Optimal Demand Response with Renewables

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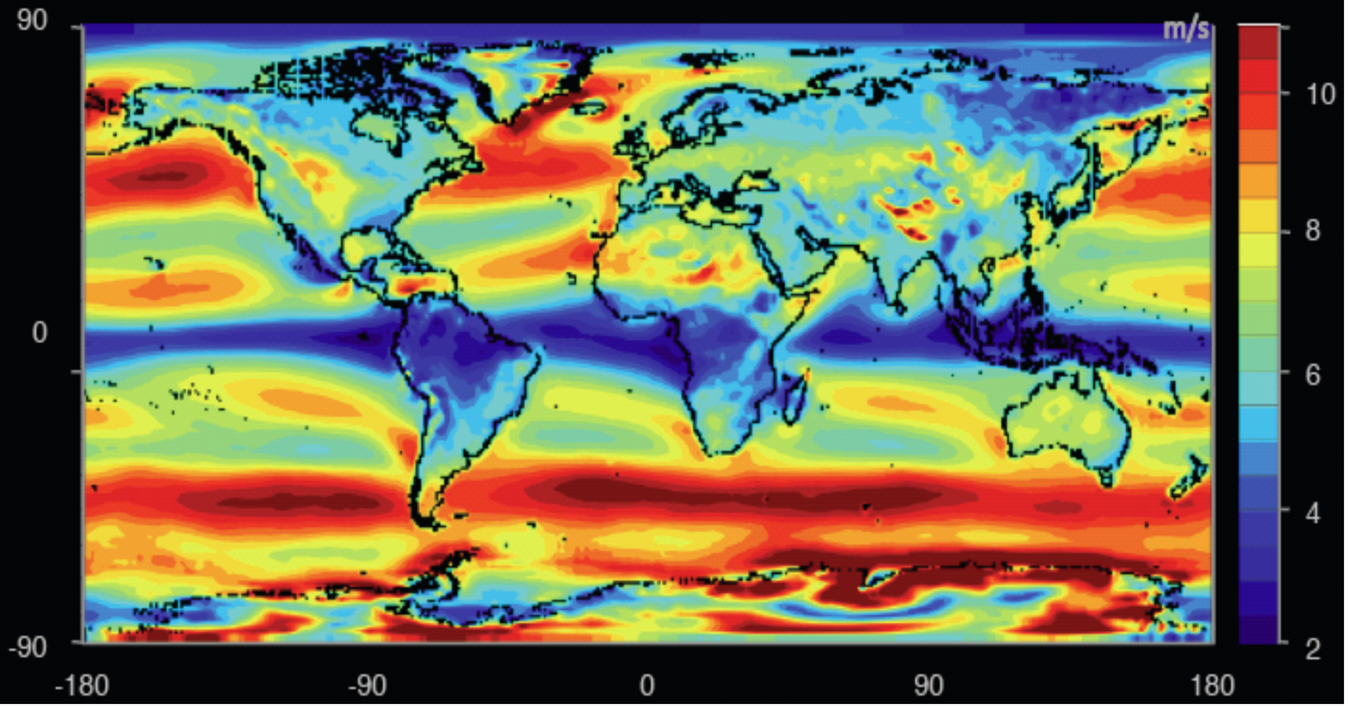
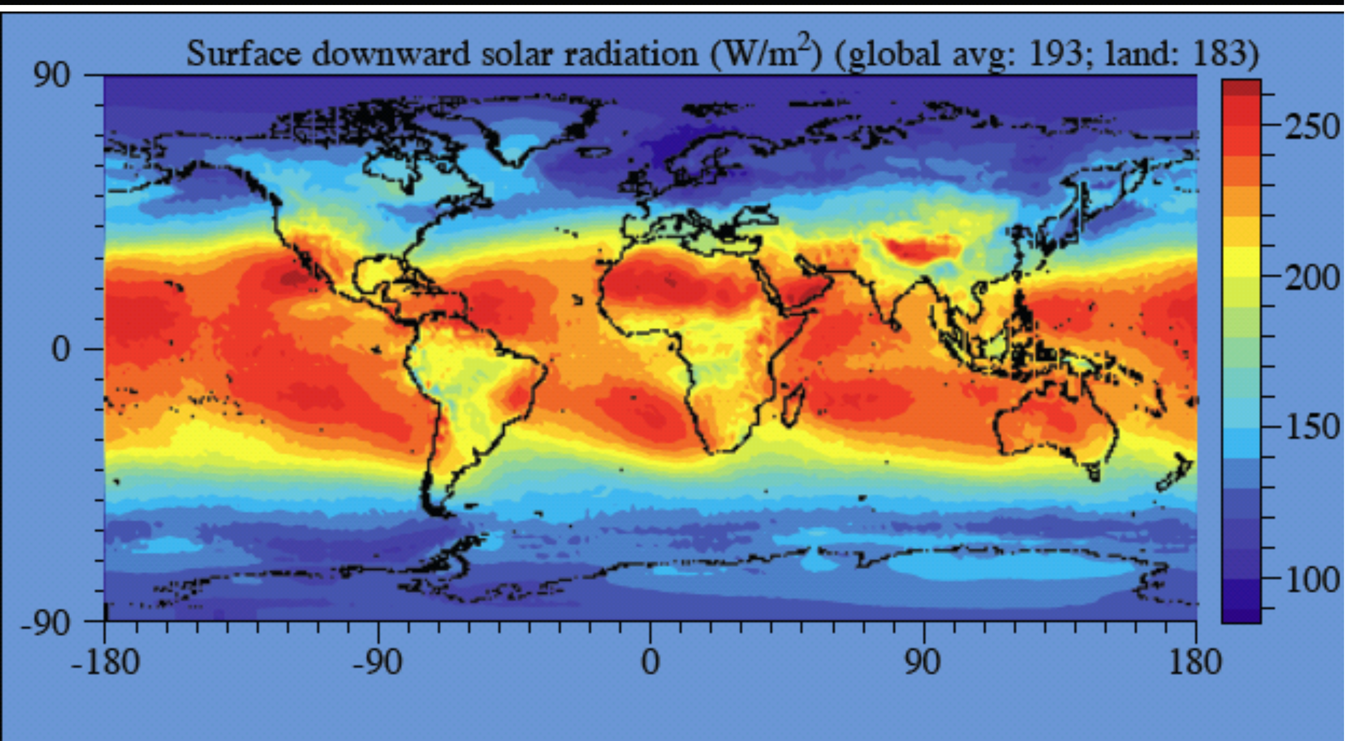
Outline

Focus: renewable integration

DR model

Preliminary results





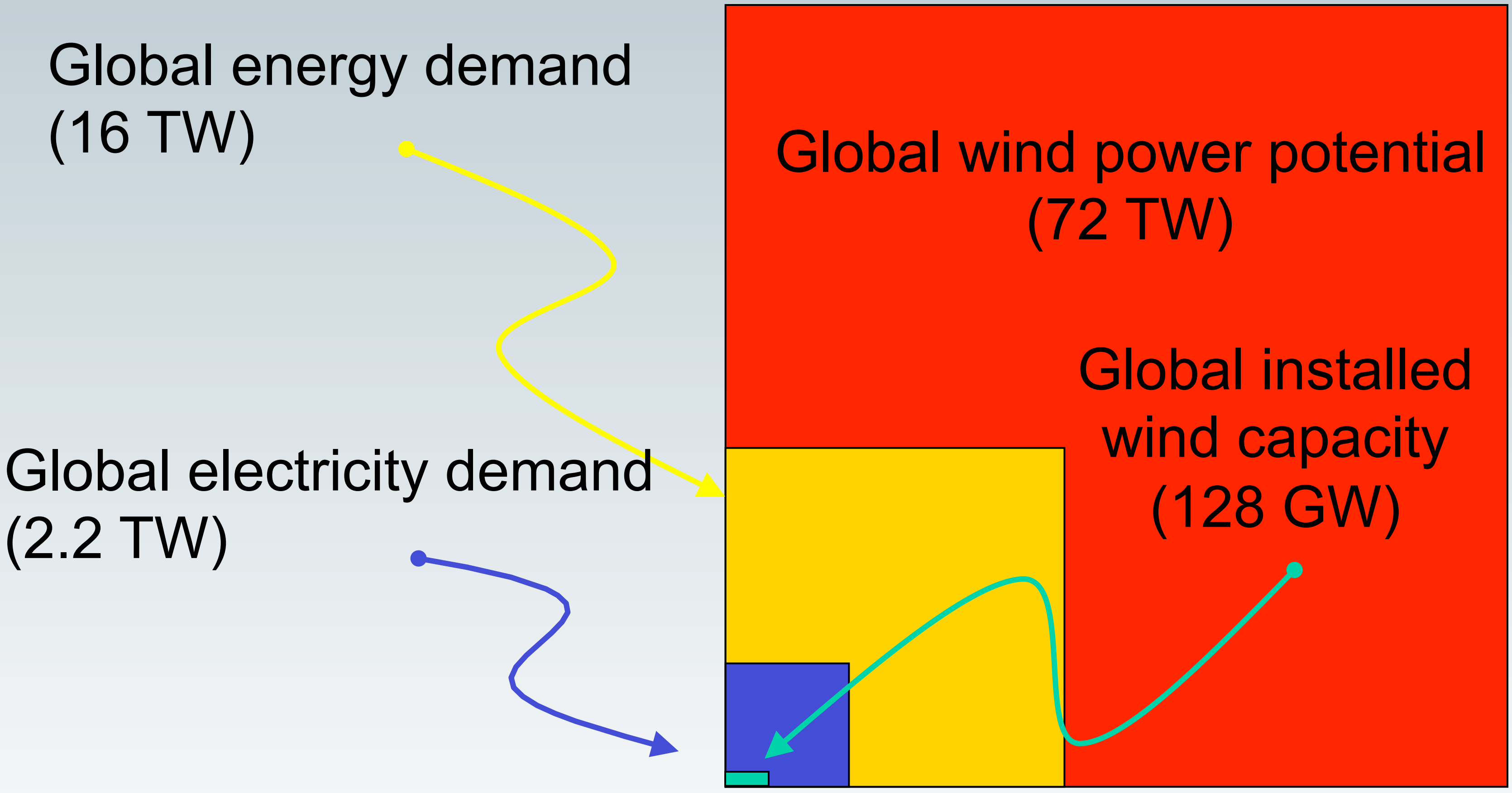
Wind power over land (outside Antartica): 70 – 170 TW

World power demand: 16 TW

Solar power over land: 340 TW

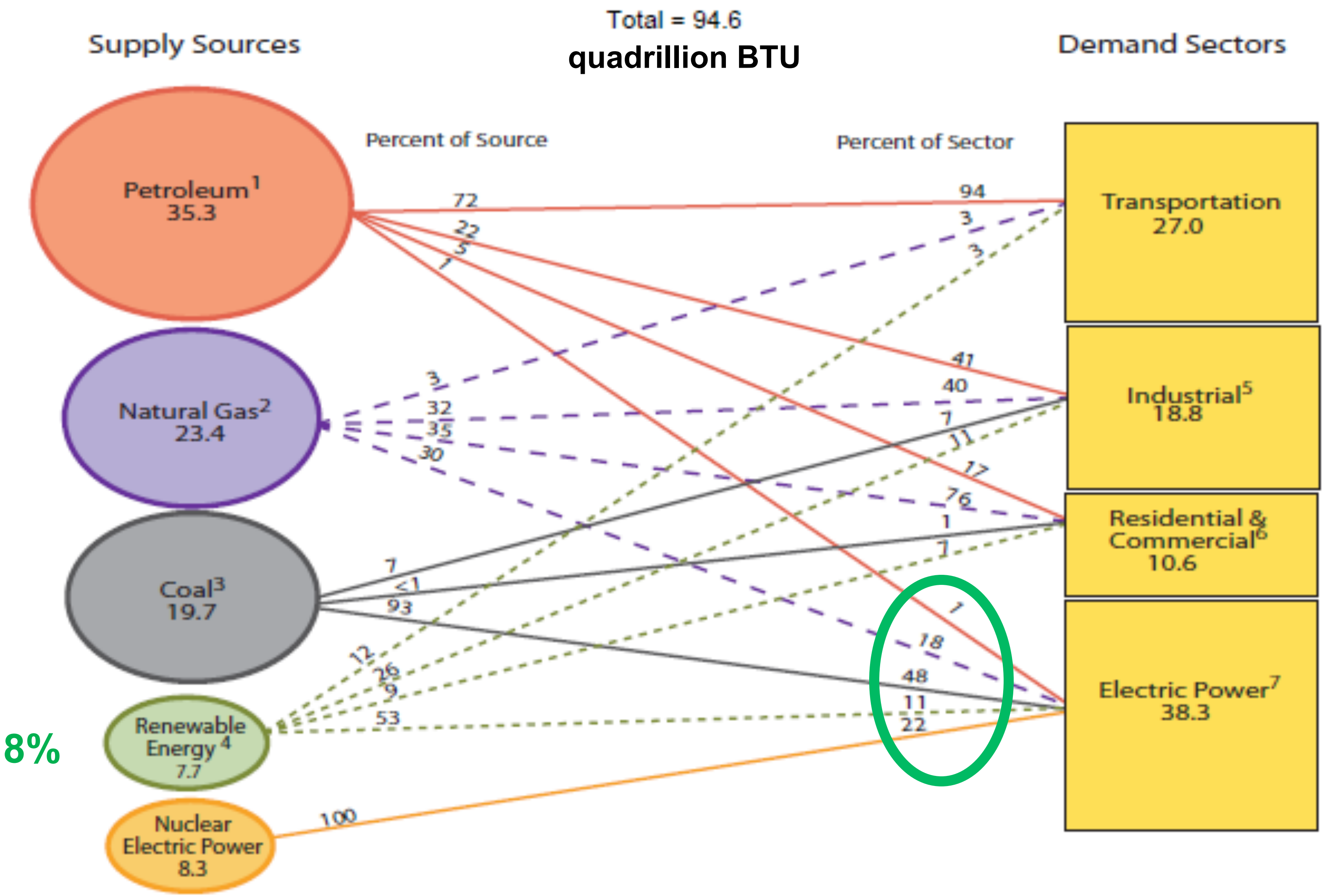
Source: M. Jacobson, 2011

Why renewable integration?



Source: Cristina Archer, 2010

US Primary Energy Flow 2009

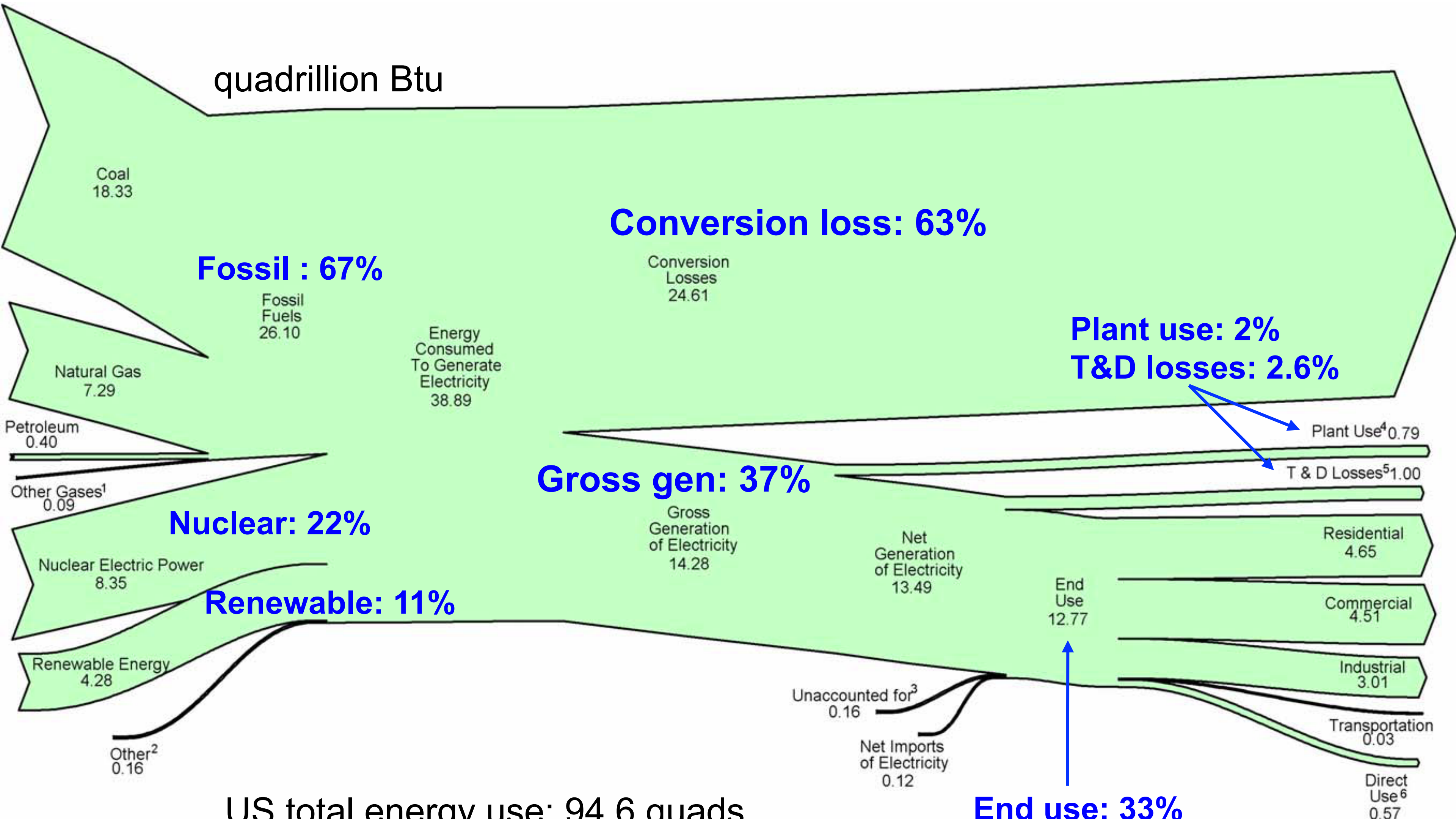


1 Does not include biofuels that have been blended with petroleum—biofuels are included in "Renewable Energy."
2 Excludes supplemental gaseous fuels.
3 Includes less than 0.1 quadrillion Btu of coal coke net exports.
4 Conventional hydroelectric power, geothermal, solar/PV, wind, and biomass.
5 Includes industrial combined-heat-and-power (CHP) and industrial electricity-only plants.
6 Includes commercial combined-heat-and-power (CHP) and commercial electricity-only plants.
7 Electricity-only and combined-heat-and-power (CHP) plants whose primary business is to sell electricity, or electricity and heat, to the public.

Note: Sum of components may not equal total due to independent rounding.

Sources: U.S. Energy Information Administration, *Annual Energy Review 2009*, Tables 1.3, 2.1b-2.1f , 10.3, and 10.4.

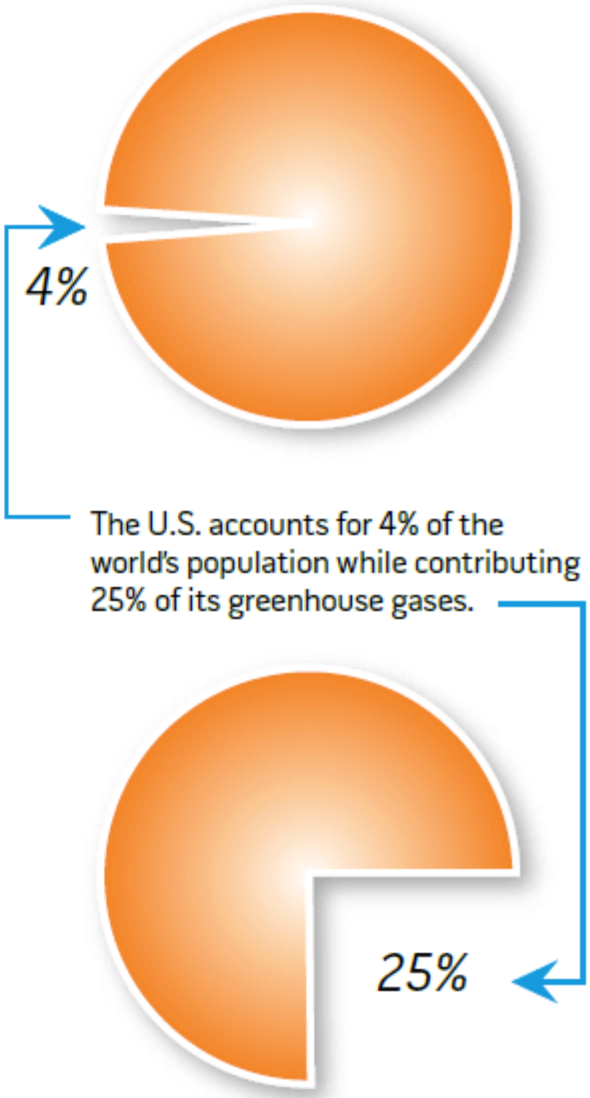
US electricity flow 2009



US total energy use: 94.6 quads
For electricity gen: 41%

Source: EIA Annual Energy Review 2009

Generate more than electricity...



US CO_2 emission

- Elect generation: 40%
- Transportation: 20%

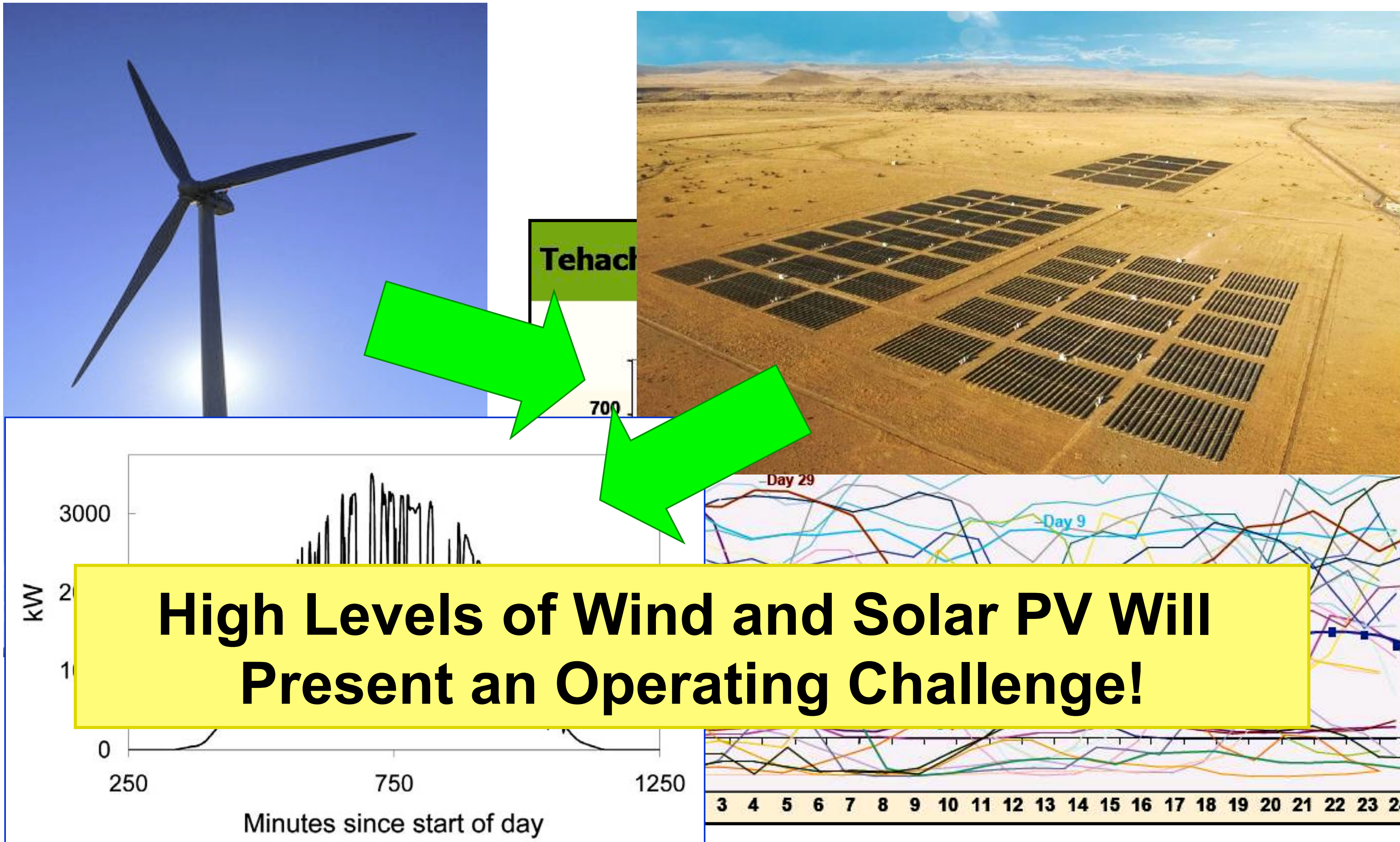
Source: DoE, Smart Grid Intro, 2008

Global trend

Renewables in 2009

- 26% of global electricity capacity
- 18% of global electricity generation
- Developing countries have >50% of world’s renewable capacity
- In both US & Europe, more than 50% of added capacity is renewable

Uncertainty of renewables



High Levels of Wind and Solar PV Will Present an Operating Challenge!

Source: Rosa Yang

Challenges of uncertainty

Matching supply and demand

- Market as well as engineering challenges
- Slower timescale (minutes and up)
- Static power flow analysis

focus of this talk

Dynamic stability

- Engineering challenges
- Fast timescale (ms and up)
- Transient dynamics

Demand response

Mitigate uncertainty

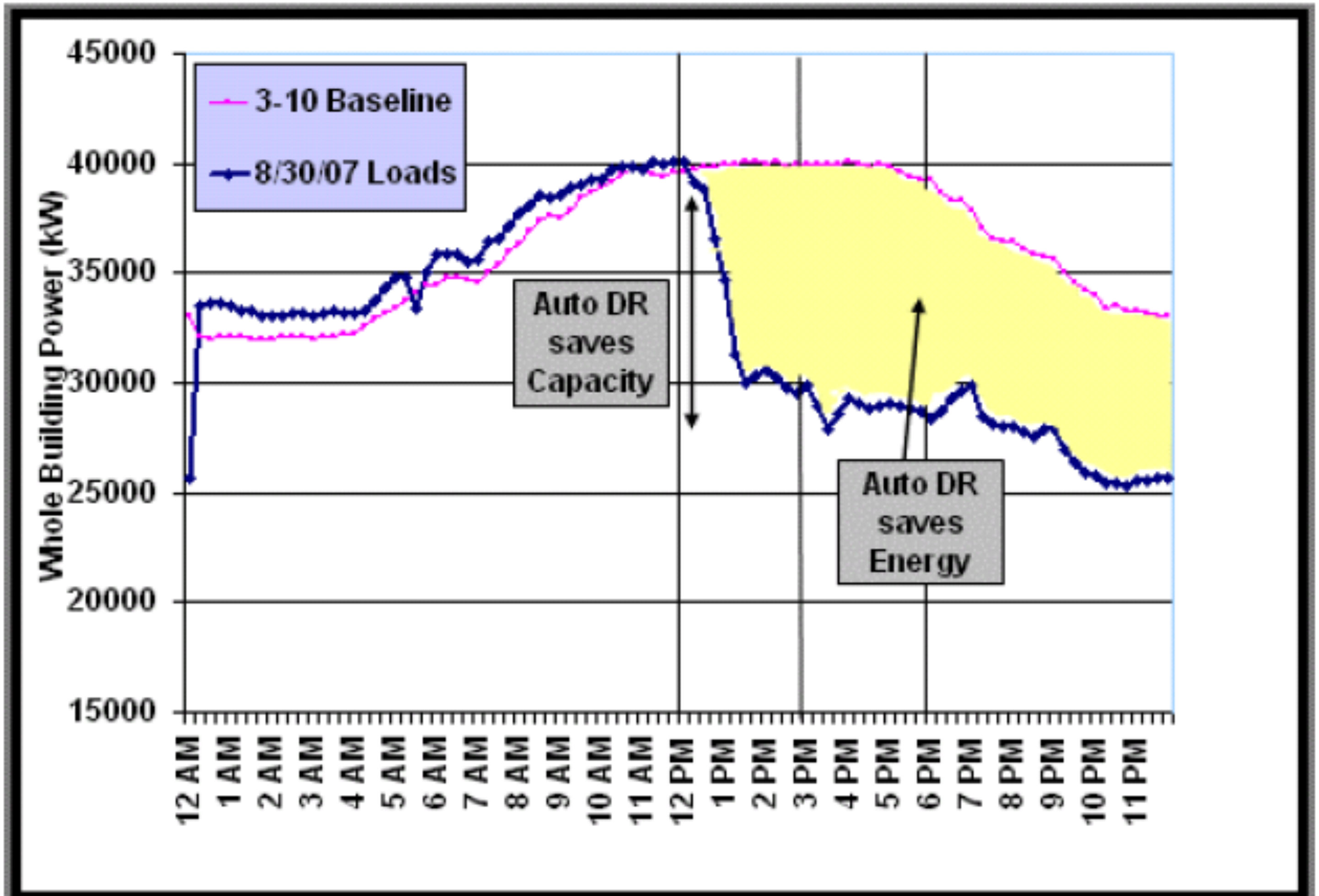
- Matching deferrable loads to uncertain supply

Reduce peak

- US load factor ~55%

Automated Demand Response Saves Capacity and Energy

Electric load profile for PG&E participants on 8/30/2007



Source: Steven Chu, GridWeek 2009

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Features to capture

Wholesale markets

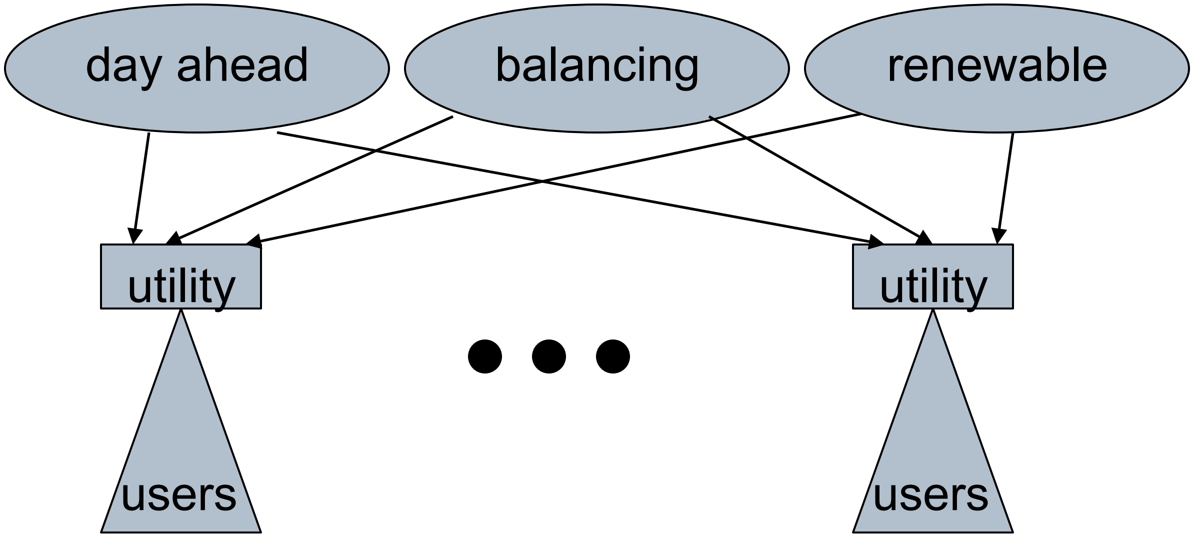
- Day ahead, real-time balancing

Renewable generation

- Non-dispatchable

Demand response

- Real-time control (through pricing)



Model: user

Each user has 1 appliance (wlog)

- Operates appliance with probability $\pi_i(t)$
- Attains utility $u_i(x_i(t))$ when consumes $x_i(t)$

$$\underline{x}_i(t) \le x_i(t) \le \overline{x}_i(t)$$

Demand at t:

$$D(t) := \sum_i \delta_i x_i(t) \qquad \delta_i = \begin{cases} 1 & \text{wp } \pi_i(t) \\ 0 & \text{wp } 1 - \pi_i(t) \end{cases}$$

Model: LSE (load serving entity)

Power procurement

- Renewable power: $P_r(t),\ c_r\left(P_r(t)\right) = 0$

  Random variable, realized in real-time

- Day-ahead power: $P_d(t),\ c_d\left(P_d(t)\right),\ c_o\left(\Delta x(t)\right)$

  Control, decided a day ahead

- Real-time balancing power: $P_b(t),\ c_b\left(P_b(t)\right)$

capacity

energy

$$P_b(t) = D(t) - P_r(t) - P_d(t)$$

- Use as much renewable as possible
- Optimally provision day-ahead power
- Buy sufficient real-time power to balance demand

Assumptions

Simplifying assumption

- No network constraints

This talk: no time correlation

- Drop t in notations

Questions

Day-ahead decision

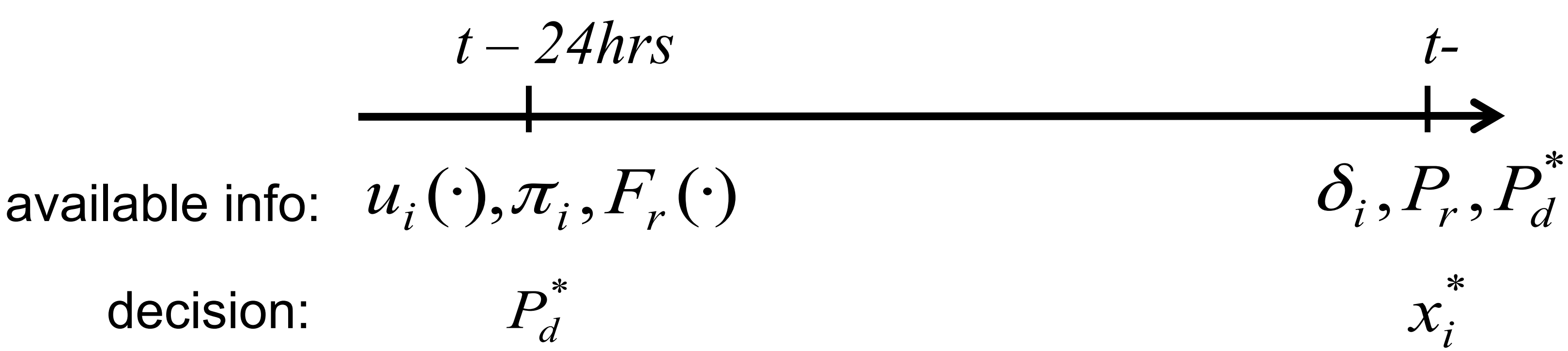
- How much power P_d should LSE buy from day-ahead market?

Real-time decision (at *t*-)

- How much x_i should users consume, given realization of wind power P_r and δ_i ?

How to compute these decisions distributively?

How does closed-loop system behave ?



Our approach

Real-time (at *t*-)

- Given P_d and realizations of P_r, δ_i, choose optimal $x_i^* = x_i^*(P_d; P_r, \delta_i)$ to max social welfare, through DR

Day-ahead

- Choose optimal P_d^* that maximizes expected optimal social welfare

available info: $u_i(\cdot), \pi_i, F_r(\cdot)$ $\quad\quad$ δ_i, P_r, P_d^*

decision: P_d^* $\quad\quad$ x_i^*

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- Distributed algorithms
- Effect of renewable on welfare

Welfare function

Supply cost

$$c\left(P_d, x\right) = c_d\left(P_d\right) + c_o\left(\Delta(x)\right)_0^{P_d} + c_b\left(\Delta(x) - P_d\right)_+$$

$$\Delta(x) := \sum_i \delta_i x_i - P_r$$

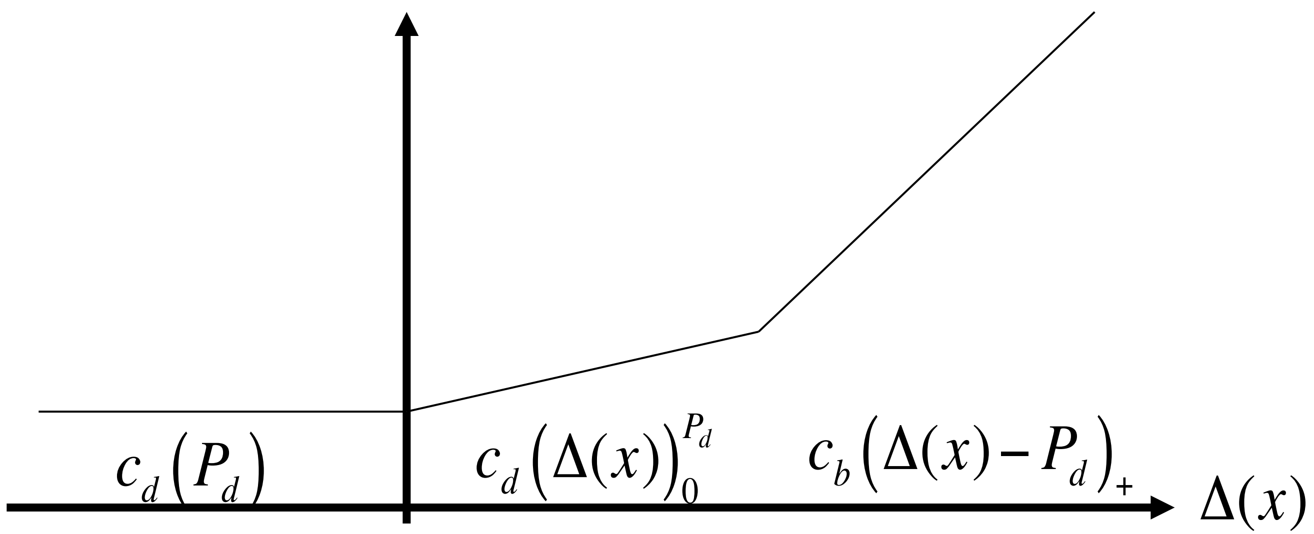
← excess demand

Welfare function

Supply cost

$$c\left(P_d, x\right) = c_d\left(P_d\right) + c_o\left(\Delta(x)\right)_0^{P_d} + c_b\left(\Delta(x) - P_d\right)_+$$

$$\Delta(x) := \sum_i \delta_i x_i - P_r$$ ← excess demand



Welfare function

Supply cost

$$c(P_d, x) = c_d(P_d) + c_o(\Delta(x))_0^{P_d} + c_b(\Delta(x) - P_d)_+$$

$$\Delta(x) := \sum_i \delta_i x_i - P_r$$

← excess demand

Welfare function (random)

$$W(P_d, x) = \sum_i \delta_i u_i(x_i) - c(P_d, x)$$

↑ user utility ↑ supply cost

Optimal operation

Welfare function (random)

$$W\left(P_d, x\right) = \sum_i \delta_i u_i(x_i) - c\left(P_d, x\right)$$

Optimal real-time demand response

$$\max_x W\left(P_d, x\right)$$

given realization of P_r, δ_i

Optimal operation

Welfare function (random)

$$W\left(P_d, x\right) = \sum_i \delta_i u_i(x_i) - c\left(P_d, x\right)$$

Optimal real-time demand response

$$x^*\left(P_d\right) \quad := \quad \arg \quad \max_x W\left(P_d, x\right)$$

given realization of P_r, δ_i

Optimal operation

Welfare function (random)

$$W\left(P_d, x\right) = \sum_i \delta_i u_i(x_i) - c\left(P_d, x\right)$$

Optimal real-time demand response

$$x^*\left(P_d\right) \quad := \quad \arg \quad \max_x W\left(P_d, x\right)$$

given realization of P_r, δ_i

Optimal day-ahead procurement

$$P_d^* \quad := \quad \arg \quad \max_{P_d} \ \mathrm{E}W\left(P_d, x^*\left(P_d\right)\right)$$

Overall problem: $\max_{P_d} \ \mathrm{E} \ \max_x W\left(P_d, x\right)$

Algorithm 1 (real-time DR)

$$\max_{P_d} \mathrm{E} \underbrace{\max_{x} W\left(P_d, x\right)}_{\text{real-time DR}}$$

Active user i computes x_i^*

- Optimal consumption

LSE computes

- Real-time price μ_b^*
- Optimal day-ahead power to use y_o^*
- Optimal real-time balancing power y_b^*

Algorithm 1 (real-time DR)

Active user i :

$$x_i^{k+1} = \left(x_i^k + \gamma \left(u_i'\left(x_i^k\right) - \mu_b^k \right) \right)_{\underline{x}_i}^{\overline{x}_i}$$

inc if marginal utility > real-time price

LSE :

$$\mu_b^{k+1} = \left(\mu_b^k + \gamma \left(\Delta\left(x^k\right) - y_o^k - y_b^k \right) \right)_+$$

inc if total demand > total supply

- Decentralized
- Iterative computation at t-

Algorithm 1 (real-time DR)

Theorem: Algorithm 1

Socially optimal

- Converges to welfare-maximizing DR $x^* = x^*\left(P_d\right)$
- Real-time price aligns marginal cost of real-time power with individual marginal utility

$$\mu_b^* = c_b'\left(y_b^*\right) = u_i'\left(x_i^*\right)$$

Incentive compatible

- x_i^* max i's surplus given price μ_b^*

Algorithm 1 (real-time DR)

Theorem: Algorithm 1

Marginal costs, optimal day-ahead and balancing power consumed:

$$c_b^{'}\left(y_b^*\right) = c_o^{'}\left(y_o^*\right) + \mu_o^*$$

↑

$$\mu_o^* = \frac{\partial W}{\partial P_d}\left(P_d^*\right)$$

Algorithm 2 (day-ahead procurement)

Optimal day-ahead procurement

$$\max_{P_d} \ \mathrm{E}W\left(P_d, x^*\left(P_d\right)\right)$$

LSE: $$P_d^{m+1} = \left(P_d^m + \gamma^m\left(\mu_o^m - c_d{}'\left(P_d^m\right)\right)\right)_+$$

↑ calculated from Monte Carlo simulation of Alg 1

Algorithm 2 (day-ahead procurement)

Optimal day-ahead procurement

$$\max_{P_d} \ \mathrm{E}W\left(P_d, x^*\left(P_d\right)\right)$$

LSE: $$P_d^{m+1} = \left(P_d^m + \gamma^m\left(\mu_o^m - c_d{}'\left(P_d^m\right)\right)\right)_+$$

Given δ^m, P_r^m : $$\mu_o^m = \frac{\partial W}{\partial P_d}\left(P_d^m\right)$$

$$\mu_b^m = \mu_o^m + c_o^{'}\left(y_o^m\right)$$

Algorithm 2 (day-ahead procurement)

<u>Theorem</u>

Algorithm 2 converges a.s. to optimal P_d^* for appropriate stepsize γ^k

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Effect of renewable on welfare

Renewable power:

$$P_r(a,b) := a \cdot \mu_r + b \cdot V_r$$

mean　　zero-mean RV

Optimal welfare

$$W\left(P_r(a,b)\right) := \max_{P_d} \mathrm{E} \ \max_{x} W\left(P_d, x\right)$$

Effect of renewable on welfare

$$P_r(a,b) := a \cdot \mu_r + b \cdot V_r$$

$$W\left(P_r(a,b)\right) := \max_{P_d} \mathrm{E} \ \max_{x} W\left(P_d, x\right)$$

Theorem

Cost increases in var of P_r

$W\left(P_r(a,b)\right)$ increases in a, decreases in b

$W\left(P_r(s,s)\right)$ increases in s but no ramp constraint!