Grid Integration of Renewable Electric Energy and Distributed Control

Pramod P. Khargonekar

Department of Electrical Engineering and Computer Science
University of California, Irvine

University of Southern California
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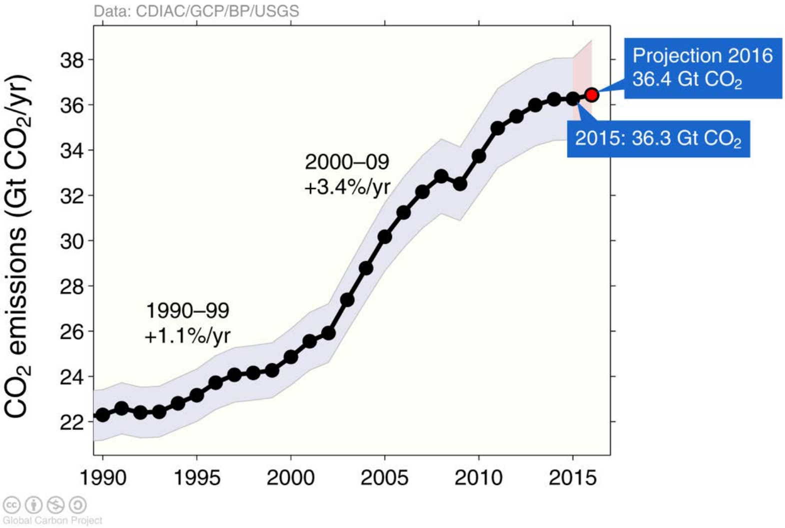
Outline

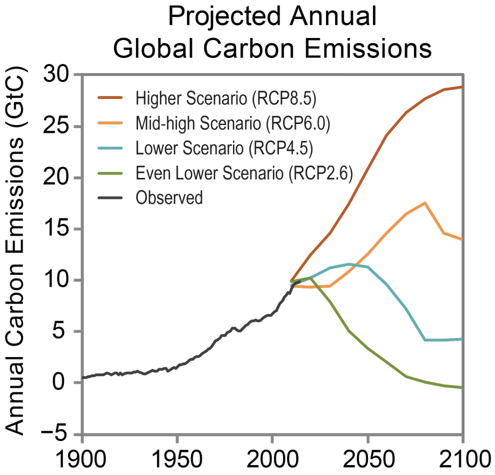
Why Renewable Electric Energy?

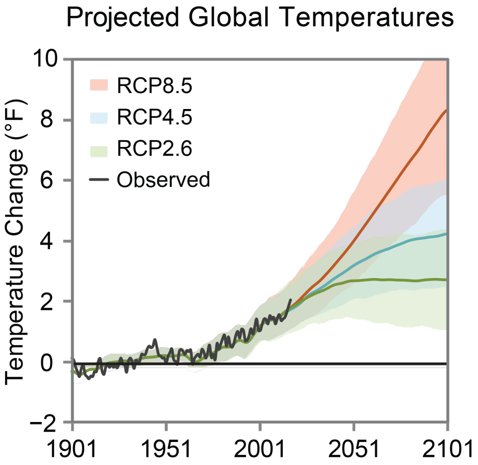
Global CO_2 Emissions



Source: CDIAC; Le Quéré et al 2016; Global Carbon Budget 2016

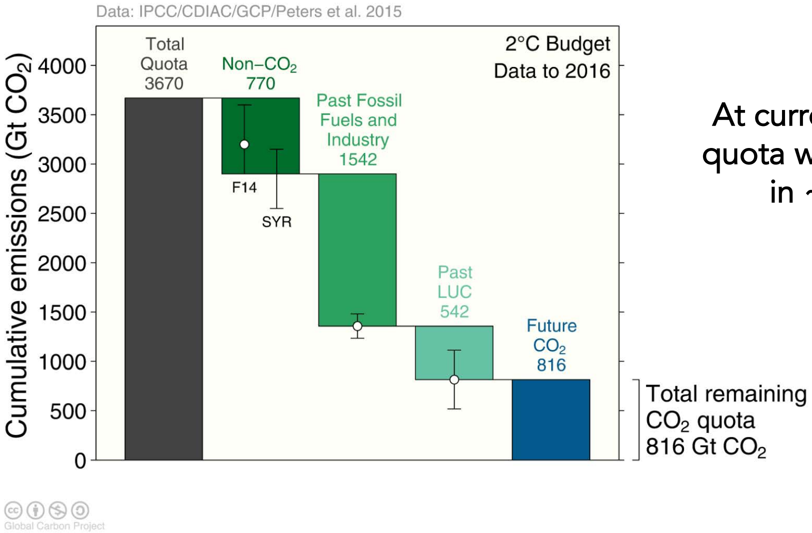
Emissions and Temperature Change





Source: USGCRP, 2017: Climate Science Special Report: Fourth National Climate Assessment, Volume I

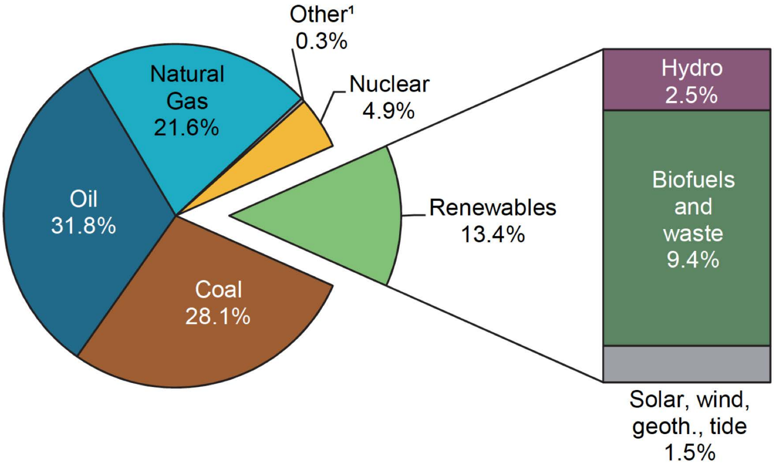
Remaining CO_2 Quota for 66% Chance to Keep Below 2^0 C



At current rates, this quota will be used up in ~23 years

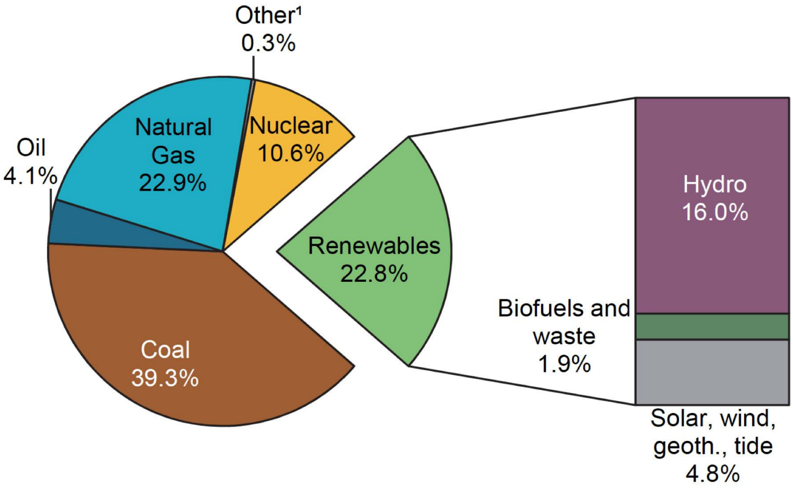
Source: Peters et al 2015; Global Carbon Budget 2016

Global Energy Consumption



Source: Renewables Information 2017, IEA

Electric Energy Sector



Source: Renewables Information 2017, IEA

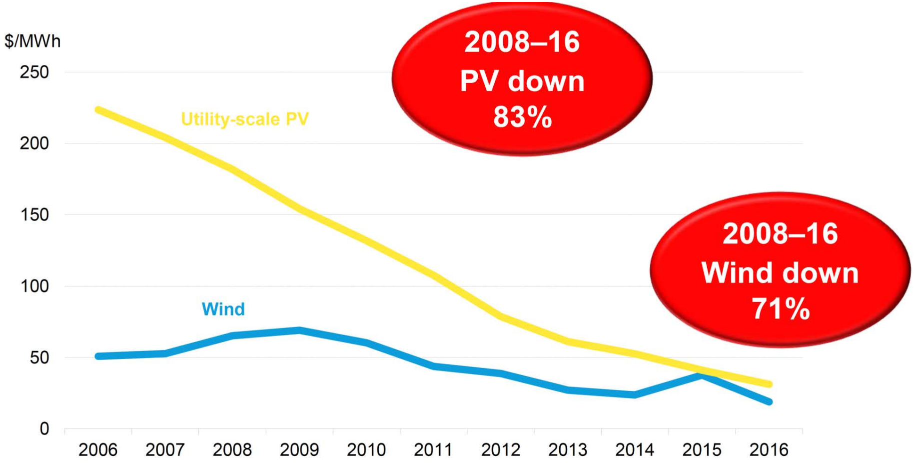
Major Energy Transitions are Slow

- Coal: 5% to 50% in 60 years starting in 1840
- Oil: 5% to 40% in 60 years starting in 1915
- Natural gas: 5% to 25% in 60 years starting in 1930
- Modern renewables $\approx$ 5%

1.2 billion people lack access to electricity
2.8 billion people rely on biomass for cooking and heating

Key Trends

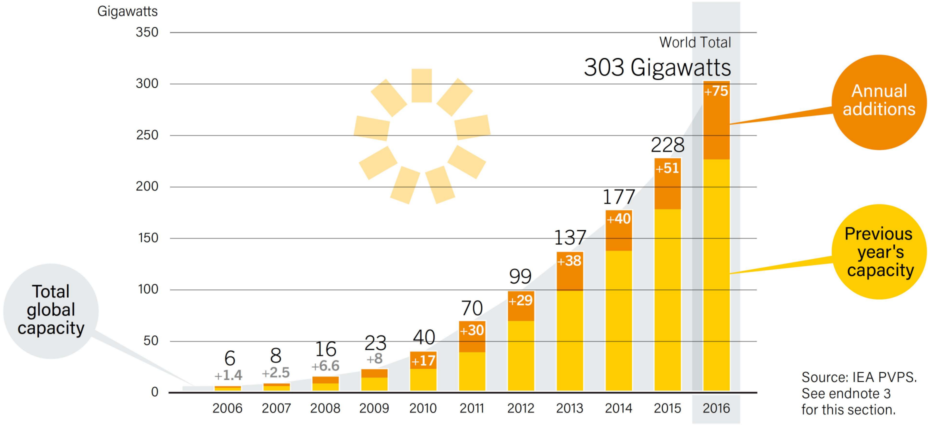
PV and Wind Get Cheaper by the Year



Source: Bloomberg New Energy Finance

Solar PV Growth

Figure 15. Solar PV Global Capacity and Annual Additions, 2006-2016

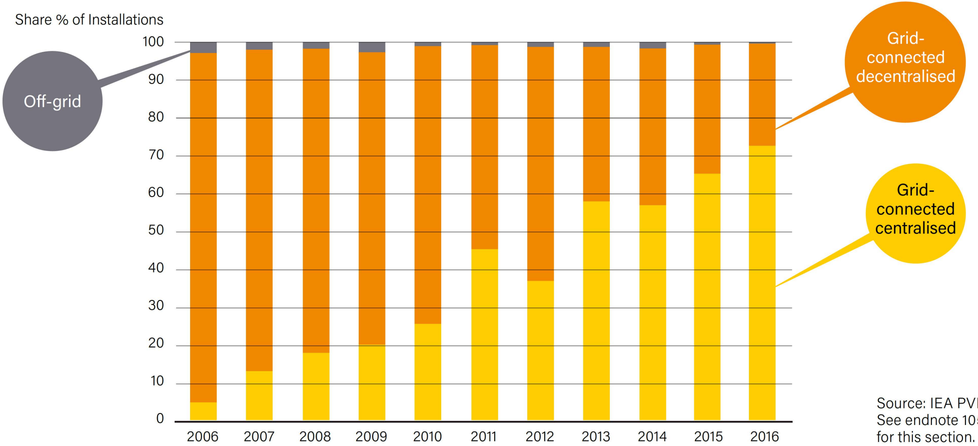


Source: IEA PVPS. See endnote 3 for this section.

Source: REN21. 2017. Renewables 2017 Global Status Report

Solar PV Deployment

Figure 19. Solar PV Global Additions, Shares of Grid-Connected and Off-Grid Installations, 2006-2016

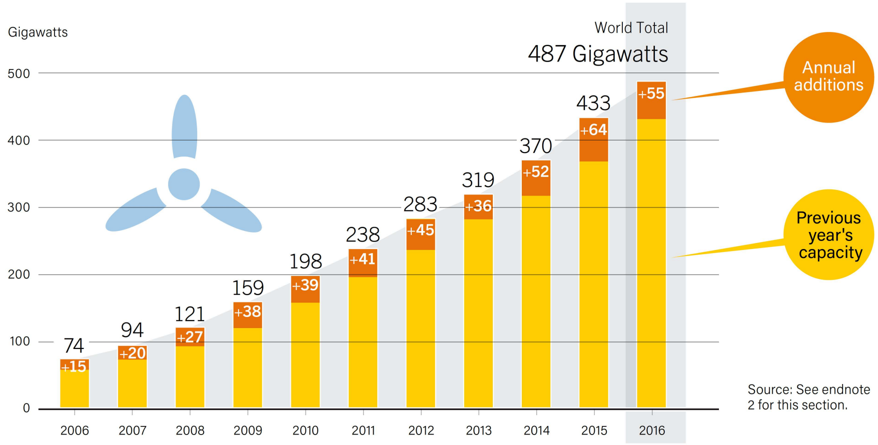


Source: IEA PVPS. See endnote 105 for this section.

Source: REN21. 2017. Renewables 2017 Global Status Report

Wind Growth

Figure 26. Wind Power Global Capacity and Annual Additions, 2006-2016



Source: See endnote 2 for this section.

Source: REN21. 2017. Renewables 2017 Global Status Report

Net Result: Record Low Prices

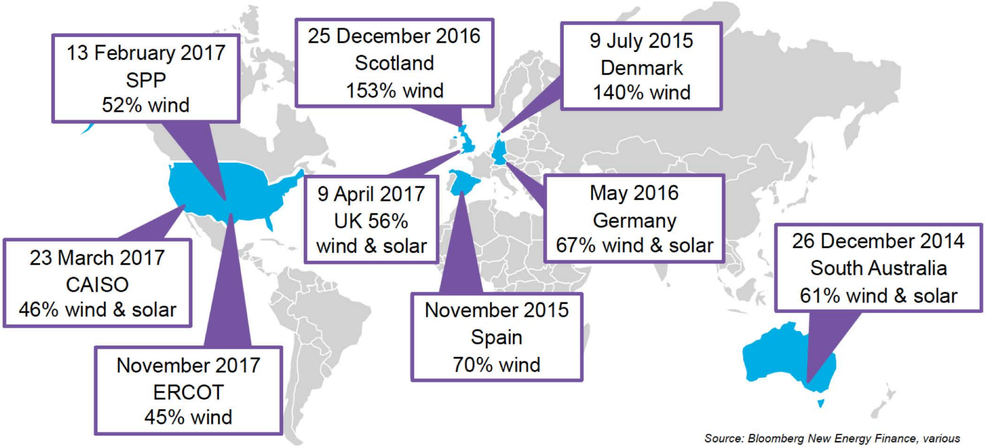
Solar PV		Onshore wind		Offshore wind	
					
Country:	Mexico	Country:	Morocco	Country:	Germany
Bidder:	FRV	Bidder:	Enel Green Power	Bidder:	DONG/EnBW
Signed:	September 2016	Signed:	January 2016	Signed:	April 2017
Construction:	2019	Construction:	2018	Construction:	2024
Price:	**US$ 2.69 c/kWh**	**Price:**	**US$ 3.0 c/kWh**	**Merchant Price:**	**US$ 4.9 c/kWh**

Note: The offshore wind merchant price is estimated based on project LCOE in real 2016 terms

Source: Bloomberg New Energy Finance; ImagesSiemens; Wikimedia Commons

Source: Bloomberg New Energy Finance

Examples of Deep Penetration of Renewable Generation



Source: Bloomberg New Energy Finance

Toward 100% Renewable Future

Electric Grid - Greatest Engineering Achievement in the 20th century

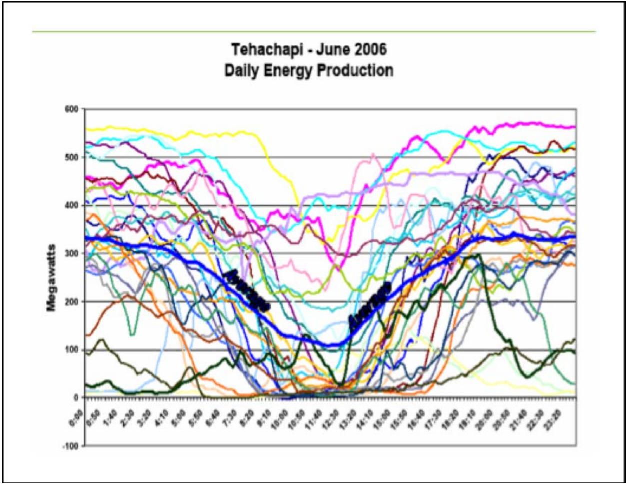
- Goals: economic, reliable, and sustainable access to electric energy
- Generation, transmission, distribution, consumption
- Governed by basic electromagnetic and circuit laws
- Deregulation and markets
- Elaborate control system - multiple time and spatial scales, feedforward and feedback loops
- Critical Constraint: Balancing: Supply = Demand at each time instant
- A cyber-physical-social system (CPSS)

Current Paradigm

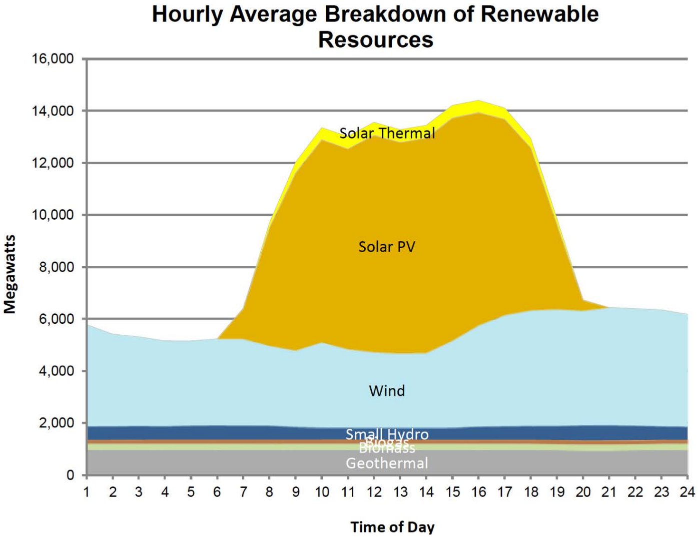
- How do we currently achieve supply-demand balance?
- Demand is inherently variable and random but has somewhat predictable patterns
- Current paradigm: adjust generation to match this variable and random demand while satisfying network constraints
- Day ahead and intra-day feedforward planning
- Frequency control in real-time
- Growing penetration of renewable energy is straining this control paradigm

PV and Wind Are Random and Variable in All Time Scales

- Wind and PV power output depend on wind speed and solar irradiance
- Power output varies at all time scales: annual, seasonal, monthly, daily, hourly, sub-hourly
- Accurate forecasts can help but inherent variability is still a challenge
- These variations pose the biggest challenge to deep integration of renewable electricity

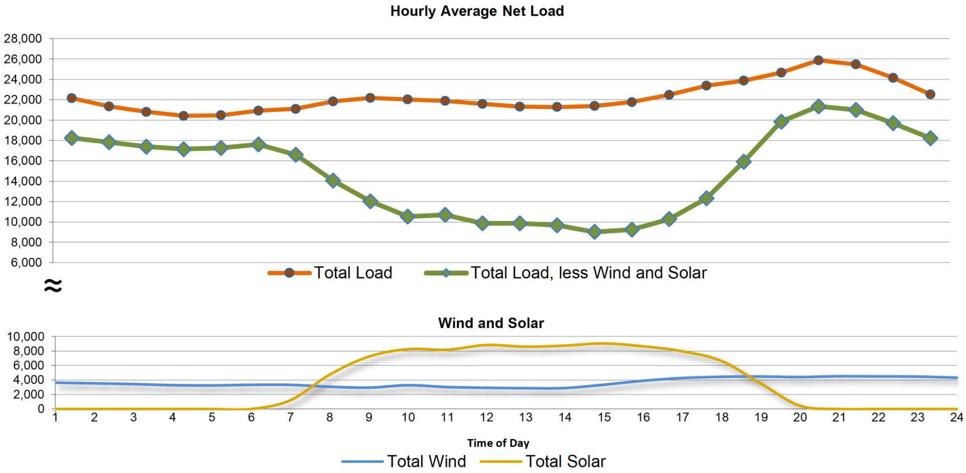


California on May 13, 2017



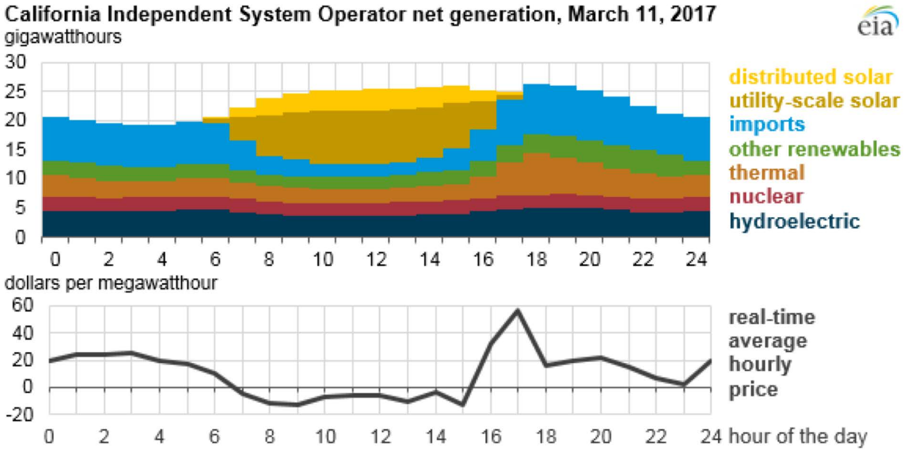
Source: CAISO

California on May 13, 2017



Source: CAISO

Negative Prices in California



Source: EIA, CAISO

Projected Solar Curtailment

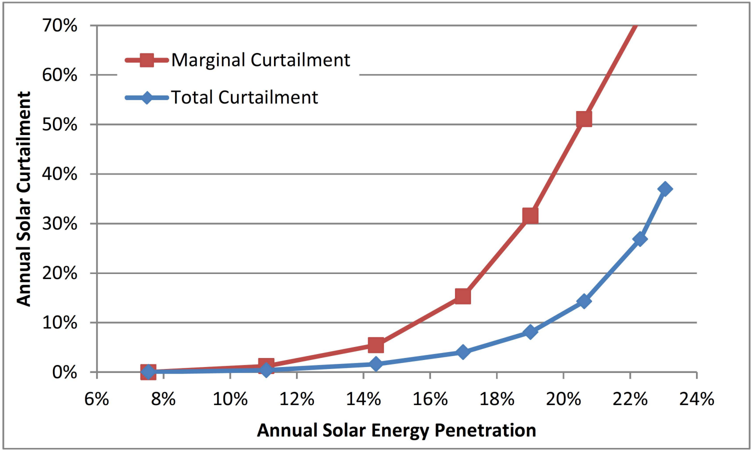


Figure 6. Annual marginal and total solar curtailment due to overgeneration under increasing penetration of PV in California in a system with limited grid flexibility

Denholm et al, On the Path to SunShot: Emerging Issues and Challenges in Integrating High Levels of Solar into the Electrical Generation and Transmission System, NREL, 2016

Impact of Curtailment on Cost of PV

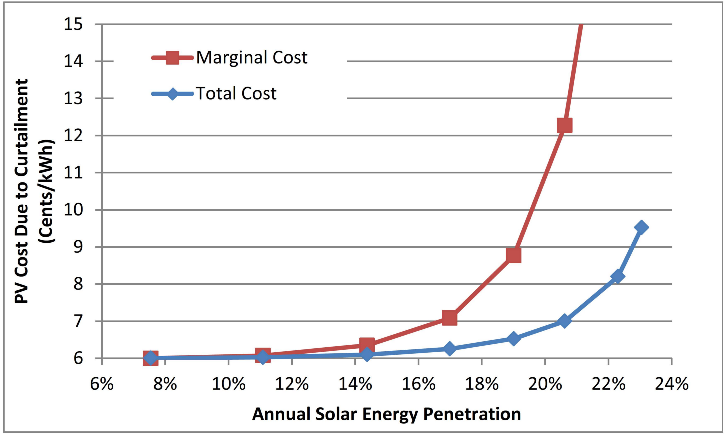


Figure 7. Marginal and average PV LCOE (based on SunShot goals) due to overgeneration under increasing penetration of PV in California in a system with limited grid flexibility

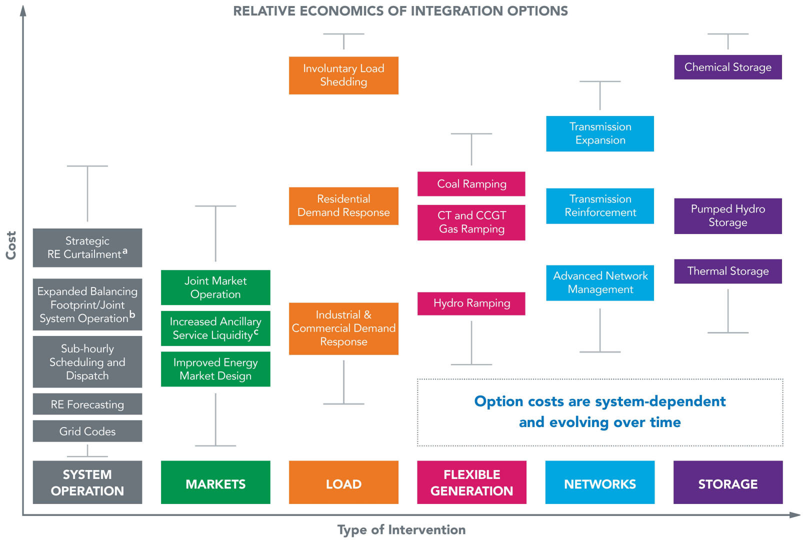
Denholm et al, On the Path to SunShot: Emerging Issues and Challenges in Integrating High Levels of Solar into the Electrical Generation and Transmission System, NREL, 2016

Flexibility

Flexibility: Maximum upward or downward change in the supply/demand balance that a power system is capable of meeting over a given time horizon and a given initial operating state.

Cochran et al., 2014

Options for Flexibility



Cochran et al.,2014

Control systems will play a major role in enabling deep renewable penetration

Grid with Intelligent Periphery

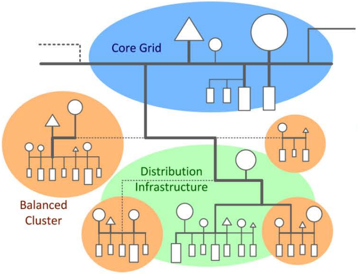


Fig. 1: Layered Architecture

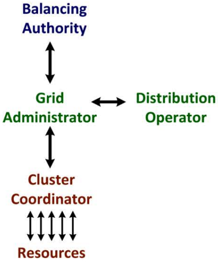


Fig. 2: Data Flow

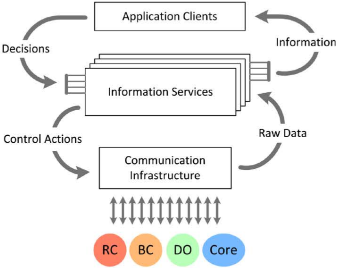


Fig. 3: Distributed Control Loops

Source: Bakken et al., SmartGridComm, 2011

Our Research Directions

Key Research Directions

- Renewable producers in electricity markets
- Strip Packing for Peak Load Minimization
- Causation based Cost Allocation Principles and Algorithms
- Cybersecurity and smart grid
- Distributed control for integration of renewable sources
- Stochastic optimization for residential energy management

Renewable Generators in Electricity Markets

- Scenario: One or more wind or solar producers operating in a wholesale electricity market
- What is the optimal bid by a renewable generator in a two-settlement market?
- Is there a benefit from several renewable generators combining their production?
- What are the strategies to keep the coalition stable?
- What is the optimal operating policy for a renewable generator with local energy storage?

Collaboration with Baeyens, Bitar, Poolla, and Varaiya

Demand Side Management

- Goal: exploit the inherent *flexibility* of electric loads
- Two approaches: incentive based and price based
- Centralized control of loads — ex: direct load control
- Distributed control
  - The central authority sends the control signal, e.g., price, to the consumers.
  - The consumers optimize their consumption schedules accordingly.
- Price of Anarchy: What is the performance loss in using distributed control over optimal centralized control?

Collaboration with Baeyens and Chakraborty

Stochastic Optimization for Residential Energy Management

- Scenario: one more more homes in a residential setting with local renewable generation, storage, and elastic and inelastic loads
- What are stable policies for servicing the loads while optimizing the total cost of operation?
- Approach: put the loads into a queue and use Lyapunov based stochastic optimization techniques that guarantee queue stability, storage limits, upper bounds on delays in serving the elastic loads, and bound on deviation from optimal performance
- Similar approach for data center optimization with local renewable generation and storage, virtual power plants, etc.

Collaboration with Guo, Fang, Pan, Gong and Geng

Strip Packing for Peak Load Minimization

- Scenario: constant interruptible and non-interruptible power flexible loads with start and end times
- How can these loads be scheduled so that the resulting peak load is as small as possible?
- NP hard problems
- Approach: strip packing algorithms from computer science literature
- Results: guaranteed bounds on deviation from optimality

Collaboration with Ranjan and Sahni

Causation based Cost Allocation Principles and Algorithms

- Variability of renewable generation imposes costs on the system
- How should these costs be allocated as tariffs?
- Principle: allocate costs to those who “cause” them
- Approach: tools from cooperative game theory
- Results: algorithms for cost allocation

Collaboration with Chakraborty and Baeyens

Cybersecurity for Smart Grid

- Scenario: Adversary attacks data in energy management system
- How can false data injection attacks be detected?
- How can sensors help mitigate such attacks?
- Results: algorithms for detection and mitigation

Collaborations with Gianni, Poolla, Bitar, Garcia, McQueen, Bretas, Baeyens, Carvalho

Sharing Storage in a Smart Grid

- The consumers $\mathcal{N} := \{1, 2, \ldots, N\}$ invest in storage.
- Scenario I, the consumers already have storage and they operate with storage devices connected to each other.
- Scenario II, the consumers wish to invest in a common storage.
- Examples of the situations include consumers in an industrial park, office buildings on a campus, or homes in a residential complex.
- Would there be benefit from sharing of storage *a al* sharing economy?
- Initial exploration using a *stylized super-simplified model*

Joint work with Chakraborty, Baeyens, Poolla and Varaiya

Set-up

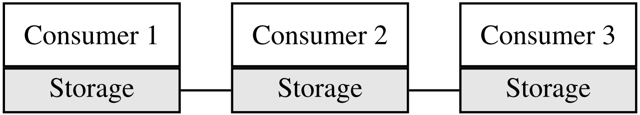


Figure: Configuration of three consumers in scenario I

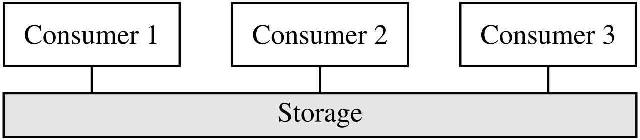


Figure: Configuration of three consumers in scenario II

Pricing

- Each day is divided into two periods –peak and off-peak. The peak and off-peak period prices are π_h and π_ℓ respectively.
- π_i : the daily capital cost of storage of the consumer $i \in \mathcal{N}$ amortized over its life span.
- The arbitrage price $\pi_\delta := \pi_h - \pi_\ell$
- The arbitrage constant $\gamma_i := \frac{\pi_\delta - \pi_i}{\pi_\delta}$
- In order to have a viable arbitrage opportunity, we need

$$\pi_i \leq \pi_\delta \tag{1}$$

which corresponds to $\gamma_i \in [0, 1]$.

Daily Cost of Energy Consumption - Notations

- The daily cost of storage of a consumer $i \in \mathcal{N}$ for the peak period consumption $\mathbf{x}_i$ depends on the capacity investment C_i and is given by

$$J(\mathbf{x}_i, C_i) = \pi_i C_i + \pi_h(\mathbf{x}_i - C_i)^+ + \pi_\ell \min\{C_i, \mathbf{x}_i\}, \tag{2}$$

- F : the joint cumulative distribution function (CDF) of the collection of random variables $\{\mathbf{x}_i : i \in \mathcal{N}\}$.
- For a subset $\mathcal{S} \subseteq \mathcal{N}$, $\mathbf{x}_\mathcal{S}$ denotes the peak consumption and its CDF is $F_\mathcal{S}$.
- The daily cost of energy for $\mathcal{S}$ with peak consumption $\mathbf{x}_\mathcal{S} = \sum_{i \in \mathcal{S}} \mathbf{x}_i$ and joint storage capacity $C_\mathcal{S}$ is

$$J(\mathbf{x}_\mathcal{S}, C_\mathcal{S}) = \pi_\mathcal{S} C_\mathcal{S} + \pi_h(\mathbf{x}_\mathcal{S} - C_\mathcal{S})^+ + \pi_\ell \min\{C_\mathcal{S}, \mathbf{x}_\mathcal{S}\} \tag{3}$$

where $\pi_\mathcal{S}$ is the daily capital cost of aggregated storage amortized during its life span.

Daily Cost of Energy Consumption - Notations

- The daily cost of energy given by (2) and (3) are random variables with expected values

$$J_{\mathcal{S}}(C_{\mathcal{S}}) = \mathbb{E} J_{\mathcal{S}}(\mathbf{x}_{\mathcal{S}}, C_{\mathcal{S}}), \quad \mathcal{S} \subseteq \mathcal{N}. \tag{4}$$

- In the sequel, we distinguish between the random variables and their realized values by using bold face fonts $\mathbf{x}_{\mathcal{S}}$ for the random variables and normal fonts $x_{\mathcal{S}}$ for their realized values.

Review of cooperative game theory

- A coalition is a subset $\mathcal{S} \subseteq \mathcal{N} = \{1, 2, \ldots, N\}$ of the finite collection of players and $\mathcal{N}$ is the grand coalition.
- A coalitional game is a pair $(\mathcal{N}, v)$ where $v(\mathcal{S})$ is the value of the coalition for any $\mathcal{S} \subseteq \mathcal{N}$.
  - Superadditive game: Its value function satisfies:
  $$v(\mathcal{S}) + v(\mathcal{T}) \leq v(\mathcal{S} \cup \mathcal{T}), \quad \mathcal{S} \cap \mathcal{T} = \emptyset, \quad \mathcal{S}, \mathcal{T} \subseteq \mathcal{N}.$$
  - Convex game: Its value function is supermodular
  $$v(\mathcal{S} \cup \{i\}) - v(\{i\}) \leq v(\mathcal{T} \cup \{i\}) - v(\{i\}), \quad \mathcal{S} \subseteq \mathcal{T} \subseteq \mathcal{N}, i \in \mathcal{N} \backslash \mathcal{T},$$
  i.e., individuals' marginal contribution to a coalition increases with the size of the coalition.

Review of cooperative game theory – Solution concepts

- An imputation is a payoff allocation for the grand coalition that is
  - Efficient: $\sum_{i \in \mathcal{N}} x_i = v(\mathcal{N})$.
  - Individually rational: $v(\{i\}) \leq x_i$.
- **Core:** Set of imputations such that no coalition has a value which is greater than the sum of its members payoffs.
  - For an imputation in the core, no subgroup of players has economic incentive to break up the coalition.
  - Convex game $\Rightarrow$ Nonempty core.

Bondareva-Shapley Theorem

Definition (Balanced Game and Balanced Map)

A cooperative game $(\mathcal{N}, v)$ for cost sharing is *balanced* if for any balanced map α, $\sum_{\mathcal{S}\in 2^{\mathcal{N}}} \alpha(\mathcal{S})v(\mathcal{S}) \geq v(\mathcal{N})$ where the map $\alpha : 2^{\mathcal{N}} \to [0,1]$ is said to be *balanced* if for all $i \in \mathcal{N}$, we have $\sum_{\mathcal{S}\in 2^{\mathcal{N}}} \alpha(\mathcal{S})\mathbf{1}_{\mathcal{S}}(i) = 1$, where $\mathbf{1}_{\mathcal{S}}$ is the indicator function of the set $\mathcal{S}$, *i.e.* $\mathbf{1}_{\mathcal{S}}(i) = 1$ if $i \in \mathcal{S}$ and $\mathbf{1}_{\mathcal{S}}(i) = 0$ if $i \notin \mathcal{S}$.

Theorem (Bondareva-Shapley Theorem)

A coalitional game has a nonempty core if and only if it is balanced.

Shapley Value and Nucleolus

- **Shapley value:** $\chi_i(v) = \sum_{\mathcal{S} \subseteq \mathcal{N} \setminus \{i\}} \frac{|\mathcal{S}|!(N-|\mathcal{S}|-1)!}{N!} \left[v(\mathcal{S} \cup \{i\}) - v(\mathcal{S}) \right].$
  - Always exists.
  - Provides an imputation in the core if the game is convex.
  - Not necessarily in the core for a nonconvex game.
- **Nucleolus:** An imputation that minimizes the dissatisfaction of the players using a lexicographic order.
  - Always exists.
  - Always in the core if the core is nonempty.
  - Computation is very demanding ($O(2^N)$ LPs.)

Scenario I: Cooperative Game

- Each consumer has a daily capital cost of storage $\{\pi_i : i \in \mathcal{N}\}$.
- For any coalition $\mathcal{S} \subseteq \mathcal{N}$, the cost of the coalition is $u(\mathcal{S})$ for joint storage investment $C_{\mathcal{S}} = \sum_{i\in\mathcal{S}} C_i$.
- The *realized cost* of energy consumption $x_{\mathcal{S}} = \sum_{i\in\mathcal{S}} x_i$ is

$$u(\mathcal{S}) = J(x_{\mathcal{S}}, C_{\mathcal{S}}) \tag{5}$$

Theorem

The cooperative game for storage investment cost sharing $(\mathcal{N}, u)$ with the cost function u defined in (5) is subadditive.

Theorem

The cooperative game for storage investment cost sharing $(\mathcal{N}, u)$ with the cost function u defined in (5) is balanced.

Scenario I: Cost Allocation

Define the cost allocation $\{\xi_i : i \in \mathcal{N}\}$ as follows:

$$\xi_i := \begin{cases} \pi_i C_i + \pi_h (x_i - C_i) + \pi_\ell C_i, & \text{if } x_{\mathcal{N}} \geq C_{\mathcal{N}} \\ \pi_i C_i + \pi_\ell x_i, & \text{if } x_{\mathcal{N}} < C_{\mathcal{N}} \end{cases} \tag{6}$$

for all $i \in \mathcal{N}$.

Theorem

The cost allocation $\{\xi_i : i \in \mathcal{N}\}$ defined in (6) belongs to the core of the cost sharing cooperative game $(\mathcal{N}, u)$.

Scenario II: Cooperative Game

- The consumer acquires the storage capacity C_i^* that minimizes the expected value of the daily cost, i.e., $C_i^* = \arg\min_{C_i \geq 0} J_i(C_i)$ where $J_i(C_i) = \mathbb{E}J(\mathbf{x}_i, C_i)$.
- Here $\pi_i = \pi_{\mathcal{S}}$ for all $i \in \mathcal{N}$, because we assume that they buy storage devices of the same technology at the same time.

Theorem

The storage capacity of a consumer $i \in \mathcal{N}$ that minimizes its daily expected cost is C_i^*, where

$$F_i(C_i^*) = \frac{\pi_\delta - \pi_{\mathcal{S}}}{\pi_\delta} = \gamma_{\mathcal{S}}$$

and the resulting optimal cost is

$$J_i^* = J_i(C_i^*) = \pi_\ell \mathbb{E}[\mathbf{x}_i] + \pi_{\mathcal{S}} \mathbb{E}[\mathbf{x}_i \mid \mathbf{x}_i \geq C_i^*]. \tag{7}$$

Scenario II: Cooperative Game

- Instead of buying individually, a group of consumers $\mathcal{S} \subseteq N$ that decide to invest in joint storage capacity.
- The peak consumption of the coalition is $\mathbf{x}_{\mathcal{S}} = \sum_{i \in \mathcal{S}} \mathbf{x}_i$ with CDF $F_{\mathcal{S}}$.
- By applying Theorem 6, the optimal investment in storage capacity of the coalition $\mathcal{S} \subseteq \mathcal{N}$ is $C^*_{\mathcal{S}}$ such that $F_{\mathcal{S}}(C^*_{\mathcal{S}}) = \gamma_{\mathcal{S}}$ and the optimal cost is

$$J^*_{\mathcal{S}} = J_{\mathcal{S}}(C^*_{\mathcal{S}}) = \pi_{\ell}\mathbb{E}[\mathbf{x}_{\mathcal{S}}] + \pi_{\mathcal{S}}\mathbb{E}[\mathbf{x}_{\mathcal{S}} \mid \mathbf{x}_{\mathcal{S}} \geq C^*_{\mathcal{S}}]. \tag{8}$$

Scenario II: Cooperative Game

Consider the cost sharing cooperative game $(\mathcal{N}, v)$ where the cost function $v : 2^{\mathcal{N}} \to \mathbb{R}$ is defined as follows

$$v(\mathcal{S}) = J_{\mathcal{S}}^{*} = \arg\min_{C_{\mathcal{S}} \geq 0} J_{\mathcal{S}}(C_{\mathcal{S}}), \tag{9}$$

where $J_{\mathcal{S}}^{*}$ was defined in (8).

Theorem

The cooperative game for storage investment cost sharing $(\mathcal{N}, v)$ with the cost function v defined in (9) is subadditive.

Theorem

The cooperative game for storage investment cost sharing $(\mathcal{N}, v)$ with the cost function v defined in (9) is balanced.

Scenario II: Expected Cost Allocation

Define the cost allocation $\{\zeta_i : i \in \mathcal{N}\}$ as follows:

$$\zeta_i := \pi_\ell \mathbb{E}[\mathbf{x}_i] + \pi_\mathcal{S} \mathbb{E}[\mathbf{x}_i \mid \mathbf{x}_\mathcal{N} \geq C^*_\mathcal{N}], \;\; i \in \mathcal{N}. \tag{10}$$

Theorem

The cost allocation $\{\zeta_i : i \in \mathcal{N}\}$ defined in (10) belongs to the core of the cost sharing cooperative game $(\mathcal{N}, v)$.

Scenario II: Realized Cost Allocation

- The cost allocation ζ_i defined by (10) is in expectation.
- The realized allocation will be different due to the randomness of the daily consumption. Here we develop a daily cost allocation for the k-th day as

$$\rho_i^k = \beta_i \pi_{\mathcal{N}}^k, \tag{11}$$

  where $\pi_{\mathcal{N}}^k$ is the realized cost for the grand coalition on the k-th day and $\beta_i = \frac{\zeta_i}{\sum_{i=1}^N \zeta_i}$.
- The realized cost allocation is budget balanced and strongly consistent with the fixed allocation ζ_i.

Scenario I: Benefits of Sharing

The benefit of cooperation by joint operation of storage reflected in the total reduction of cost is given by

$$\sum_{i\in\mathcal{S}} J_i - J_S = \pi_h\Big(\sum_{i\in\mathcal{S}}(x_i - C_i)^+ - (x_{\mathcal{S}} - C_{\mathcal{S}})^+\Big) + \pi_\ell\Big(\sum_{i\in\mathcal{S}}\min\{C_i, x_i\} - \min\{C_{\mathcal{S}}, x_{\mathcal{S}}\}\Big), \tag{12}$$

where the reduction for individual agent with cost allocation (6) is

$$J_i - \zeta_i := \begin{cases} \pi_\delta(C_i - x_i)^+, & \text{if } x_{\mathcal{N}} \geq C_{\mathcal{N}} \\ \pi_\delta(x_i - C_i)^+, & \text{if } x_{\mathcal{N}} < C_{\mathcal{N}} \end{cases} \tag{13}$$

Scenario II: Benefits of Sharing

The benefit of cooperation given by the reduction in the expected cost that the coalition $\mathcal{S}$ obtains by jointly acquiring and exploiting the storage is

$$\sum_{i\in\mathcal{S}} J_i^* - J_{\mathcal{S}}^* = \pi_{\mathcal{S}} \sum_{i\in\mathcal{S}} \mathbb{E}[\mathbf{x}_i \mid \mathbf{x}_i \geq C_i^*] - \pi_{\mathcal{S}} \mathbb{E}[\mathbf{x}_{\mathcal{S}} \mid \mathbf{x}_{\mathcal{S}} \geq C_{\mathcal{S}}^*], \tag{14}$$

and the reduction in expected cost of each participant assuming that the expected cost of the coalition is split using cost allocation (10) is

$$J_i^* - \zeta_i = \pi_{\mathcal{S}} \mathbb{E}[\mathbf{x}_i \mid \mathbf{x}_i \geq C_i^*] - \pi_{\mathcal{S}} \mathbb{E}[\mathbf{x}_i \mid \mathbf{x}_{\mathcal{S}} \geq C_{\mathcal{S}}^*]. \tag{15}$$

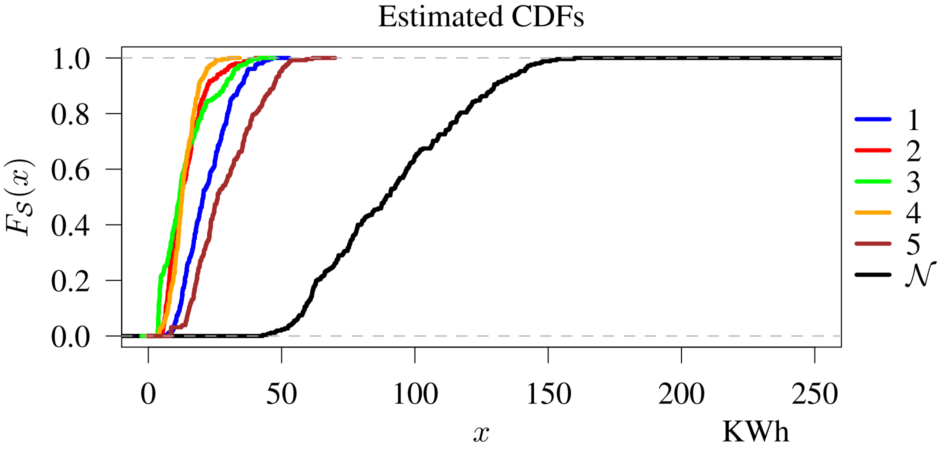
Case Study

- Data from the Pecan St project.
- We consider a two-period ToU tariff with $\pi_h = 55$¢/KWh, and $\pi_\ell = 20$¢/KWh.
- Electricity storage is currently expensive. The amortized cost of Tesla's Powerwall Lithium-ion battery is around 25¢/KWh per day. But storage prize is projected to reduce by 30% by 2020.
- With this background, we consider $\pi_{\mathcal{S}} = 15$¢/KWh.

Estimated CDFs

Scenario II: A group of five households decide to jointly acquire storage.

Figure: Estimated CDFs of the peak consumptions and aggregated consumption



Case Study

Although the shape of the CDFs are similar, the peak consumptions are not completely dependent.

Table: Correlation coefficients for the five households

	1	2	3	4	5
1	1.000000	0.363586	0.297733	0.292073	0.486665
2	0.363586	1.000000	0.132320	0.453056	0.157210
3	0.297733	0.132320	1.000000	0.085868	0.365212
4	0.292073	0.453056	0.085869	1.000000	-0.056696
5	0.486665	0.157210	0.365212	-0.056696	1.000000

Cost Savings by Sharing

- The reduction in cost $\left(\frac{\sum_i J_i^* - \zeta_{\mathcal{N}}}{\sum_i J_i^*}\right)$ - 5%.
- Consumers 3 and 4 have cost reductions $\left(\frac{J_i^* - \zeta_i}{J_i^*}\right)$ higher than 7%, while consumer 1 saves about 2.4%.

Table: Optimal storage capacity investments without sharing(in KWh), optimal expected cost of consumption without sharing (in $) and expected cost allocation of the grand coalition while sharing(in $)

	1	2	3	4	5	$\mathcal{N}$
C_i^*	22.98	14.09	12.64	13.21	29.82	95.58
J_i^*	9.00	5.80	6.01	5.26	11.89	36.04
ζ_i	8.82	5.43	5.50	4.88	11.40	36.04

Case Study - Scenario I

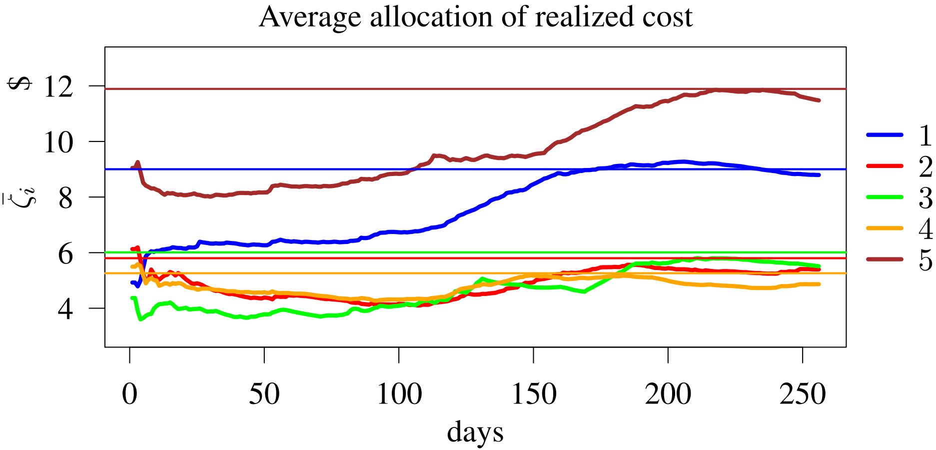
Scenario I: The five households buy storage independently and then decide to cooperate by sharing their storage to reduce the realized cost. We assume each buys individual optimal storage.

Table: Allocation of the realized cost for Scenario I for the first ten days of the year (in $)

Day	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5
1	4.93	6.13	4.37	5.50	9.05
2	4.65	6.25	3.44	5.67	9.47
3	5.41	4.83	3.00	5.41	8.20
4	6.76	3.74	3.78	4.18	7.34
5	7.61	4.03	4.06	3.72	7.99
6	6.46	5.17	4.05	5.73	8.13
7	6.54	7.61	3.88	5.37	7.97
8	5.84	4.11	5.33	4.56	8.32
9	6.40	3.94	4.83	4.83	7.87
10	6.04	4.46	4.75	3.10	7.92

Convergence of Allocated Costs

The average values of the realized allocations converge to values lower than individual optimal costs but greater than Scenario II optima.



Future Opportunities

- Control for flexibility in grid for renewable integration: storage, demand, cooperation
- Information and control architectures for renewables, demand, storage, grid
- Wide area stability and control under deep renewable penetration scenarios
- Long term: negative carbon technologies

Evolutionary Nature of Infrastructure Technological Change

- Infrastructure systems have long life spans - decades to centuries
- Technological change is grafted onto existing systems
- Particular case: electric energy system and its operations and control
- Evolution as a model for understanding this transformation?

Conclusions

- Grid integration of renewable energy will be an increasingly important and difficult challenge
- Many opportunities for the systems and control field
- Energy systems present a unique mix of science, engineering, economics and social policy
- Decarbonization of the energy system remains a true grand challenge for humanity