Electric Grid Integration of Renewable Electric Energy and Distributed Control

Pramod P. Khargonekar

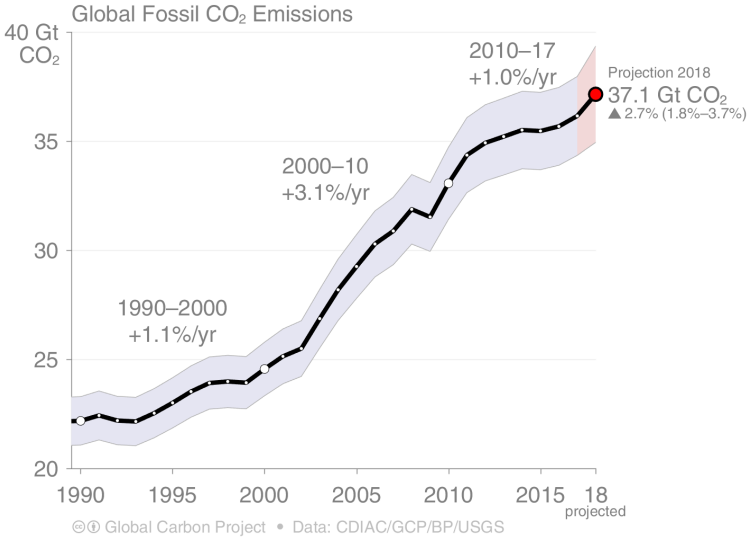
Department of Electrical Engineering and Computer Science
University of California, Irvine

Conference on Information Sciences and Systems
Johns Hopkins University
20 March 2019

Outline

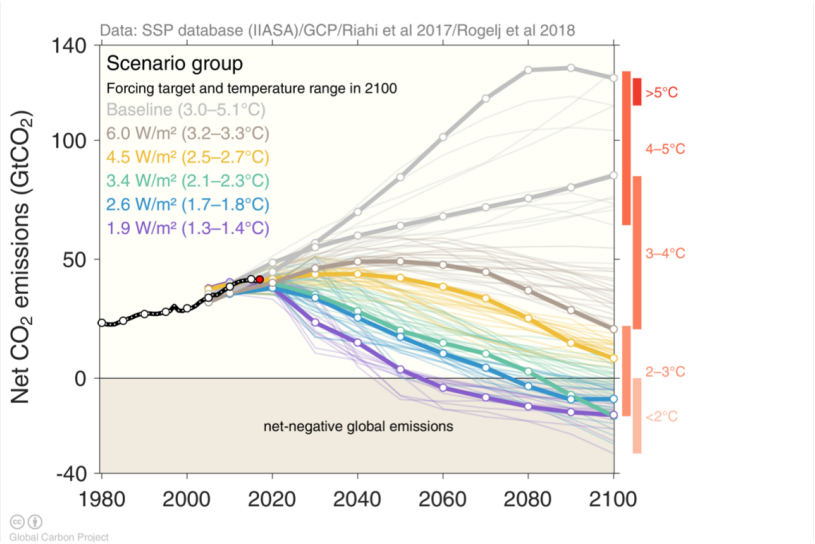
Why Renewable Electric Energy?

Global CO_2 Emissions



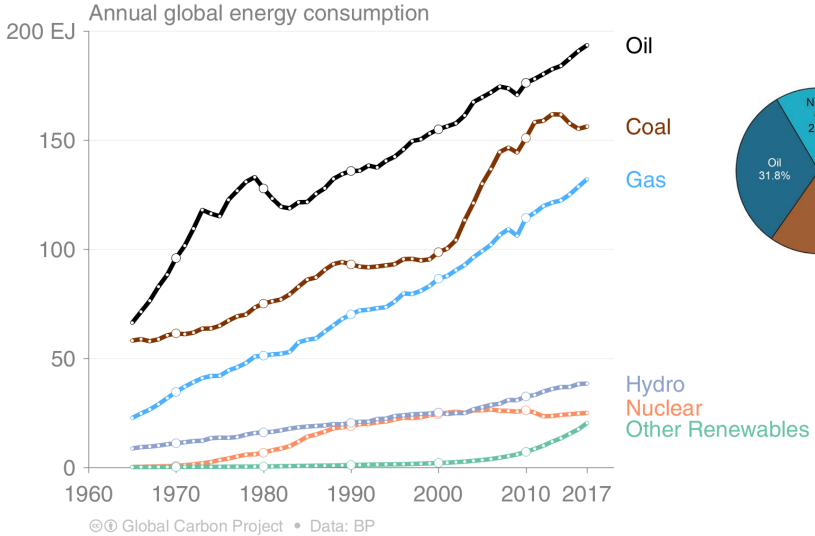
Source: Global Carbon Project

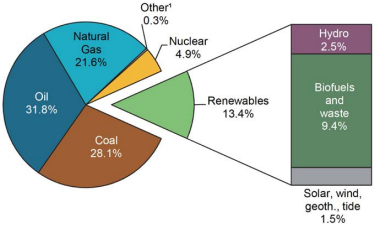
Projected CO_2 Emissions and Temperature Change



Source: Global Carbon Project

Global Energy Consumption

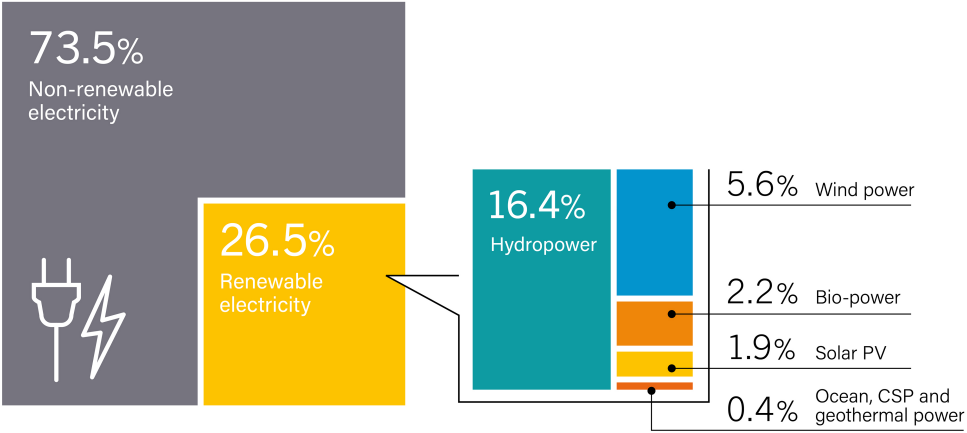




Source: Global Carbon Project, BP

Electric Energy Sector

Estimated Renewable Energy Share of Global Electricity Production, End-2017



REN21 RENEWABLES 2018 GLOBAL STATUS REPORT

Source: Ren21

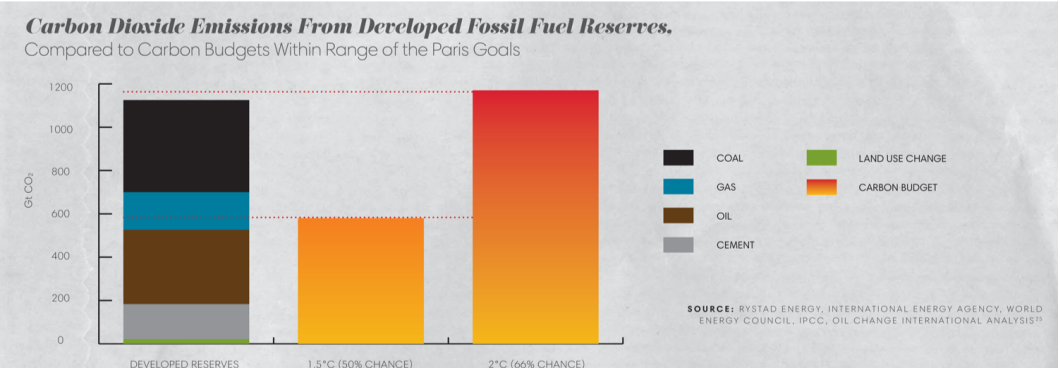
Major Energy Transitions are Slow

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

Source: V. Smil

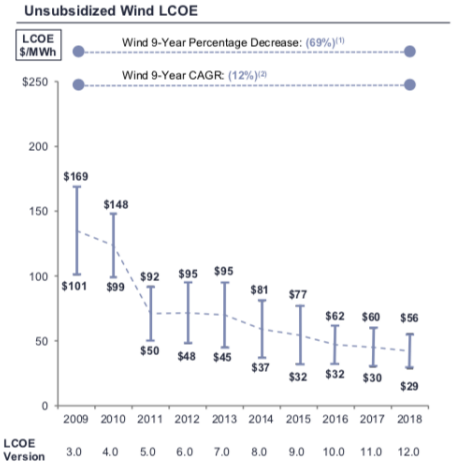
How Much Carbon is Left to Emit?

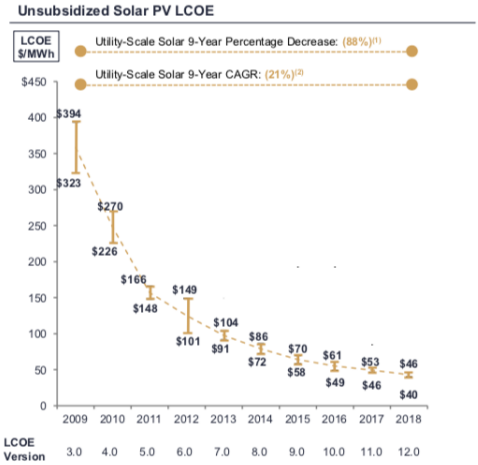


Source: Banking on Climate Change, 2019

Key Trends

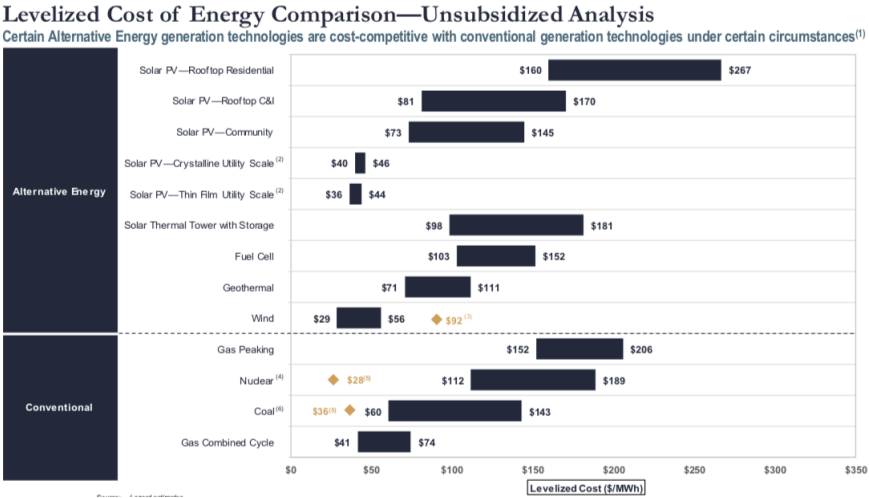
PV and Wind Get Cheaper by the Year





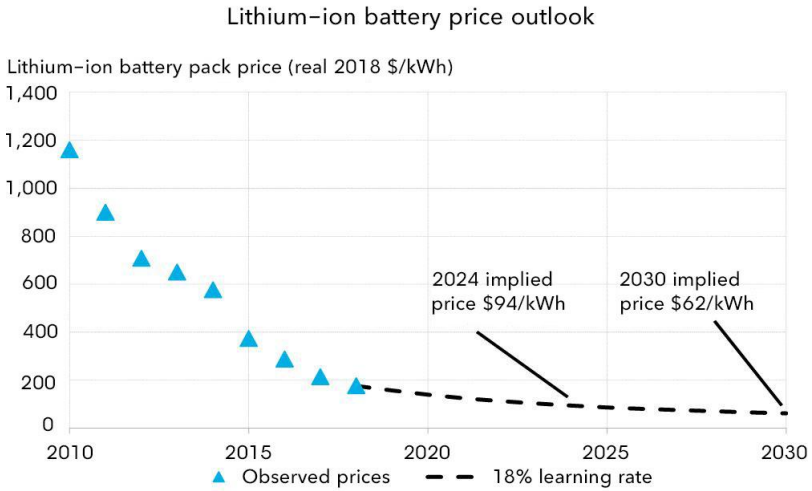
Source: Lazard

PV and Wind are Now the Cheapest Option



Source: Lazard

Battery Storage is Getting Cheaper Leading to EV Acceleration



Source: BloombergNEF

PV and Wind Deployment is Accelerating

"If you look right now, we have over 20,000 MW of generation in our queue, and 85% of it is either wind, solar, batteries, hydro, biomass or fuel cells," he said. "The 15% that's left over is natural gas, so what resource developers are saying . . . these are the resources that are coming forward . . . this has changed dramatically since just 2017."

S. J. Rourke, VP, ISO-New England

Toward 100% Renewable Future

Electric Grid - Greatest Engineering Achievement in the 20th Century

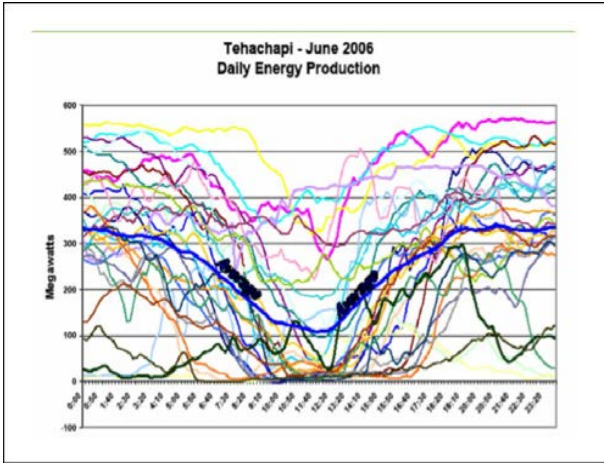
- Goals: economic, reliable, and sustainable access to electric energy
- Generation, transmission, distribution, consumption
- Governed by basic electromagnetic and circuit laws
- Deregulation and markets in generation and transmission
- Elaborate control system - multiple time and spatial scales, feedforward 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

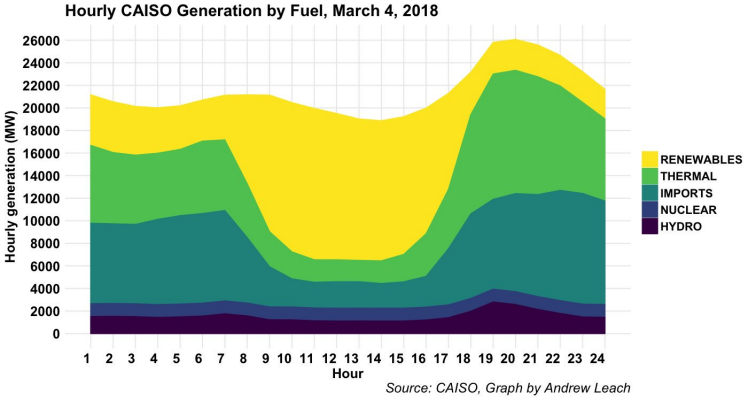
PV and Wind Are Random and Variable in All Time Scales

- 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



Source: CAISO

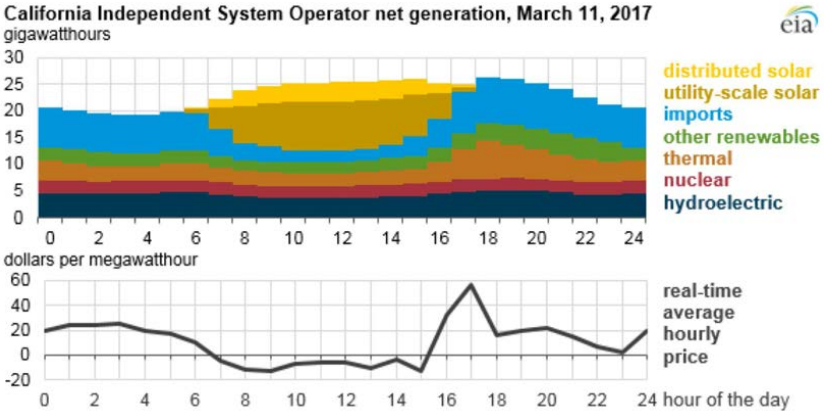
Recent California Data



- Peak demand on September 1, 2017: 50.1 GW
- Minimum net load on February 18, 2018: 7.2 GW
- Maximum ramps on March 4, 2018: 3 hour ramp of 14.8 GW and 1 hour ramp of 7.5 GW

Source: CAISO

Negative Prices in California



Source: EIA, CAISO

Projected Solar Curtailment

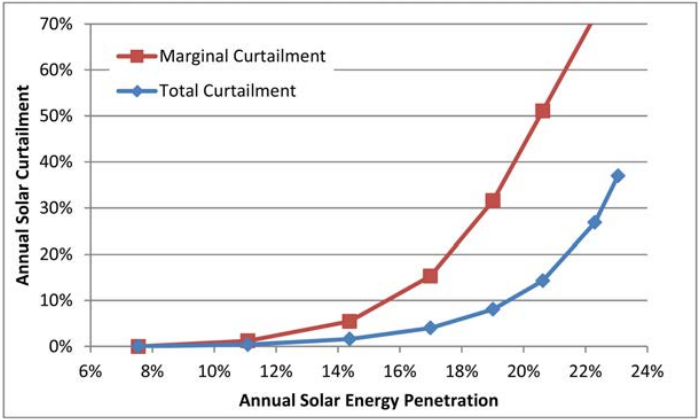


Figure 6. Annual marginal and total solar curtailment due to overgeneration under increasing penetration of PV in California in a system with limited grid flexibility

Source: Denholm et al, NREL, 2016

Impact of Curtailment on Cost of PV

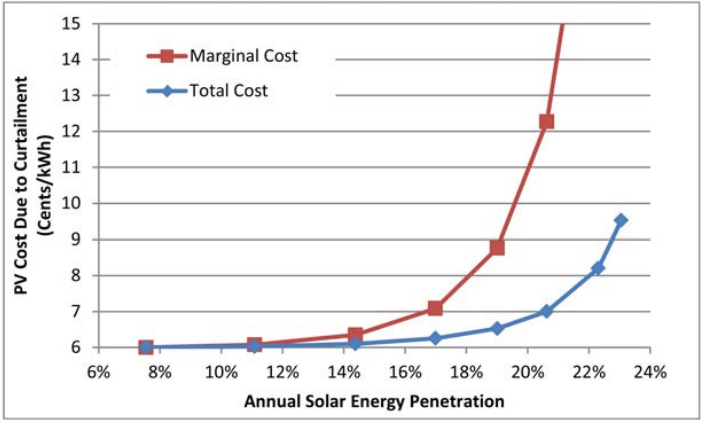


Figure 7. Marginal and average PV LCOE (based on SunShot goals) due to overgeneration under increasing penetration of PV in California in a system with limited grid flexibility

Source: Denholm et al, 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.

Source: Cochran et al, NREL, 2014

Enablers of Flexibility

- System operations: forecasting, sub-hourly dispatch, larger balancing areas
- Markets: market design, flexible ramp products
- Load management: demand response, direct load control
- Flexible generation: CCGT, Hydro
- Transmission: expansion, network management
- Storage: thermal, pumped hydro, battery

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

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

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

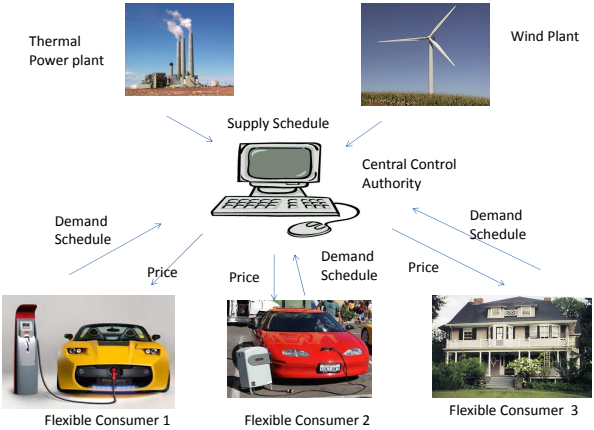
Demand Side Management

- Solution: Centralized control [Ex. South Florida pool pumps]
- Drawbacks:
  - Violation of consumer privacy
  - Potentially huge computational burden
- Solution Approach: Distributed Control
  - The central authority sends control signal, e.g. price, to the consumers.
  - The consumers optimize their consumption schedules accordingly.
- Major Assumption: Consumers are price-takers
- Reality- this assumption may not be true in smart grid with active consumers
- Consumer behavior will change as a result of prices

Price Anticipating Consumers

- Game theoretic modeling to capture the price anticipating behavior
- Key Issue: Loss of efficiency in terms of the social objective due price anticipating behavior and distributed control
- Price of Anarchy(PoA) : Ratio of the worst-case objective function value of an equilibrium solution of the game using distributed control to that of a centralized optimal solution

System Model



Distributed Control using Proportional Allocation Mechanism and its Efficiency

We develop an *intra-day demand control* process where we

- model flexible consumers with operational constraints and utility functions.
- formulate and solve
  - a centralized control problem.
  - a distributed control problem with price taking consumers where the price is set up by proportional allocation mechanism (Kelly [1997]).
  - a distributed game problem with price anticipating consumers.
- show that PoA is 25% in the worst case.
- analyze the methods of improving efficiency.

Notations

- The time slots are denoted by $t \in \mathcal{T} = (1, 2, ..., T)$.
- Flexible consumers are denoted by $i \in \mathcal{N} = (1, 2, ..., N)$.
- $q_i(t)$: The power consumption of the i-th consumer at time t
- $\mathbf{q}_i := (q_i(t) : t \in \mathcal{T})$ denotes the power demand vector of the i-th consumer over the time period T
- $c(t)$: The total scheduled power generation of all the thermal power plants at time t
- $w(t)$: The total predicted power supply of the renewable generators at time t
- $n(t)$: Total power consumption of uncontrolled loads/consumers at time t
- $U_i(\mathbf{q}_i)$: The utility for consuming power q_i in monetary unit. U_i is assumed to be a concave, strictly increasing and continuously differentiable function.

Balancing Constraints

- Supply=Demand

$$c(t) + w(t) = n(t) + \sum_{i=1}^{N} q_i(t) \quad \forall\, t \in \mathcal{T}. \tag{1}$$

- Define $v(t) := c(t) + w(t) - n(t)$. So, (1) becomes

$$v(t) = \sum_{i=1}^{N} q_i(t) \quad \forall\, t \in \mathbb{T}. \tag{2}$$

- Assumption: $v(t) > 0$ for all t.
- $\mathbf{v} := (v(t) : t \in \mathbb{T})$ denotes the net generation available for flexible demand over the time period T

Operational Constraints of a Consumer

Flexible load operational constraints can be expressed by the following linear inequalities

$$\mathbf{H}_i \mathbf{q}_i \leq \mathbf{b}_i, \;\; i \in \mathcal{N}, \tag{3}$$

where $\mathbf{H}_i \in \mathbb{R}^{M \times T}$, $\mathbf{b}_i \in \mathbb{R}^M$

Centralized Control

The centralized control problem is defined as follows:

$$\max_{\mathbf{q}_i} \left\{ \sum_{i \in \mathcal{N}} U_i(\mathbf{q}_i) : \mathbf{q}_i \in \mathcal{S} \right\} \tag{4}$$

where the search space

$$\mathcal{S} := \left\{ \mathbf{q}_i \in \mathbb{R}^T : \mathbf{v} - \sum_{i \in \mathcal{N}} \mathbf{q}_i = \mathbf{0}, \mathbf{b}_i - \mathbf{H}_i \mathbf{q}_i \geq \mathbf{0} \right\} \tag{5}$$

is assumed to be nonempty.

Distributed Control with Price Taking Consumers

- Assumption: The consumers are price takers, selfish and rational.
- Notation: $k_i(t)$ denotes the *monetary value/expenditure* for power demand of i-th consumer at time t.
- At first the control authority, after obtaining the values of $c(t)$, $w(t)$ and $n(t)$, calculates $v(t)$ and broadcasts the value to all the consumers.
- Each consumer then submits its $k_i(t)$ to the authority for all t. The authority calculates $\sum_{i=1}^{N} k_i(t)$ and sets price as

$$p(t) = \frac{\sum_{i=1}^{N} k_i(t)}{v(t)} \tag{6}$$

Distributed Control with Price Takers

- Inspired by the *proportional allocation mechanism*, the allocation of $q_i(t)$ to the i-th consumer is given by

$$q_i(t) = \frac{k_i(t)}{p(t)} \tag{7}$$

  for all i and t.

- The distributed control problem for price takers is given by

$$\max_{\mathbf{q}_i} \left\{ U_i(\mathbf{q}_i) - \mathbf{p}^\top \mathbf{q}_i : \mathbf{q}_i \in \mathcal{S}_i^{pt} \right\}, \ i \in \mathcal{N} \tag{8}$$

  where the set of feasible power consumptions is

$$\mathcal{S}_i^{pt} := \{\mathbf{q}_i : \mathbf{b}_i - \mathbf{H}_i \mathbf{q}_i \geq 0\}, \ i \in \mathcal{N}.$$

Competitive Equilibrium

Definition

The set $\{(\mathbf{q}_i^E, \mathbf{p}^E) : i \in \mathcal{N}\}$ is a *competitive equilibrium* if each consumer selects its consumption vector $\mathbf{q}_i^E$ by solving the optimization problem (8) for the price vector $\mathbf{p}^E$ and the control authority obtains the price vector $\mathbf{p}^E$ using the proportional allocation mechanism (6)–(7).

Theorem

The set $\{(\mathbf{q}_i^E, \mathbf{p}^E) : i \in \mathcal{N}\}$ is a competitive equilibrium if and only if the set of consumptions $\{\mathbf{q}_i^E : i \in \mathcal{N}\}$ is a solution to the centralized control problem.

Price Anticipating Users

- Price anticipating consumers will try to account for the impact of their decisions on $p(t)$ and adjust their decisions accordingly.
- Suppose they know that $p(t)$ is set by the formula $p(t) = \frac{\sum_{i=1}^{N} k_i(t)}{v(t)}$.
- We model the resulting situation as a noncooperative game as each consumer's optimization problem depends on sum of monetary values of all other consumers.

Notations

- The problem can be formulated in terms of only the monetary expenditures by eliminating the price and the consumptions variables.
- Let $\mathbf{k}_{-i} = \{\mathbf{k}_j : j \in \mathcal{N} \backslash \{i\}\}$ denote the collection of monetary value vectors of all flexible consumers other than the consumer i.
- Note that $\mathbf{p}$ and $\mathbf{q}_i$ can be expressed as functions of $\mathbf{k}_i$ as follows:

$$\begin{aligned}
\mathbf{p}(\mathbf{k}_i; \mathbf{k}_{-i}) &= \mathbf{D}^{-1}(\mathbf{v}) \sum_{j \in \mathcal{N}} \mathbf{k}_j \\
\mathbf{q}_i(\mathbf{k}_i; \mathbf{k}_{-i}) &= \mathbf{D}^{-1}(\mathbf{p}(\mathbf{k}_i; \mathbf{k}_{-i}))\mathbf{k}_i \\
&= \mathbf{D}^{-1}(\sum_{i \in \mathcal{N}} \mathbf{k}_i)\mathbf{D}(\mathbf{v})\mathbf{k}_i
\end{aligned}$$

Let us define the search space:

$$\mathcal{S}_i^{pa}(\mathbf{k}_{-i}) := \left\{ \mathbf{k}_i : \mathbf{b}_i - \mathbf{H}_i \mathbf{D}^{-1}(\sum_{i \in \mathcal{N}} \mathbf{k}_i)\mathbf{D}(\mathbf{v})\mathbf{k}_i \geq \mathbf{0} \right\}$$

Game Formulation

The game of energy consumption is as follows:

1. Players: Set of N consumers
2. Strategy: Consumer i's strategy $\mathbf{k}_i$
3. Payoff: For each consumer i, the payoff is given by

$$\max_{k_i} \left\{ U_i(\mathbf{D}^{-1}(\sum\nolimits_{j\in\mathcal{N}} \mathbf{k}_j)\mathbf{D}(\mathbf{v})\mathbf{k}_i) - \mathbf{1}^\top \mathbf{k}_i : \mathbf{k}_i \in \mathcal{S}_i^{pa}(\mathbf{k}_{-i}) \right\} \tag{9}$$

where $\mathbf{v}$ is the available generation for flexible consumption and $\mathbf{D}(\mathbf{x})$ denotes a diagonal square matrix whose main diagonal is given by vector $\mathbf{x}$.

Nash Equilibrium

- The Nash equilibrium for the distributed control problem with price anticipators is the set of expenditures $\{\mathbf{k}_i^G : i \in \mathcal{N}\}$ such that

$$U_i(\mathbf{q}_i(\mathbf{k}_i^G, \mathbf{k}_{-i}^G)) - \mathbf{1}^\top \mathbf{k}_i^G \geq U_i(\mathbf{q}_i(\mathbf{k}_i, \mathbf{k}_{-i}^G)) - \mathbf{1}^\top \mathbf{k}_i, \quad \mathbf{k}_i \in \mathcal{S}_i^{pa}(\mathbf{k}_{-1}^G), \ i \in \mathcal{N}. \tag{10}$$

Theorem (Existence of Nash equilibrium)

The non-cooperative game has a Nash equilibrium if the search space is nonempty.

Result on Price of Anarchy

Theorem

Let $\{\mathbf{q}_i^C : i \in \mathcal{N}\}$ *be a solution of the centralized problem (4) and* $\{\mathbf{q}_i^G : i \in \mathcal{N}\}$ *a Nash equilibrium for the distributed problem with price anticipating consumers. Let PoA be defined by:*

$$\mathrm{PoA} := \frac{\sum_{i \in \mathcal{N}} U_i(\mathbf{q}_i^G)}{\sum_{i \in \mathcal{N}} U_i(\mathbf{q}_i^C)}.$$

then $\mathrm{PoA} \geq 0.75$ *and the bound is tight.*

Efficiency Improvement

Corollary

If all the consumers have same utility function, i.e., $U_i = U$, there is no efficiency loss at Nash equilibrium solution, i.e. PoA is 1.

Corollary

Suppose $\mathbf{q}_i = \mathbf{0}$ for all $i \in \mathcal{N}$ belongs to the set of load operational constraints, then the PoA approaches 1 as the number N of flexible consumers goes to infinity.

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 innovations are grafted into 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