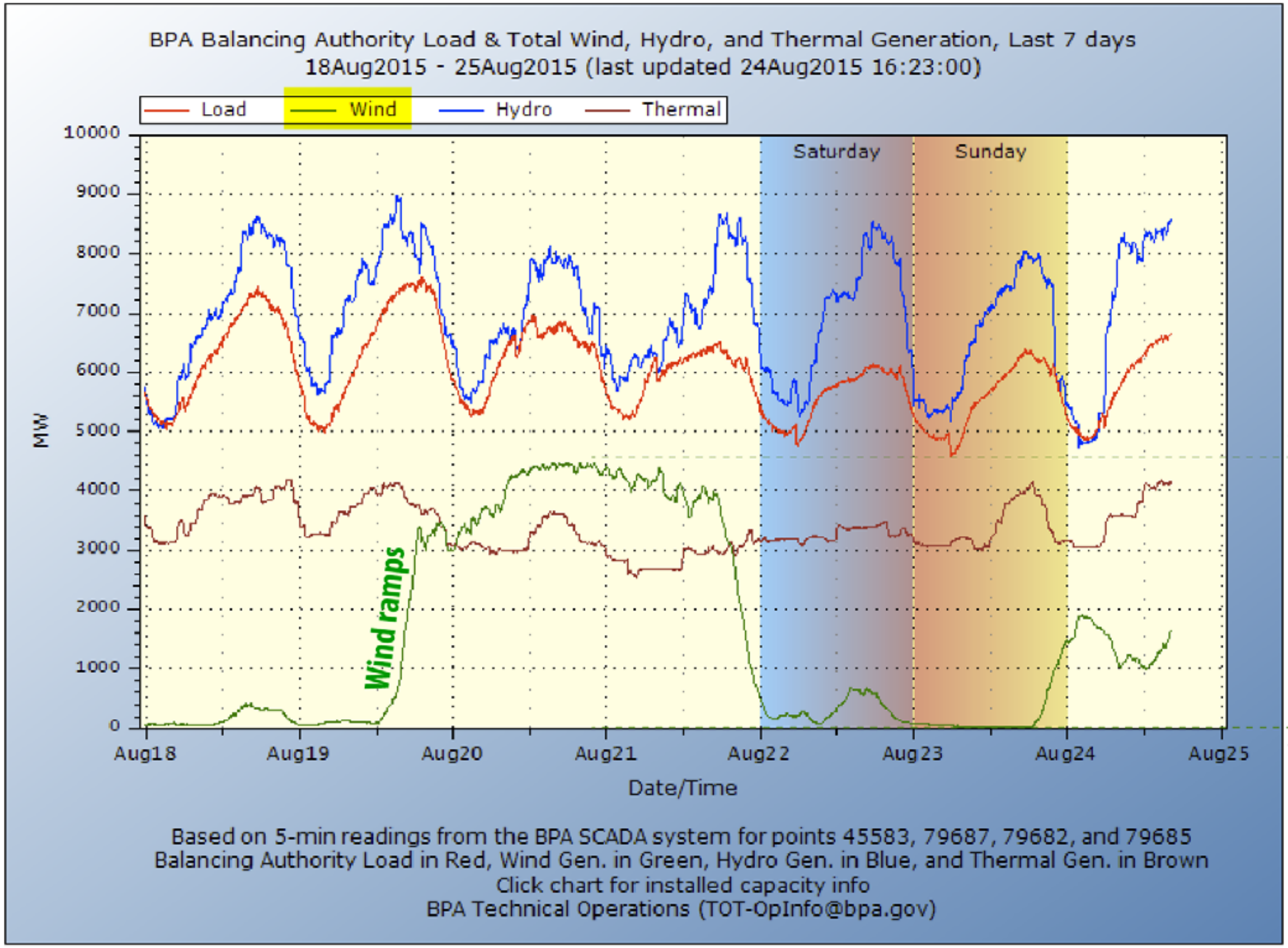
PCI
ENERGY IN FOCUS

Ramps in *net-load* stress equipment and markets

Network Today: Balancing Energy, Frequency, and Phase View of the Balancing Authority

Ducks, Peaks, Ramps, Voltage, Power, Energy …

Wind in the North West

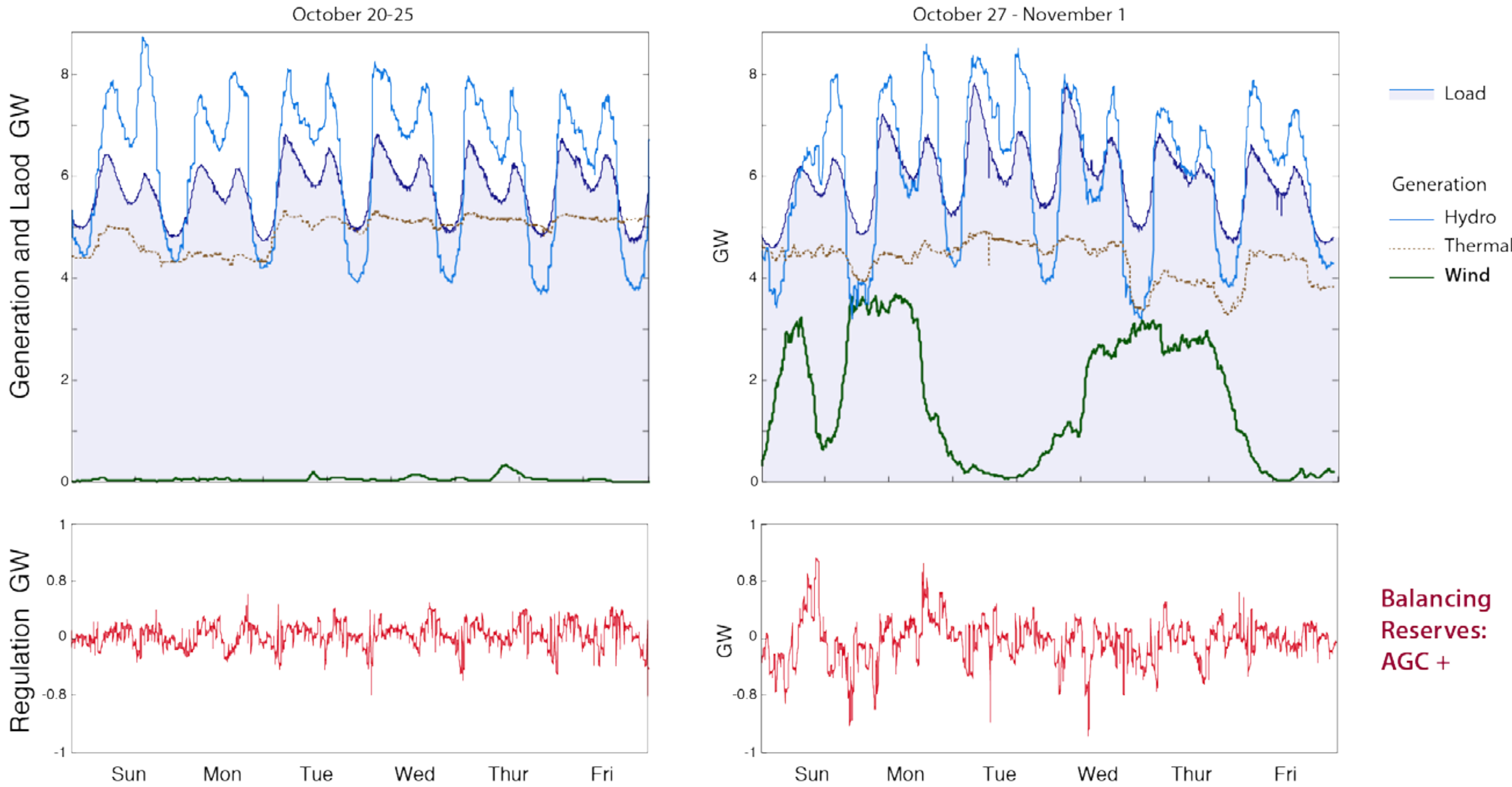


3 or 4 Nuclear power plants

Network Today: Balancing Energy, Frequency, and Phase Secondary Control

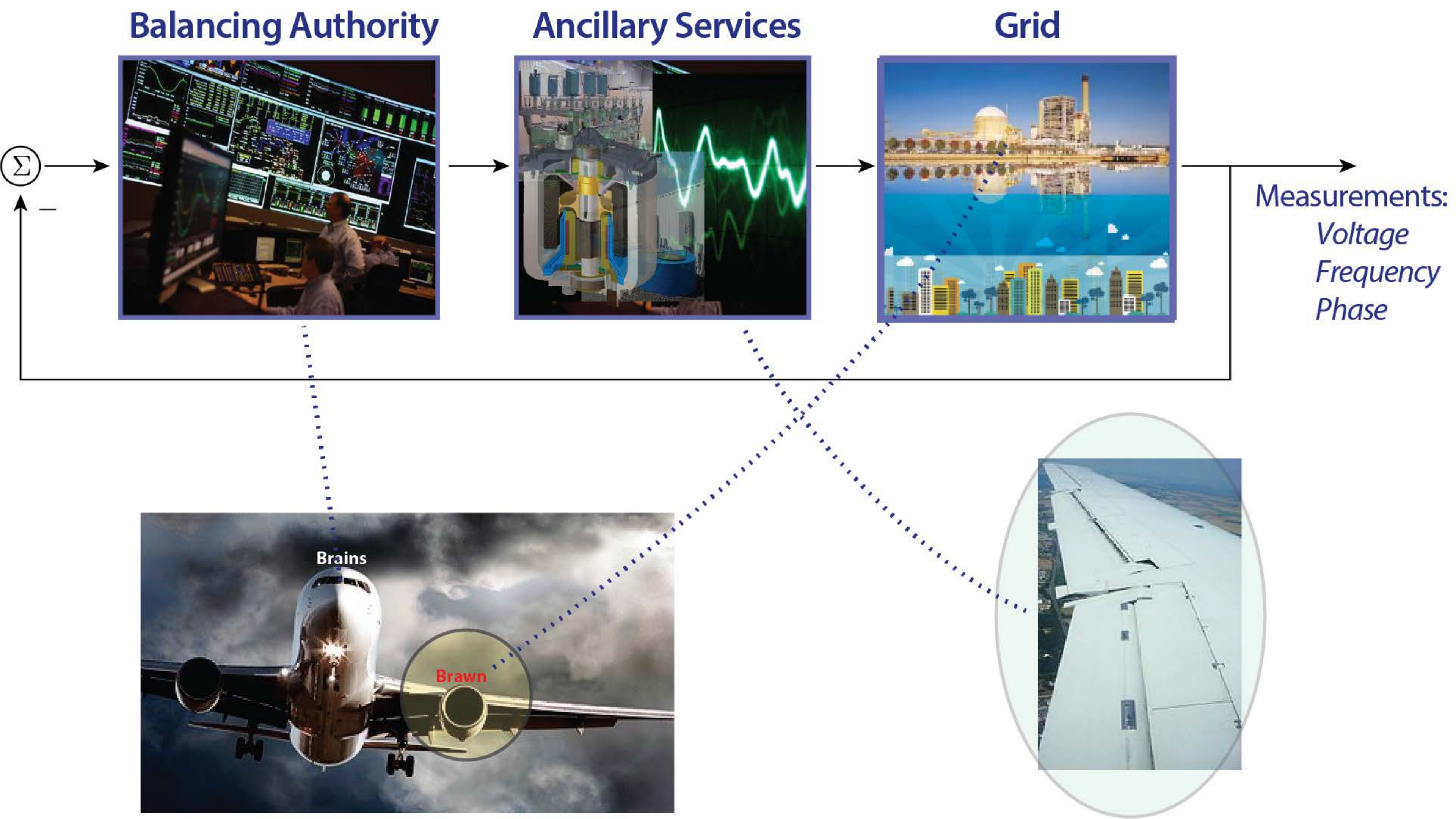
Balancing Authority Broadcasts to Resources

Generators and other resources ramp up and down power output



Analogy: ailerons on an airplane

New Balancing Resources



Network Tomorrow: New Balancing Resources
Secondary Control
Balancing Authority: In need of Balancing Services

Where do they find Ancillary Services to provide needed actuation?

Many generalized storage solutions. If we are stuck with generators, then gas-combustion or hydro generation are best in terms of responsiveness.

Also, compressed air, flywheels, molten salt, trains pulled up a hill, …

https://en.wikipedia.org/wiki/Grid_energy_storage

Network Tomorrow: New Balancing Resources
Secondary Control
Balancing Authority: In need of Balancing Services

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California believes the answer is massive batteries

Network Tomorrow: New Balancing Resources
Demand Dispatch & Virtual Energy Storage

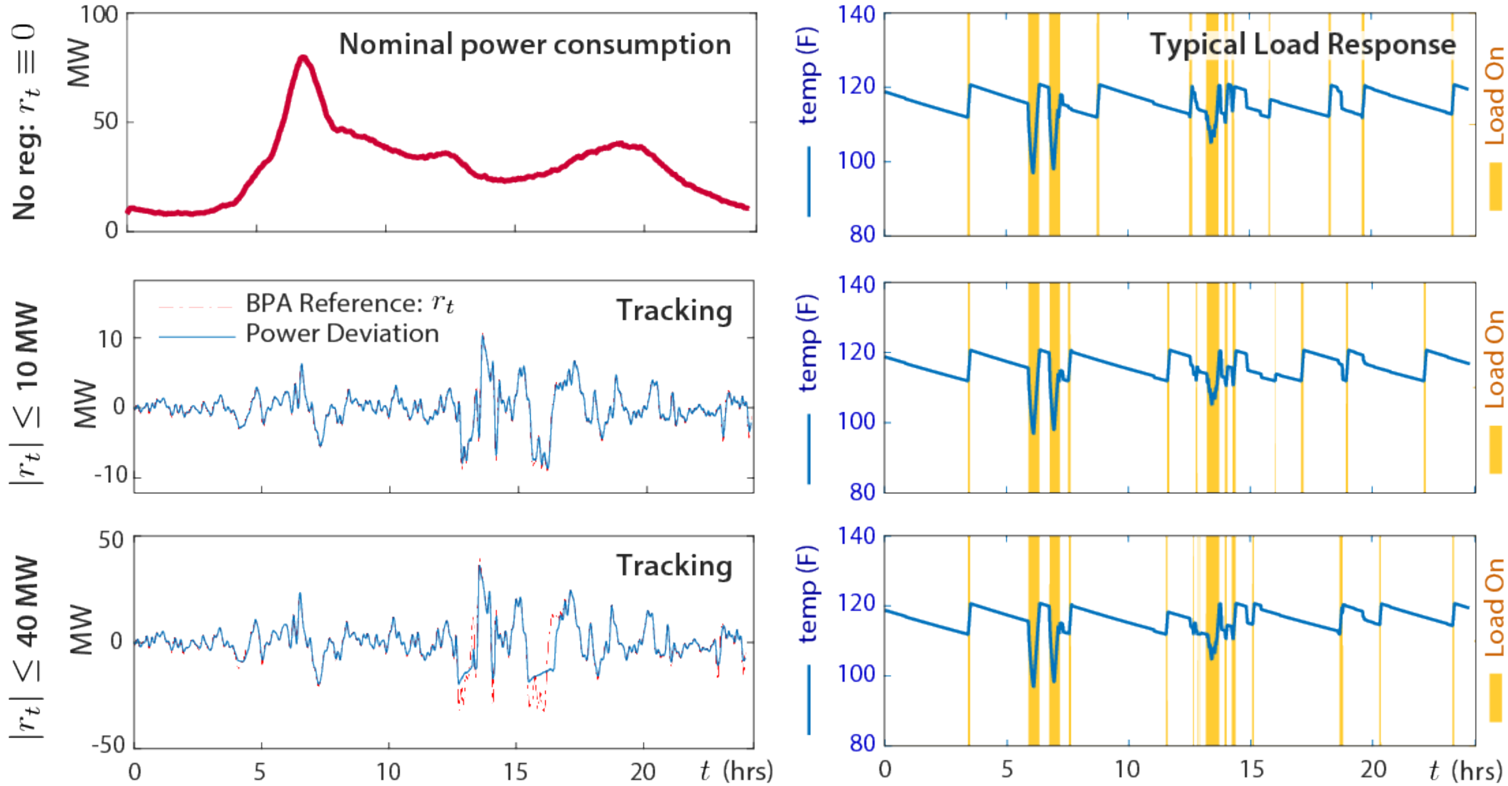
Demand Dispatch:

battery services from inherent flexibility of loads

Network Tomorrow: New Balancing Resources
Demand Dispatch & Virtual Energy Storage

Demand Dispatch: battery services from inherent flexibility of l oads

Example: Tracking balancing reserves with 100,000 water heaters

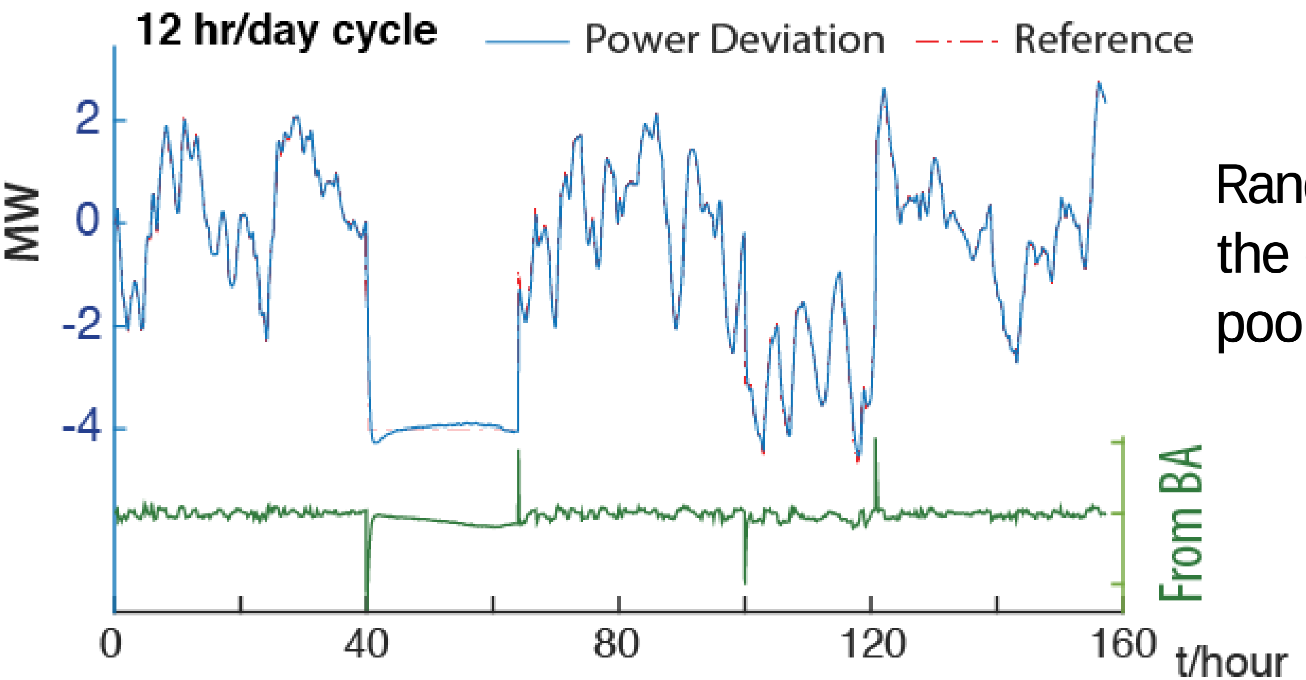


Three cases, distinguished by the reference signal
(3rd is too big!)

Network Tomorrow: New Balancing Resources Demand Dispatch & Virtual Energy Storage

Demand Dispatch: battery services from inherent flexibility of loads

Example: Tracking with 10^4 residential swimming pools



Simulation using 10,000 pool pumps that consume on average 5MW

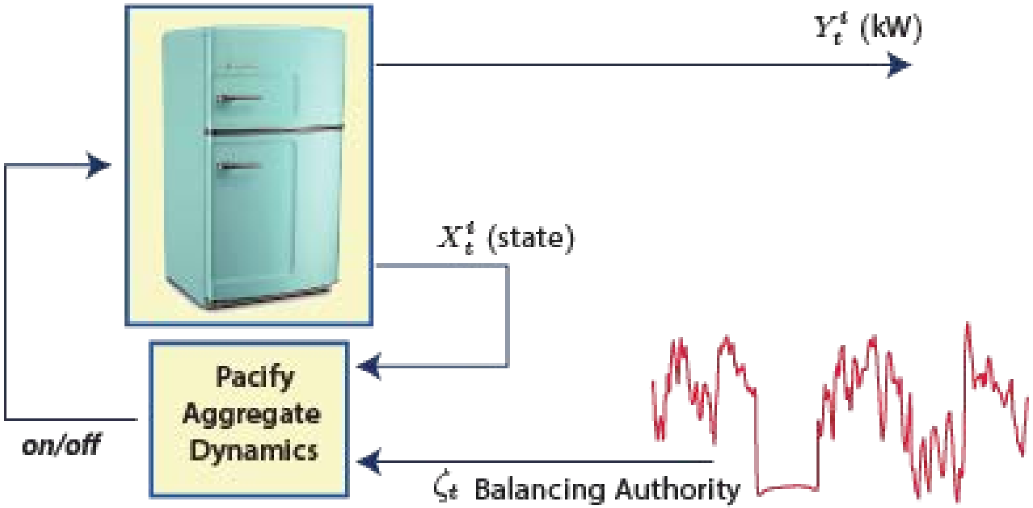
Range of services provided by the one million residential pools in California

From Yue Chen's thesis [3]

Network Tomorrow: New Balancing Resources
Demand Dispatch & Virtual Energy Storage

Point of view at UF/Inria

Local Intelligence at each load



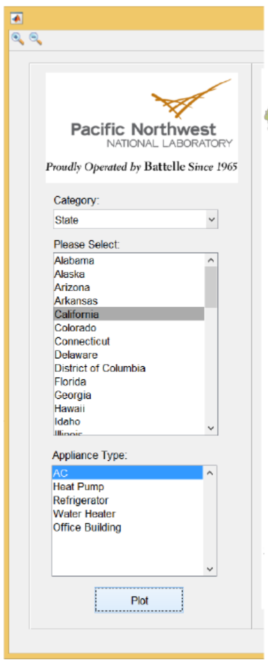
Mean-field model of large population of loads

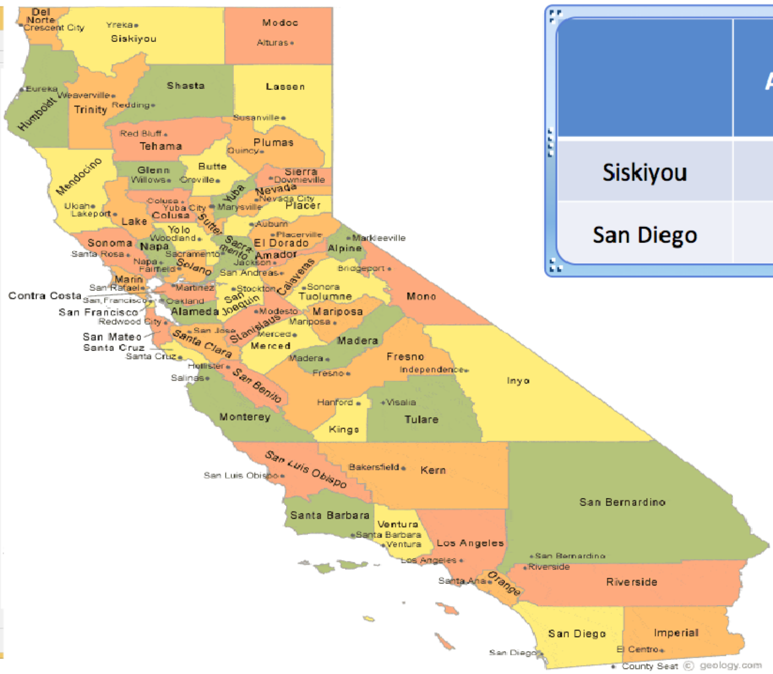
Aggregate dynamics: passive, predictable input-output system

Network Tomorrow: New Balancing Resources Demand Dispatch & Virtual Energy Storage DER Flexibility Assessment & Valuation

Ongoing GMLC project – PNNL/ORNL/UF

Virtual Battery-Based Characterization and Control of Flexible Building Loads Using VOLTTRON



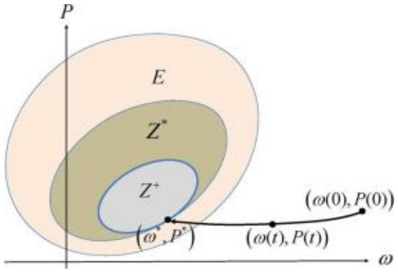


	Energy Arbitrage $/year	Regulation Up $/year	Regulation Down $/year	Spinning Reserve $/year	Total $/year
Siskiyou	10,983	150,501	25,651	2,559	189,696
San Diego	1,534	11,764	42,447	0	55,746

Value in Siskiyou vs San Diego

Conclusions

Today: managing the grid is an enormous distributed control problem
The future: new communication and control architectures are required

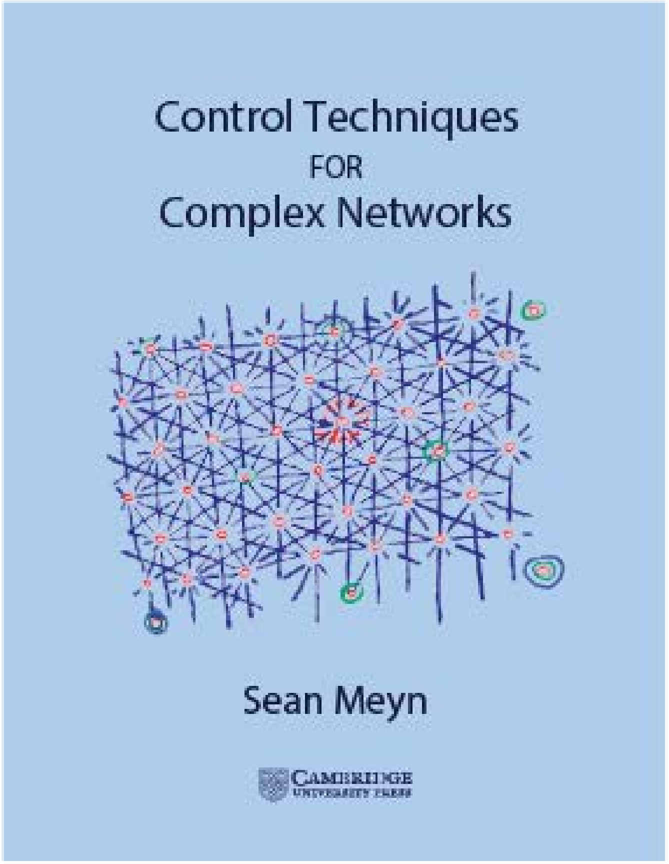


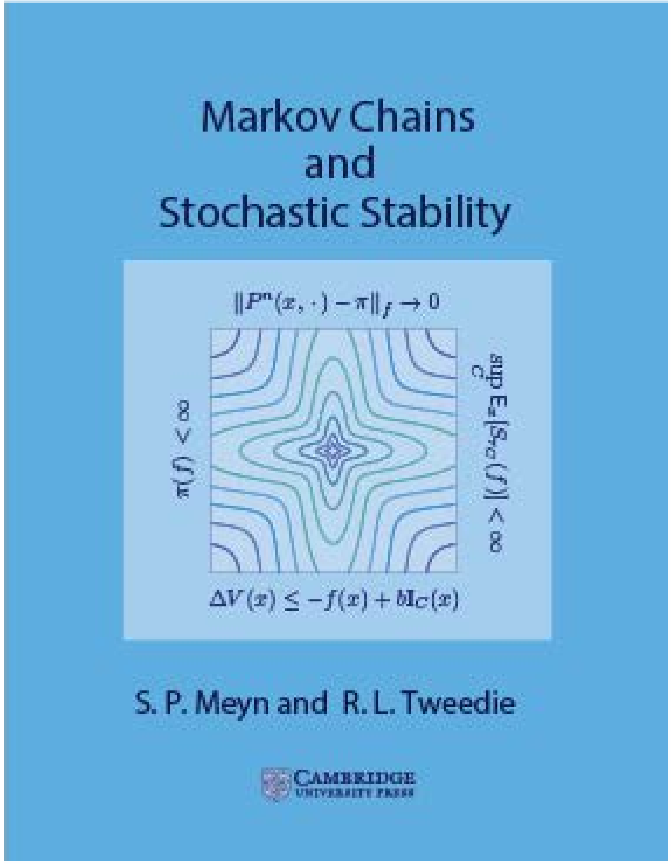
Questions:

- Will frequency remain the global information signal?
- What is the impact of further increased decentralized resources? (power and storage)
- How will markets evolve to provide incentives for *zero marginal-cost resources*?

Thank You

References


Control Techniques
FOR
Complex Networks
Sean Meyn
Cambridge University Press


Markov Chains
and
Stochastic Stability
$\|P^n(x,\cdot)-\pi\|_f \to 0$
$\pi(f) < \infty$
$\sup_C \mathsf{E}_x[S_{\tau_C}(f)] < \infty$
$\Delta V(x) \le -f(x) + b\mathbb{I}_C(x)$
S. P. Meyn and R. L. Tweedie
Cambridge University Press

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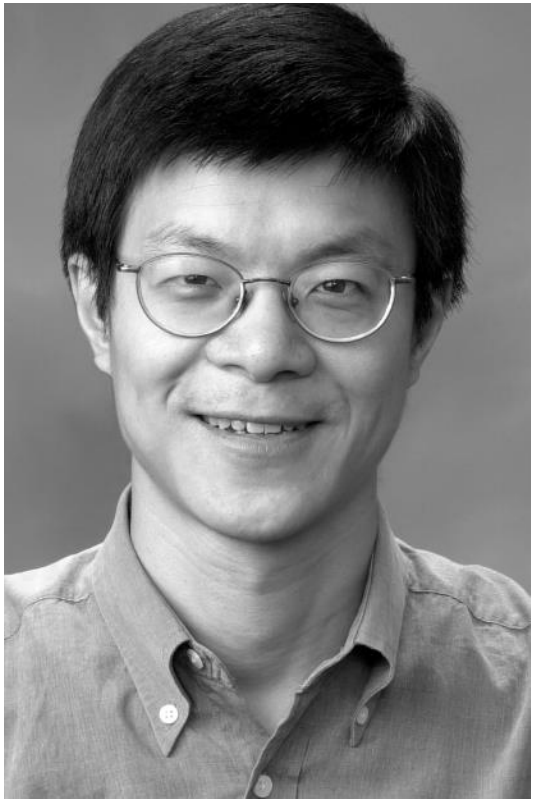


Steven Low, Caltech

Frank J. Gilloon Professor of Computing & Mathematical Sciences and Electrical Engineering

Autonomous Grid

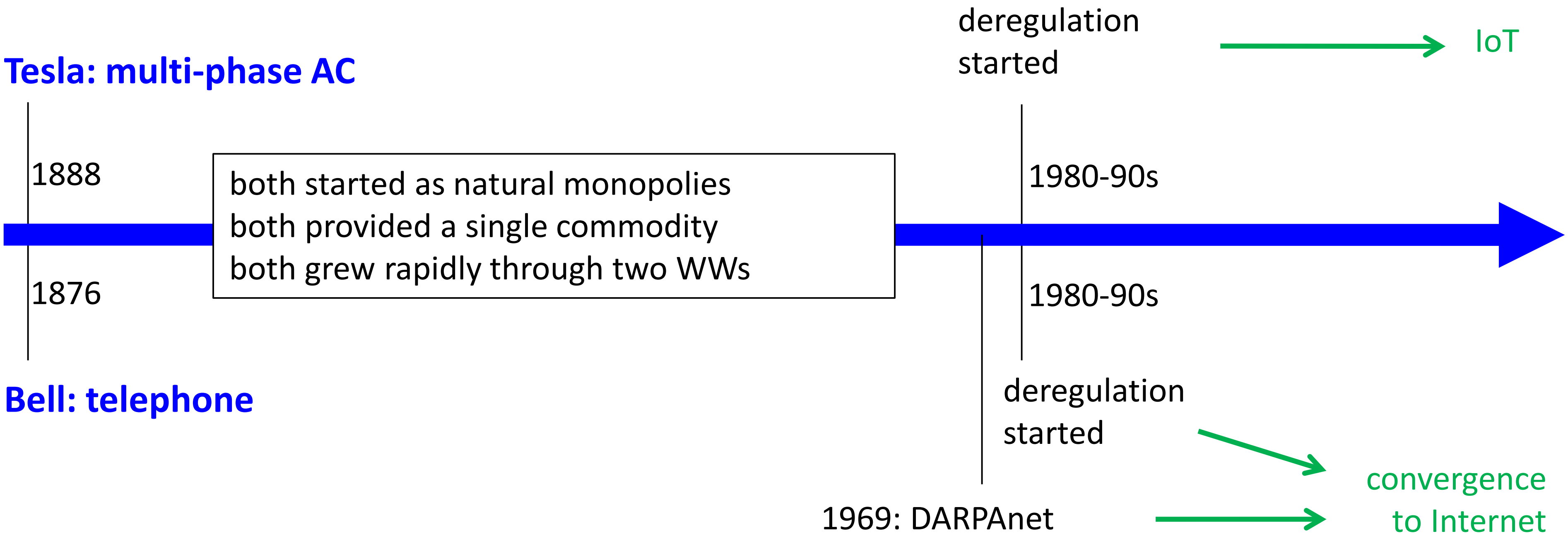
Autonomous Grid

Steven Low

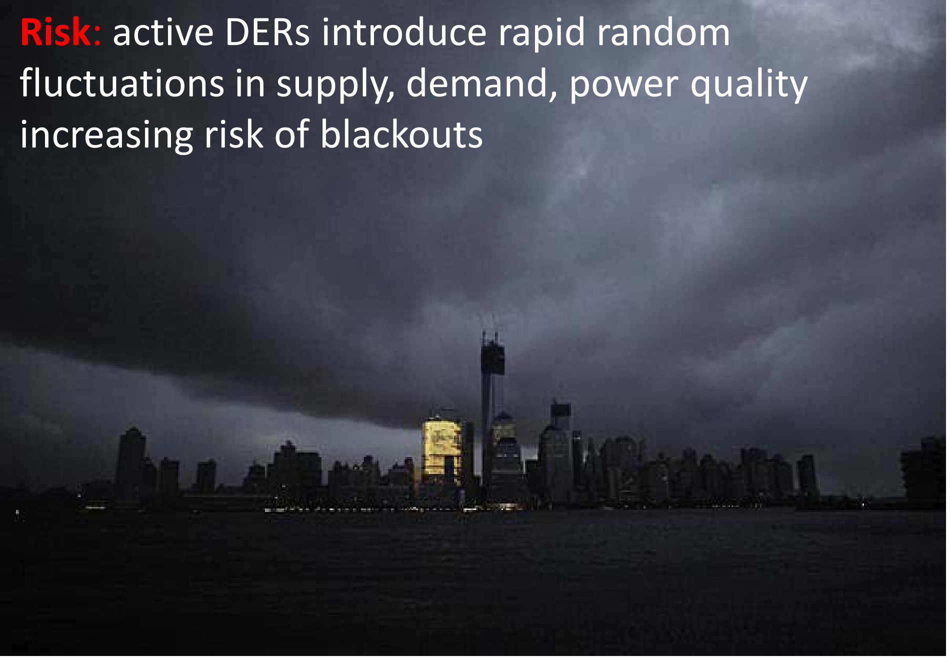
Caltech

Watershed moment

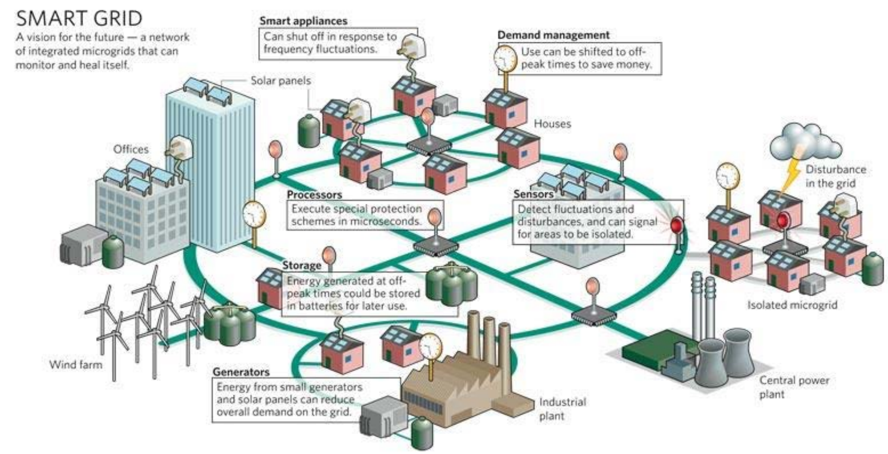
Energy network will undergo similar architectural transformation that phone network went through in the last two decades to become the world's largest and most complex IoT



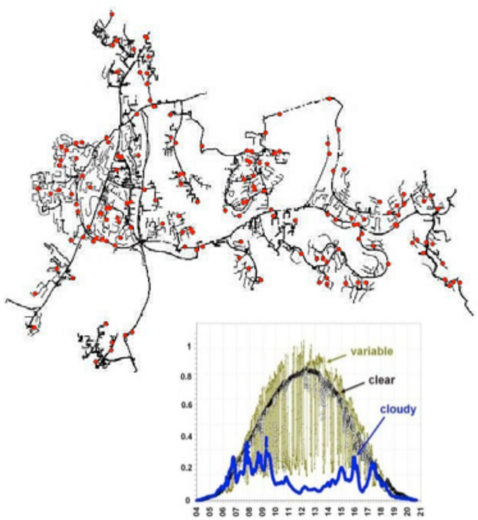
Risk: active DERs introduce rapid random fluctuations in supply, demand, power quality increasing risk of blackouts



Opportunity: active DERs enables realtime dynamic network-wide feedback control, improving robustness, security, efficiency



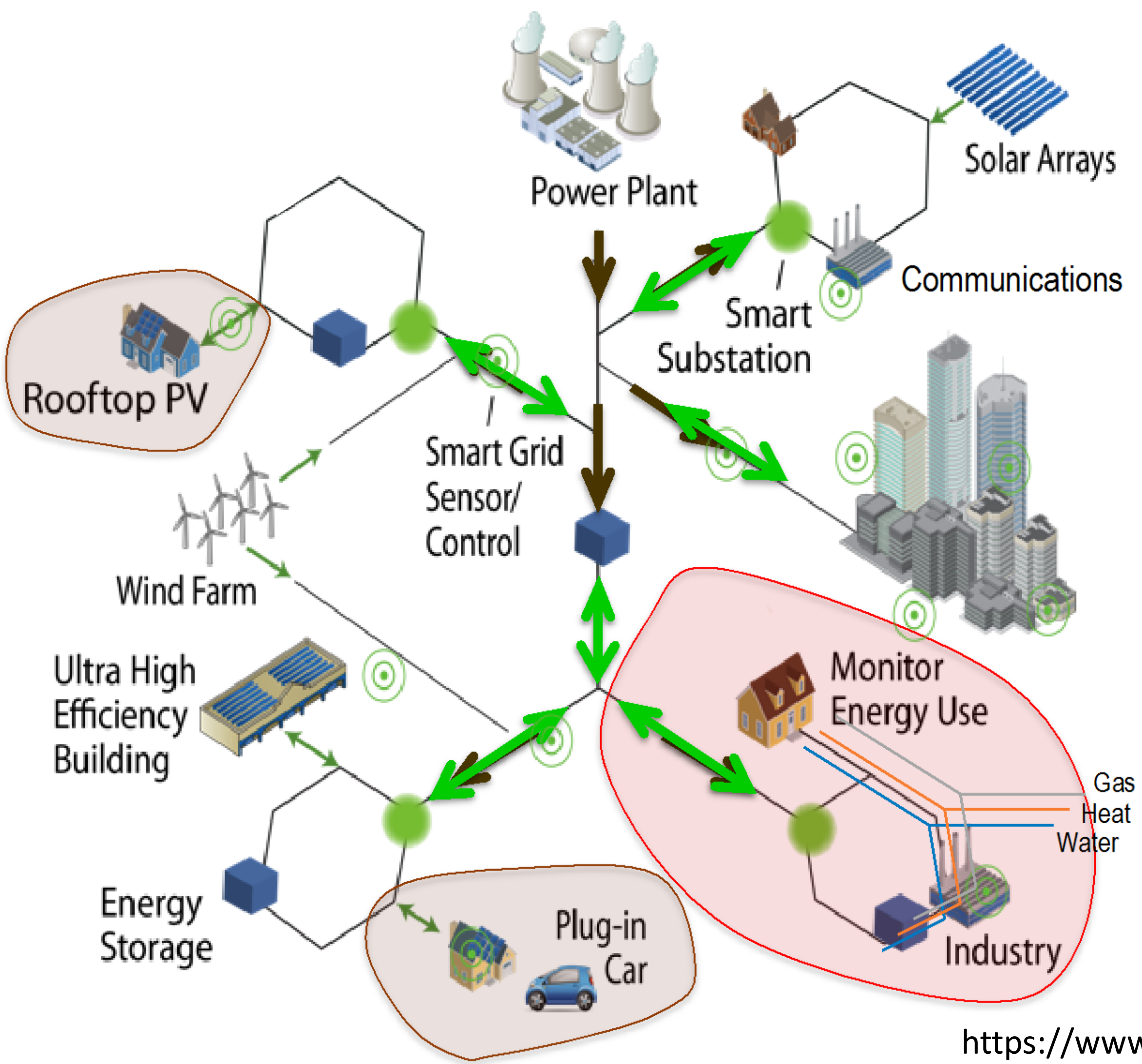
Caltech research: distributed control of networked DERs



- Foundational theory, practical algorithms, concrete applications
- Integrate engineering and economics
- Active collaboration with industry

Autonomous Energy Grids

op#mized for secure, resilient and economic opera#ons



Ben Kroposki
NREL workshop 2017

https://www.nrel.gov/grid/autonomous-energy.html

Autonomous grid

Computational challenge
- nonlinear models, nonconvex optimization

Increased volatility
- in supply, demand, voltage, frequency

Scalability challenge
- billions of intelligent DERs

Limited sensing and control
- design of/constraint from cyber topology

Incomplete or unreliable data
- local state estimation & closed-loop system identification

Data-driven modeling and control
- real-time learning at scale

many other important problems, inc. economic, regulatory, social, ...

Autonomous grid

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Autonomous energy grid

Two examples as illustration

- dealing with nonconvexity
- dealing with volatility

… close with a research challenge in each

Optimal power flow (OPF)

OPF is solved routinely for

- state estimation, stability analysis, topology reconfiguration
- generator commitment and dispatch
- pricing electric services
- at timescales of mins, hours, days, …

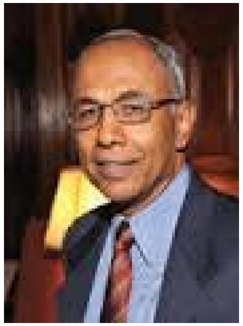
Non-convex and hard to solve

- Huge literature since 1962
- Common practice: DC power flow (linear program)
- Also: Newton-Raphson, interior point, …

Relaxations of OPF

dealing with nonconvexity


Bose (UIUC)


Chandy


Farivar (Google)


Gan (FB)


Lavaei (UCB)


Li (Harvard)

many others at & outside Caltech …

Low, Convex relaxation of OPF, 2014
http://netlab.caltech.edu

Optimal power flow

$$\begin{aligned} \min \quad & \operatorname{tr}\left(CVV^H\right) \\ \text{over} \quad & (V, s, l) \\ \text{subject to} \quad & s_j = \operatorname{tr}\left(Y_j^H V V^H\right) \\ & l_{jk} = \operatorname{tr}\left(B_{jk}^H V V^H\right) \\ & \underline{s}_j \le s_j \le \overline{s}_j \\ & \underline{l}_{jk} \le l_{jk} \le \overline{l}_{jk} \\ & \underline{V}_j \le |V_j| \le \overline{V}_j \end{aligned}$$

gen cost, power loss

power flow equation

line flow

injection limits

line limits

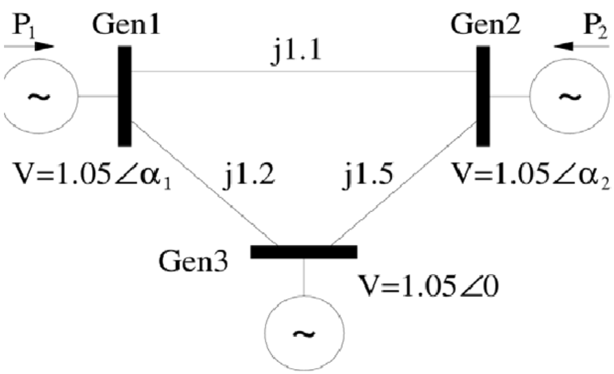
voltage limits

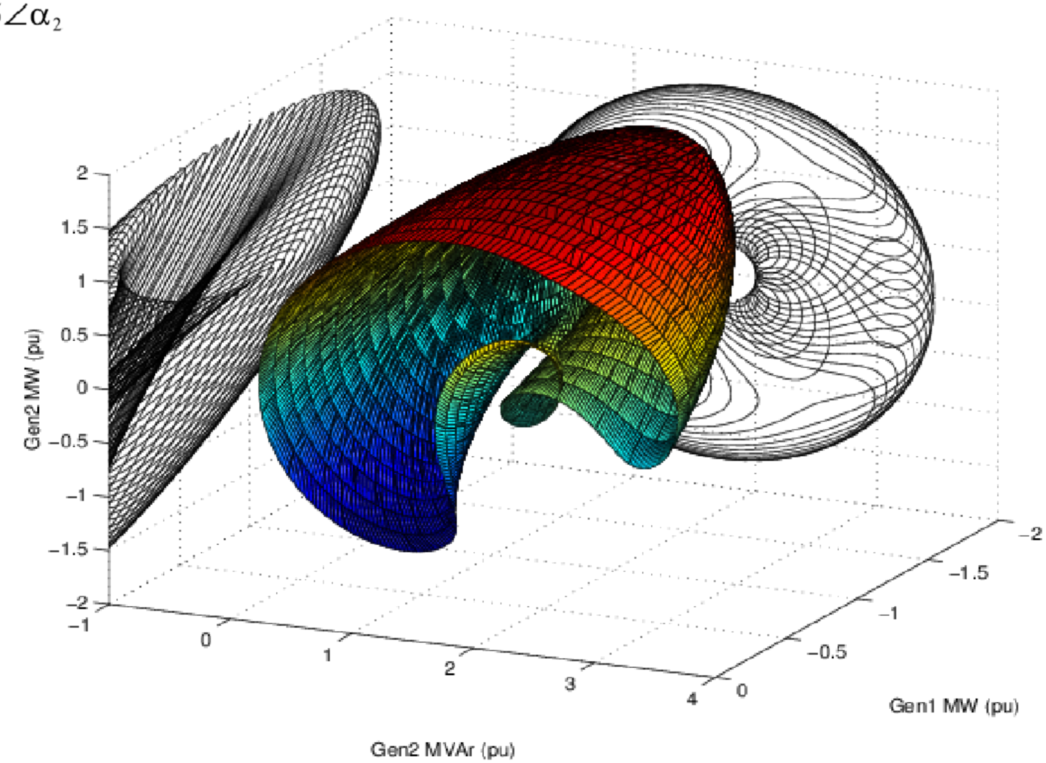
nonconvex QCQP

Challenges

1. Nonconvexity: Kirchhoff's laws (Y_j^H not positive semidefinite)
2. Volatility: time-varying optimization

Optimal power flow





Ian Hiskens, Michigan

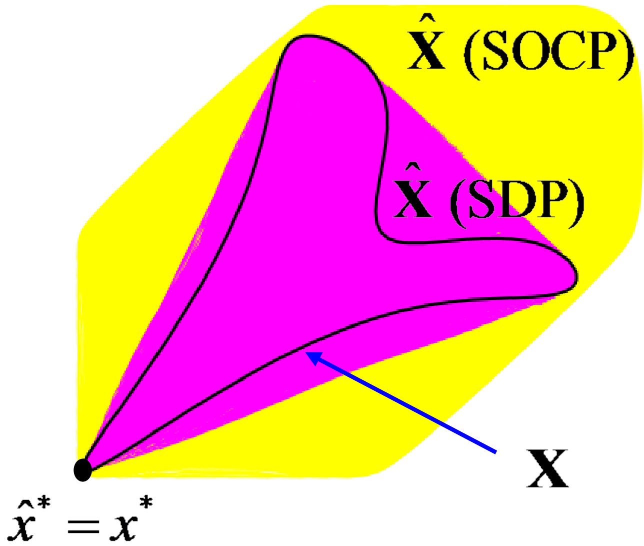
Dealing with nonconvexity

- Linearization
  - DC approximation
- Convex relaxations
  - Semidefinite relaxation (Lasserre hierarchy, ...)
  - QC relaxation (van Hentenryck, Michigan)
  - Strong SOCP (Sun, GATech)
- Realtime OPF
  - Online algorithm, as opposed to offline
  - Also tracks time-varying OPF

Semidefinite relaxation

OPF: $\min_{x \in \mathbf{X}} f(x)$

relaxation: $\min_{\hat{x} \in \mathbf{X}^+} f(\hat{x})$

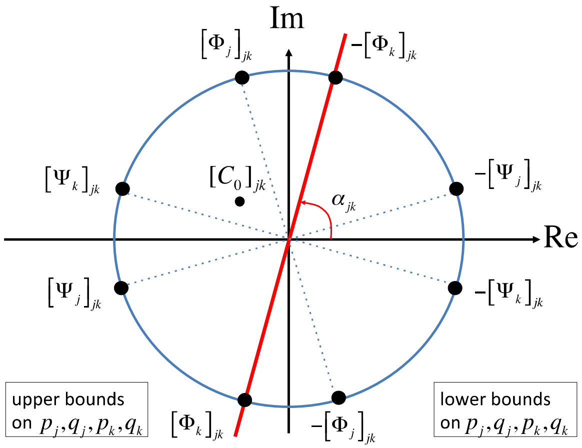


If optimal solution $\hat{x}^*$ satisfies easily checkable conditions, then optimal solution x^* of OPF can be recovered

Is OPF really hard?

For tree networks, sufficient conditions on

- power injections bounds, or
- voltage upper bounds, or
- phase angle bounds



Is OPF really hard?

For tree networks, sufficient conditions on

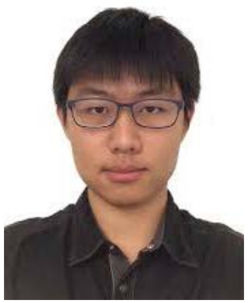
- power injections bounds, or
- voltage upper bounds, or
- phase angle bounds

For mesh networks: observations

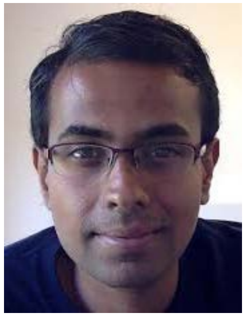
- no guarantee for general mesh networks (complexity: NP-hard)
- yet, relaxations often exact for practical networks
- ... and local algorithms often produce global solutions
- Do practical networks have special structure that make OPF easy ?

Realtime OPF
dealing with volatility

Gan (FB)



Tang (Caltech)



Dvijotham (DeepMind)

Gan & L, JSAC 2016
Tang et al, TSG 2017

Realtime OPF

$$\begin{array}{ll} \text{min} & f_t(x, y(x);\ \mu_t) \\ \text{over} & x \in X_t \end{array}$$

Quasi-Newton algorithm:

$$x(t+1) = \left[x(t) - \eta\left(H(t)\right)^{-1} \frac{\partial f_t}{\partial x}(x(t)) \right]_{X_t} \qquad \text{active control}$$

$$y(t) = y(x(t)) \qquad \text{law of physics}$$

Gan & Low 2016; Dall'Anese et al 2016; Arnold et al 2016; Hauswirth et al 2016
Dall'Anese & Simonetto 2016; Wang et al 2016; Tang et al 2017; Simonetto 2017

Realtime OPF

$$\text{error} := \frac{1}{T}\sum_{t=1}^{T}\left\| x^{\text{online}}(t) - x^*(t) \right\|$$

Theorem: tracking performance

$$\text{error} \le \frac{\varepsilon}{\sqrt{\lambda_m / \lambda_M} - \varepsilon} \cdot \frac{1}{T}\sum_{t=1}^{T}\left(\left\| x^*(t) - x^*(t-1) \right\| + \Delta_t \right)$$

- rate of OPF drifting
- approximation of Hessian
- conditioning of Hessian

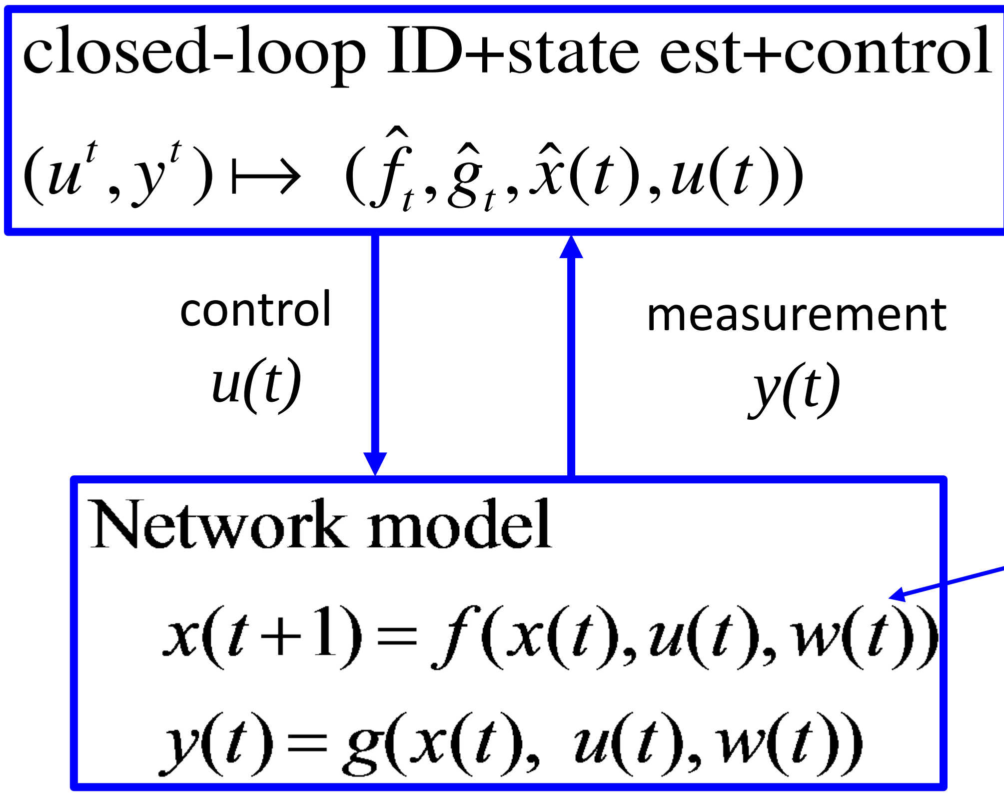
Tang, Dj, & Low, TSG 2017

Learning + control ?

New challenges:

Strategic agents (human, organizations) in the loop hard to model

Learning + control ?



$$\min \frac{1}{T}\sum_{t=1}^{T}\left\| x^{\text{online}}(t) - x^{*}(t) \right\|$$

New challenges:
Strategic agents (human, organizations) in the loop hard to model

Classical joint identification and control

Astrom & Wittenmark 1971; Gevers & Ljung 1986; Gu & Khargonekar 1992; ...

Learning + control ?

closed-loop ID+state est+control

$$(u^t, y^t) \mapsto (\hat{f}_t, \hat{g}_t, \hat{x}(t), u(t))$$

control $u(t)$ ↓ measurement $y(t)$ ↑

Network model

$$x(t+1) = f(x(t), u(t), w(t))$$

$$y(t) = g(x(t),\ u(t), w(t))$$

$$\min \frac{1}{T}\sum_{t=1}^{T}\left\| x^{\text{online}}(t) - x^{*}(t) \right\|$$

How to integrate new tools ?

- Statistical learning theory; advances in ML
- Learning high-dim data
- Diversity of data
- Algorithms & computing power

Classical joint identification and control

Astrom & Wittenmark 1971; Gevers & Ljung 1986; Gu & Khargonekar 1992; ...

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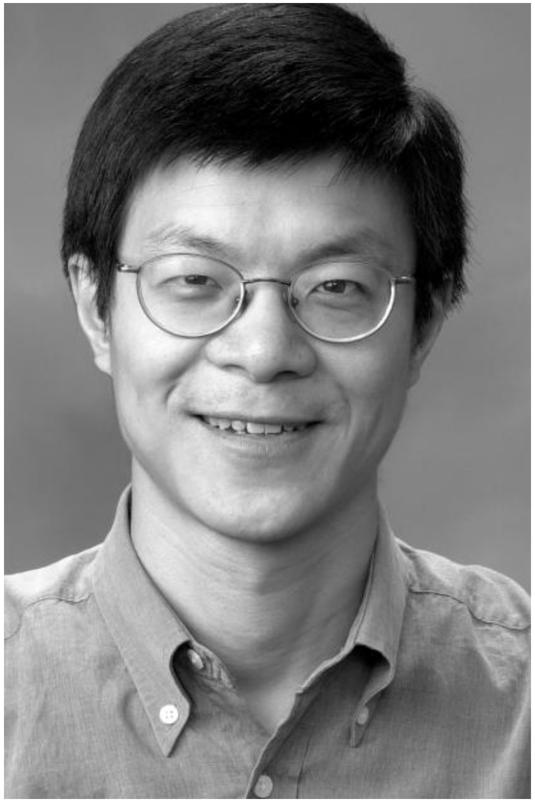
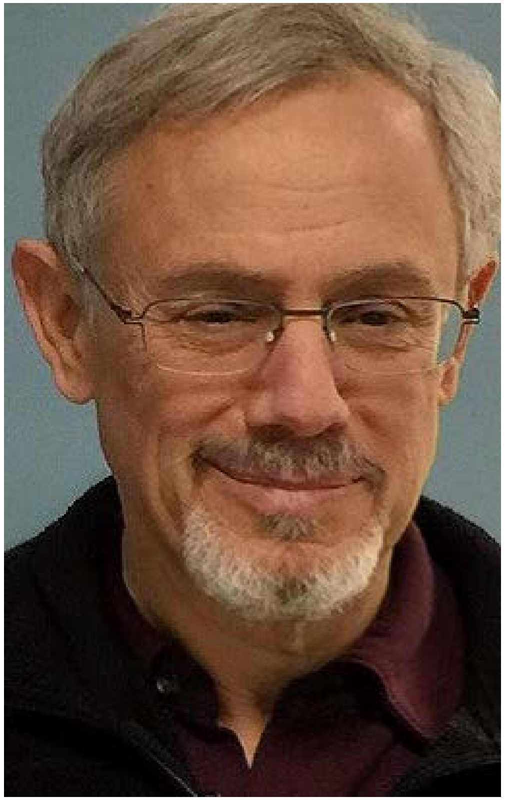
Mathematics of the Electric Grid – Q&A

Sean Meyn,
University of Florida



Steven Low,
Caltech



Mark Green,
UCLA (moderator)

MATHEMATICAL FRONTIERS
Mathematics of the Electric Grid

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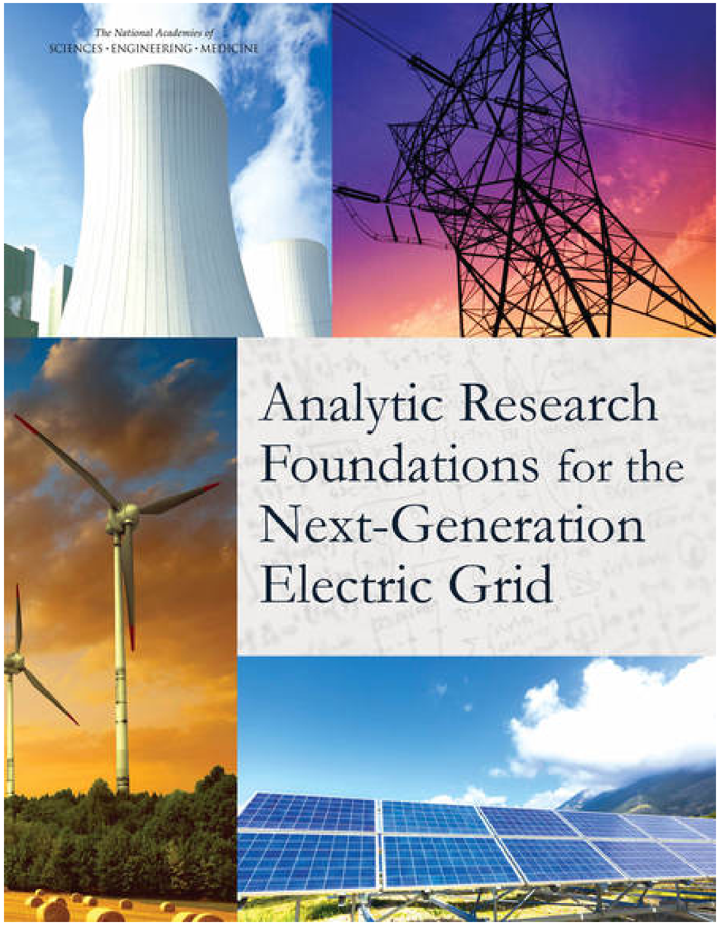

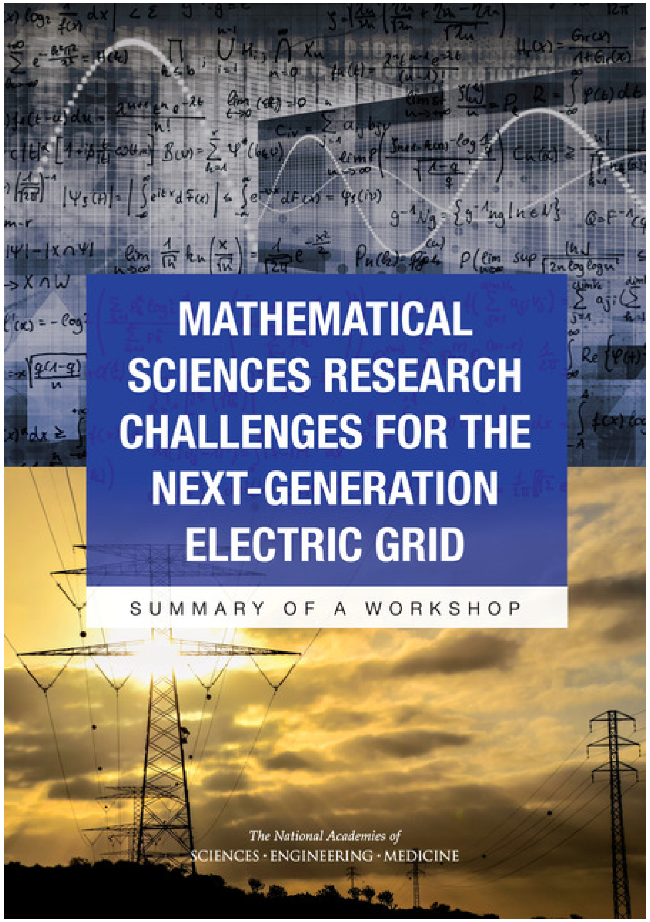

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