ENERGY STORAGE AND REAL-TIME GENERATION SCHEDULING

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joint work with

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ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

quanticol

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Outline

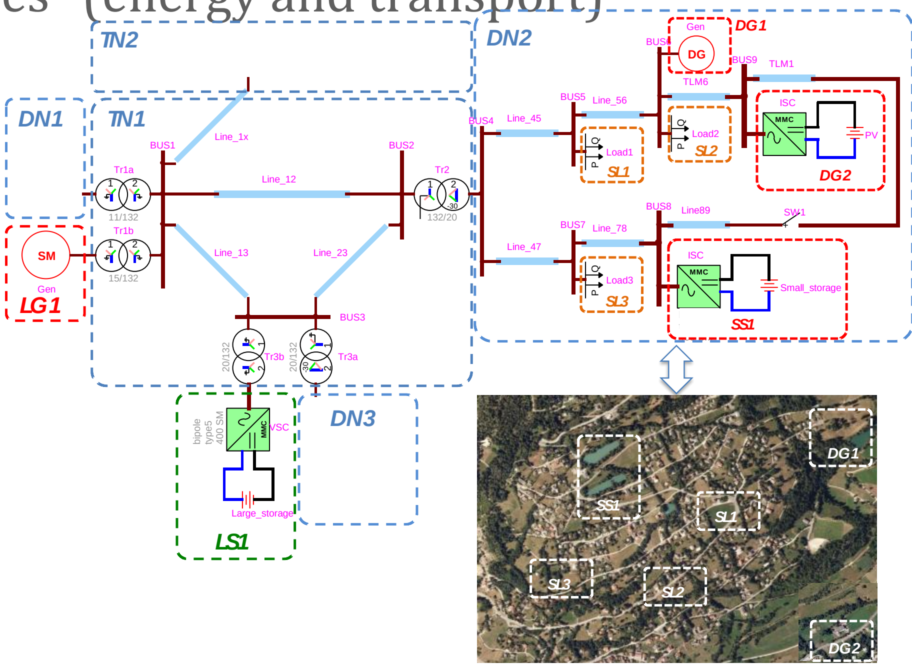
1. Introduction and motivation

2. Socially optimal scheduling of generation and storage

3. Real-time Market efficiency and distributed control

Storage and Demand Response can be used to mitigate volatility of renewables

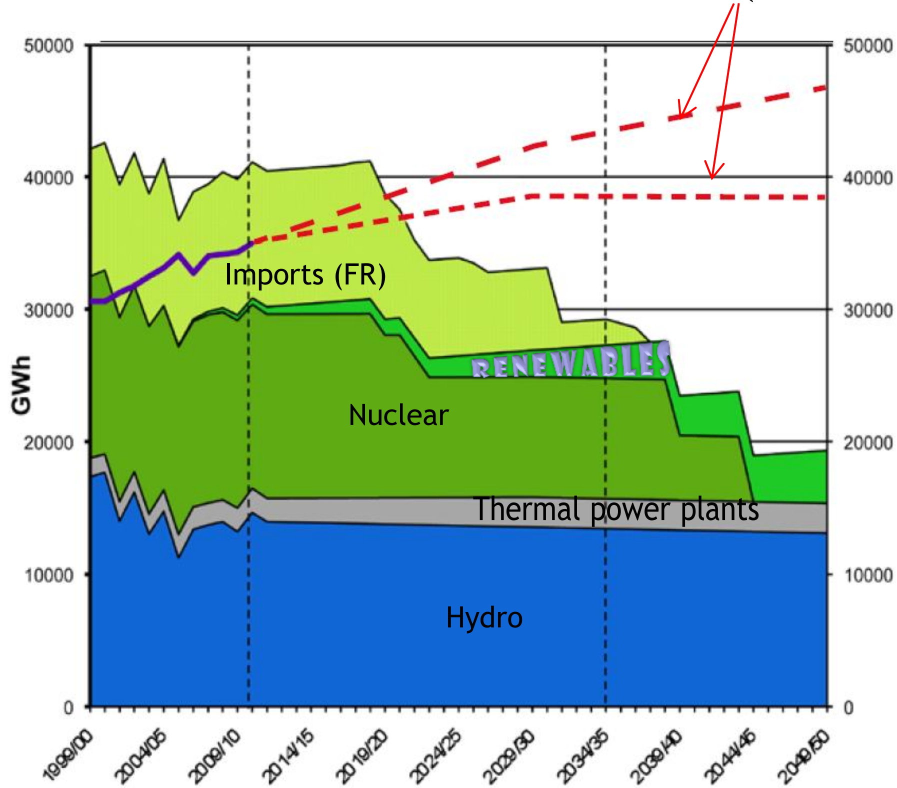
- Motivation:
  - Swiss Nanotera S^3grid (M. Kayal, M. Paolone) use of storage in active distribution network
  - European FP7: Quanticol: Quantitative methods for collective adaptive systems. Applications in "smart cities" (energy and transport)
- In this talk:
  1. can we use storage to compensate for renewable forecast errors ?
  2. can we control storage with prices ?



[Bianchi et al, 2012]

Motivation: energy transition

Forecasted demand (two scenarios)



Planned swiss annual electricity production

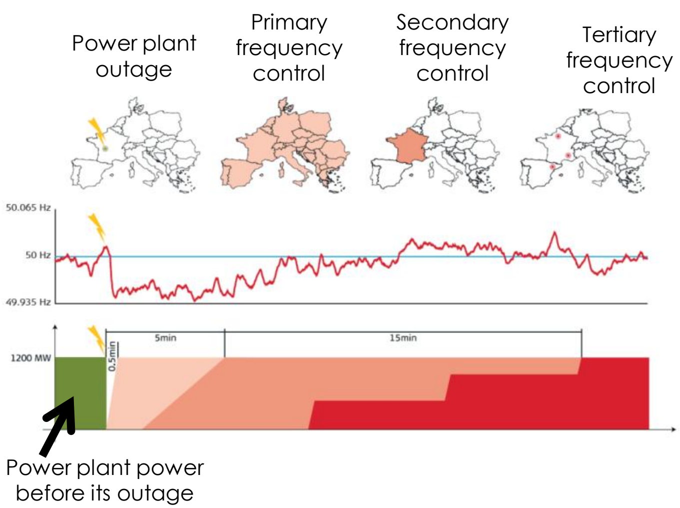
Switzerland plans to shut down nuclear power plants by 2030-2050

- Current options
  - Reduce consumption
    - Problem: population growth
  - Gas, coal, oil
    - Pollution
    - Empowers owners of resource
  - Renewables
    - Clean!
    - Slow (expensive?) deployment
    - Volatile: need for storage!

Real-time control problem

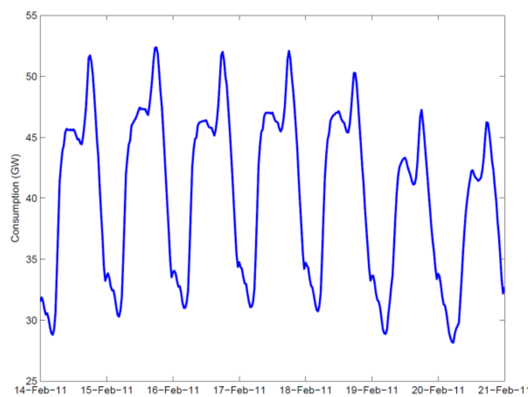
1. Energy Balance and Frequency control

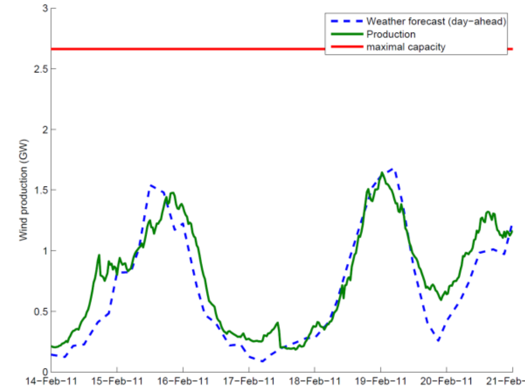
- Conventional generators have delays
- A fixed “reserve” has to be available (deterministic, empirically decided).



2. Voltage control (distribution network, will not be discussed today)

- Demand is predictable
- Renewables are not



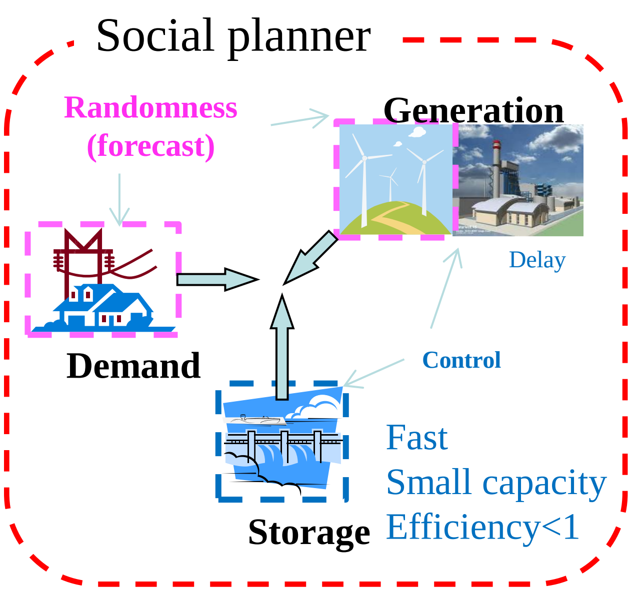


Example: national data from the UK

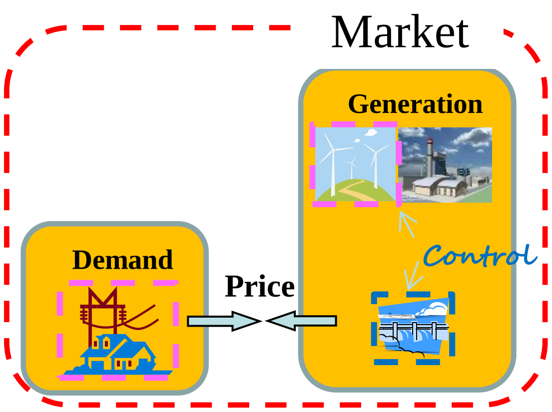
- Deterministic approach
  - Large security margin / reliability
- Stochastic optimization
  - NP-hard problem or worse
- Solution: approximate solutions
  - Approximate dynamic programming

Two topics in this talk

- Socially optimal scheduling of generation and storage
  - Use of storage to compensate for forecast uncertainties



- Market efficiency
  - Is there a price such that Consumer and Producer agree?
  - Will it lead to a socially optimal use of resources (or losses due to over-cycle of storage)
  - Consequences on investment?



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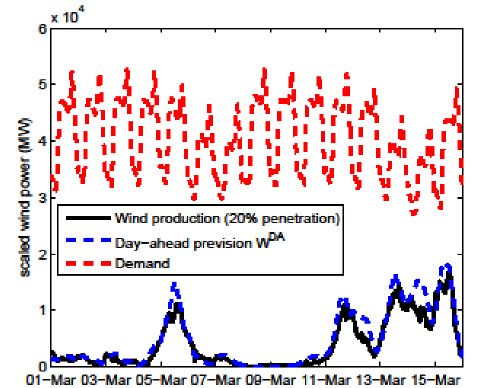
Production scheduling w. forecasts errors

- Base load production scheduling
  - Deviations from forecast
  - Use storage to compensate

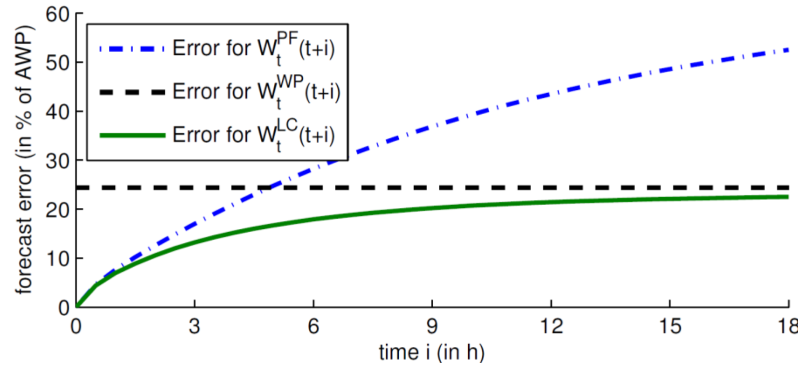


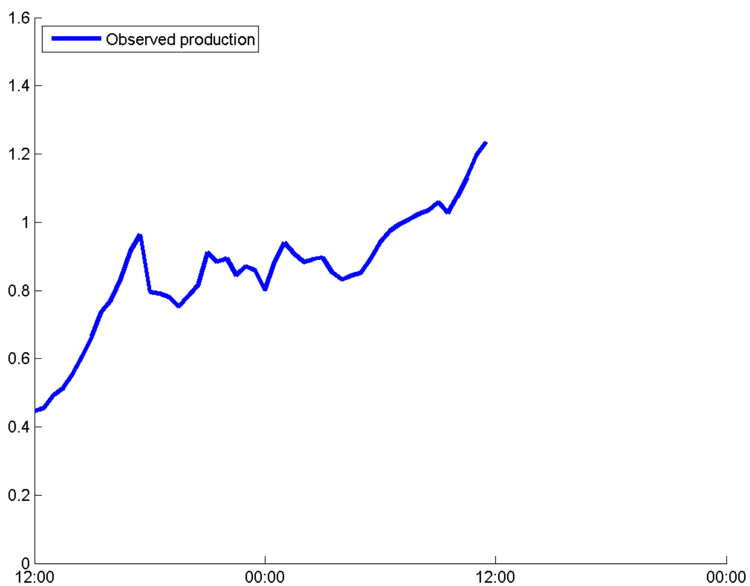
- Compare two approaches
  1. Deterministic approach (model predictive control, rolling horizon, …)
     - try to maintain storage level at e.g. ½ of its capacity using updated forecasts
  2. Stochastic approach
     - Use statistics of past errors.

Pump hydro, Cycle efficiency ≈ 80%

Wind forecasting errors

- At time t, we are given a forecast of future production or demand
- We schedule the “baseload production” using this forecast

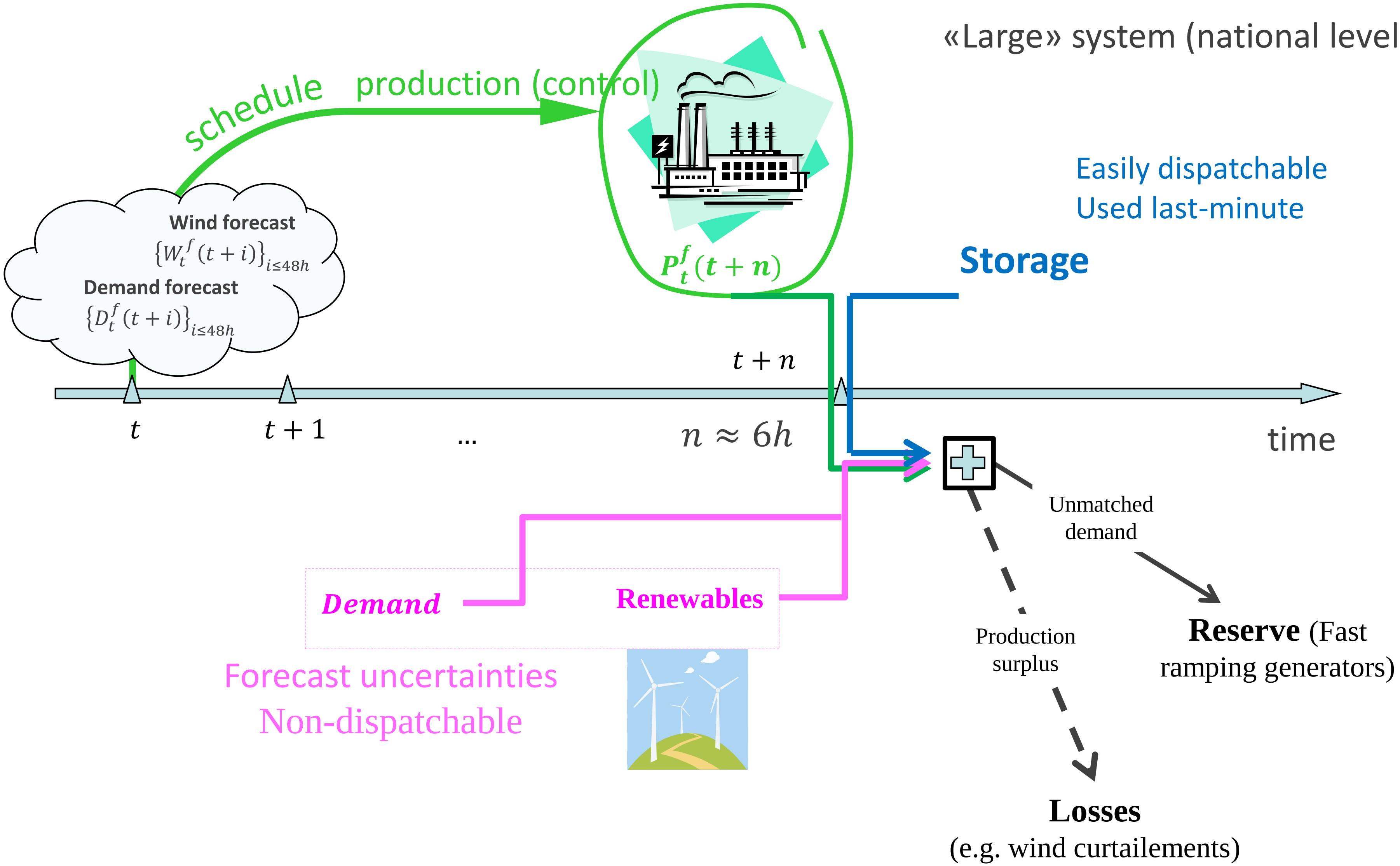




- Social planner point of view
  - Quantify the benefit of storage
  - Obtain performance baseline
    - what could be achieved
    - no market aspects

- Given a forecast, what can be achieved?

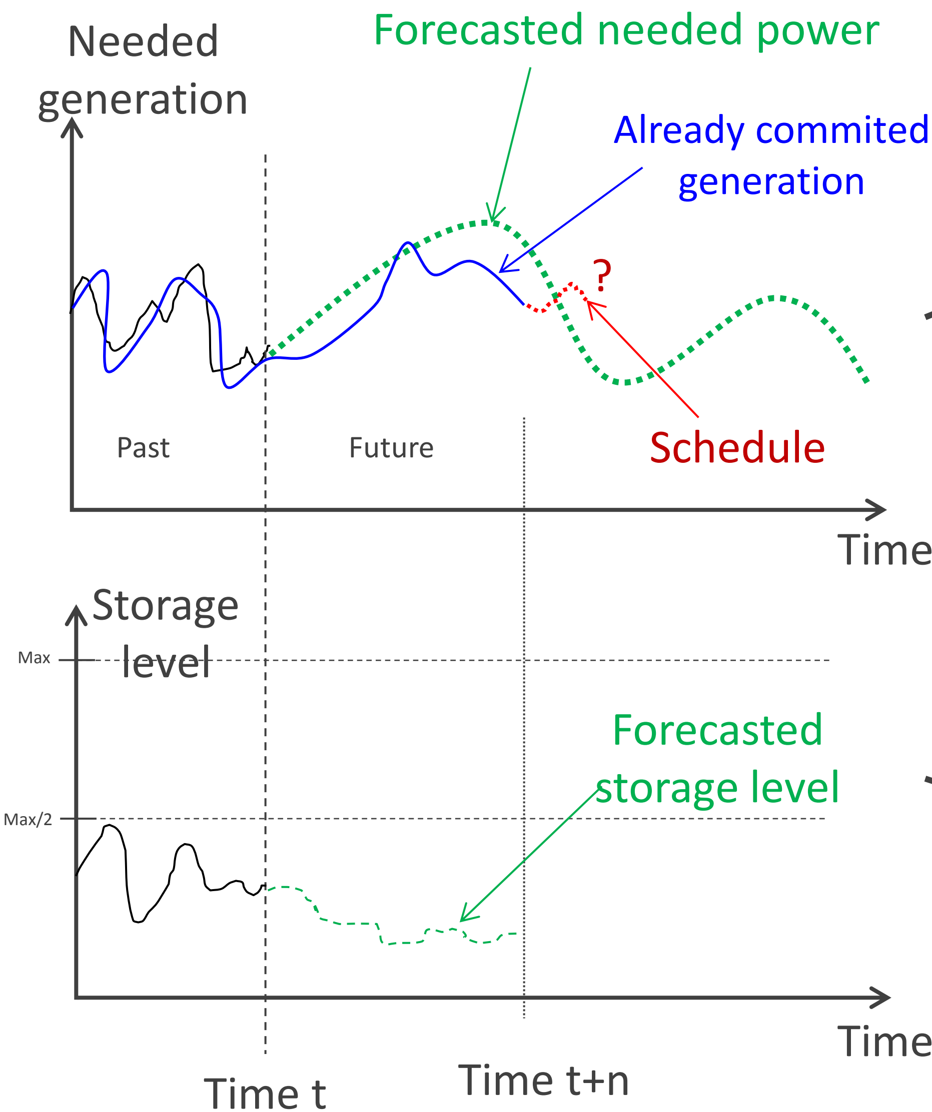
Energy scheduling with delays

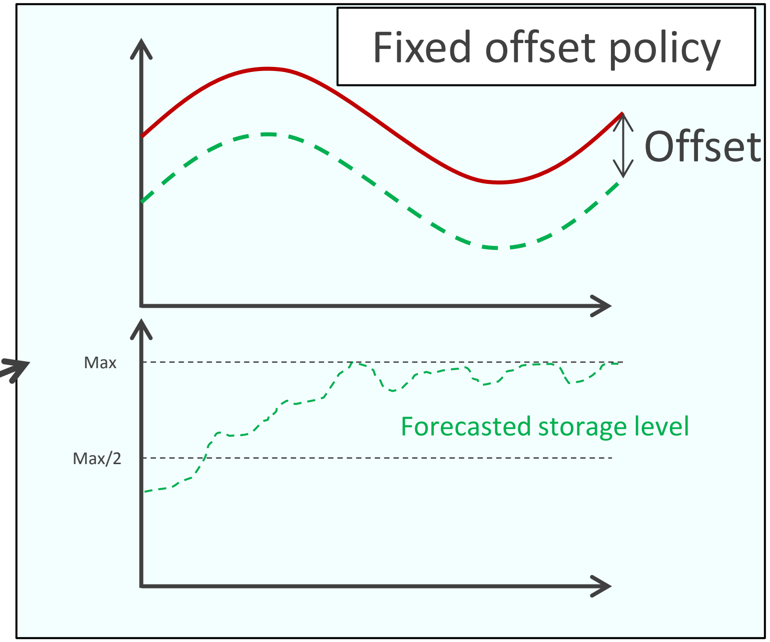


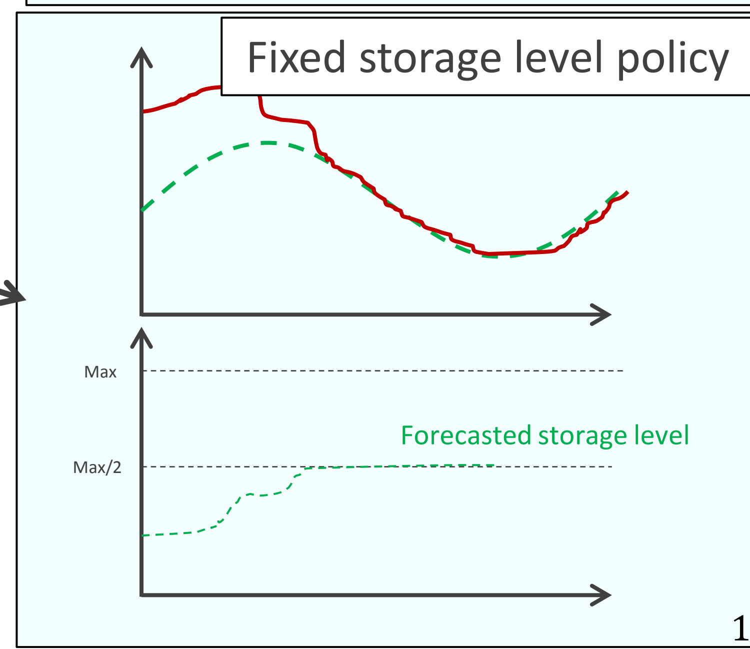
Difficulty: Markov decision processes with delays

- Optimal control problem intractable

Example of scheduling heuristics



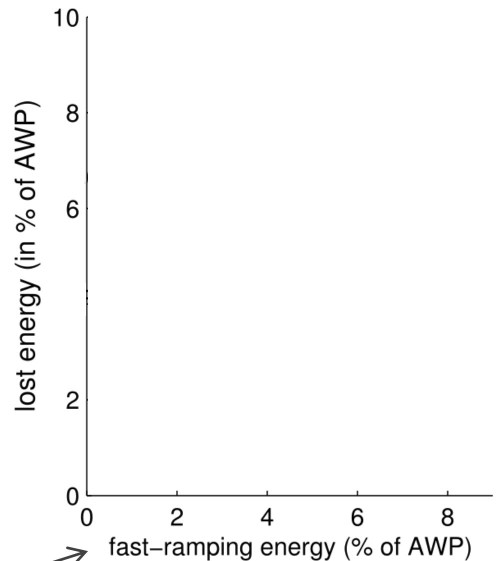




Metric and performance (large storage)

- Energy may be wasted when
  - Storage is full
  - Unnecessary storage (cycling efficiency $< 100\%$)

- Fast ramping energy sources (CO_2 rich) is used when storage is not enough to compensate fluctuation



AWP = average wind power

Numerical evaluation: data from the UK (BMRA data archive https://www.elexonportal.co.uk/)
- National data (wind prod & demand)
- 3 years
- Corrected day ahead forecast: MAE = 19%

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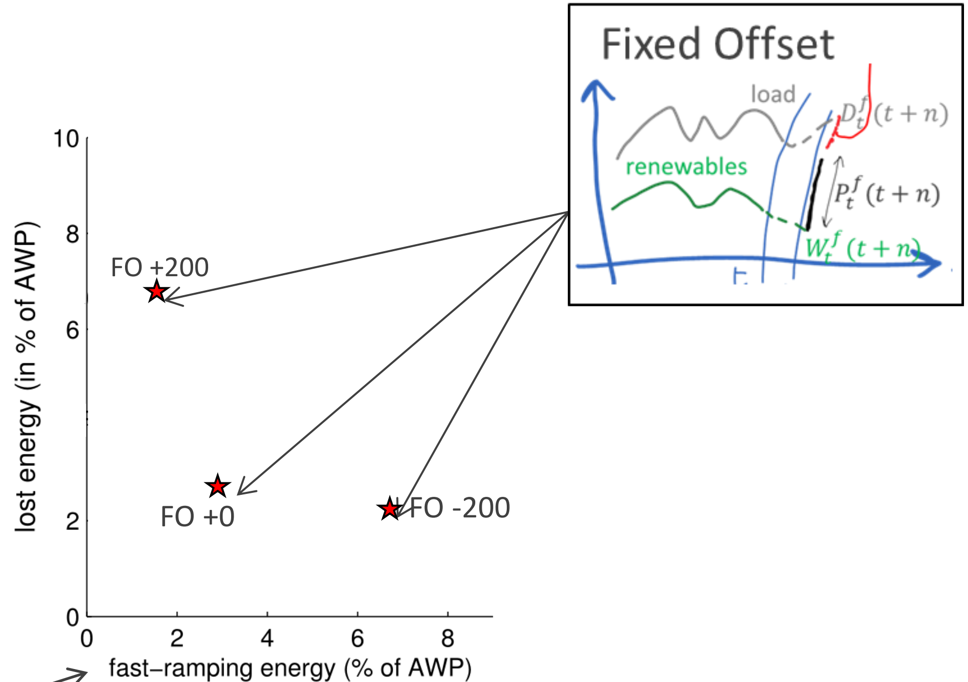

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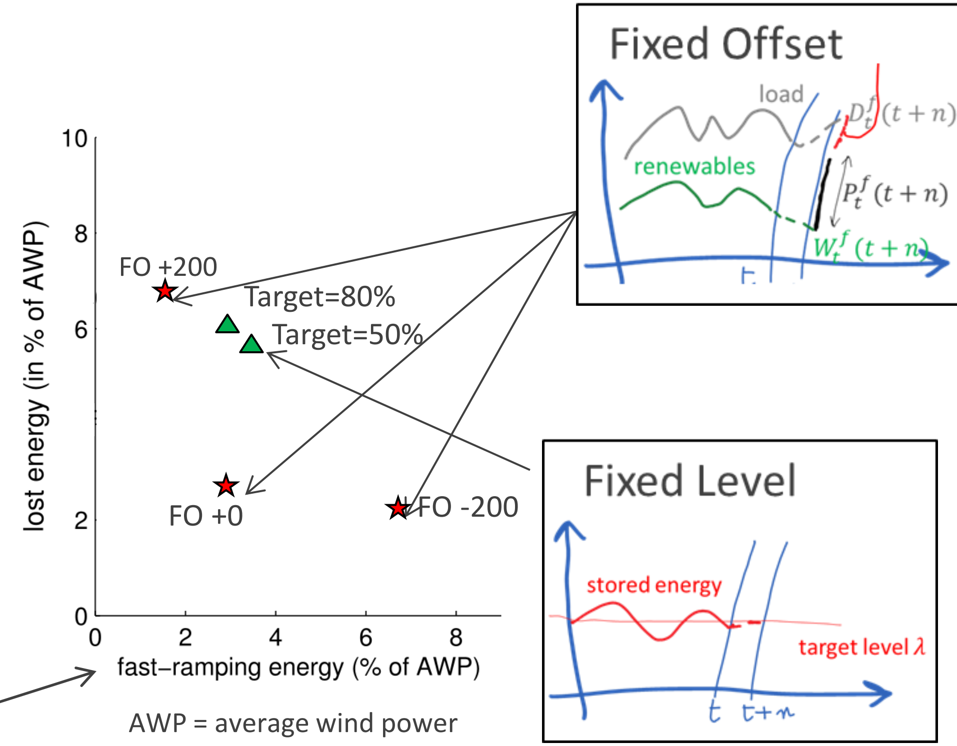

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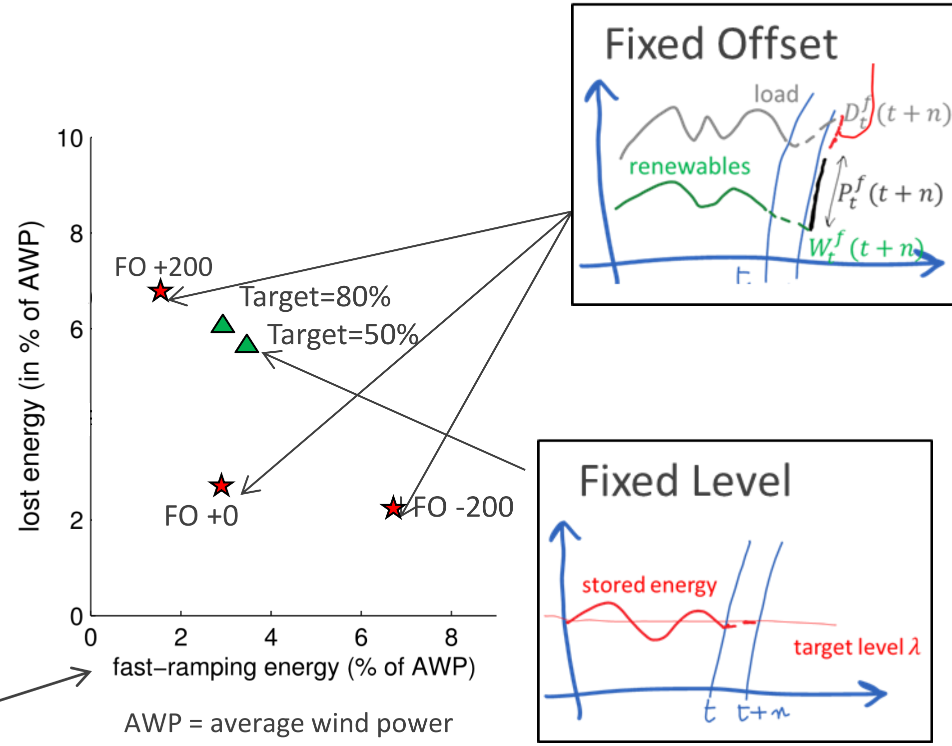

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- Corrected day ahead forecast: MAE = 19%

Questions:

- Can we do better?
- How to compute optimal offset?

Fixed offset is optimal for large storage

Let $\begin{array}{l}\ell(u) := \mathbb{E}\left[(\varepsilon+u)^+\right] - f(u)\\ g(u) := \mathbb{E}\left[(\varepsilon+u)^-\right] - f(u)\end{array}$ with $f(u) := \min\left(\eta\mathbb{E}\left[\min\left((\varepsilon+u)^+, C_{\max}\right)\right], \mathbb{E}\left[\min\left((\varepsilon+u)^-, D_{\max}\right)\right]\right)$

Theorem. *If the forecast error is distributed as* $\mathcal{E}$ *Then:*

1. (ℓ, g) is a **lower bound**: for any policy π, there exists u such that:
   $$\bar{G}^\pi(T) \geq g(u) - \frac{B_{\max}}{T} \qquad \bar{L}^\pi(T) \geq \ell(u) - \frac{B_{\max}}{T}$$
2. **FO is optimal for large storage**: if th… B_δ, then
   $\bar{G}^{\mathrm{FR}(u)} \leq$ …
3. Th…
   …$, C_{\max}) = \mathbb{E}\left[\min\left((\varepsilon+u)^-, D_{\max}\right)\right]$

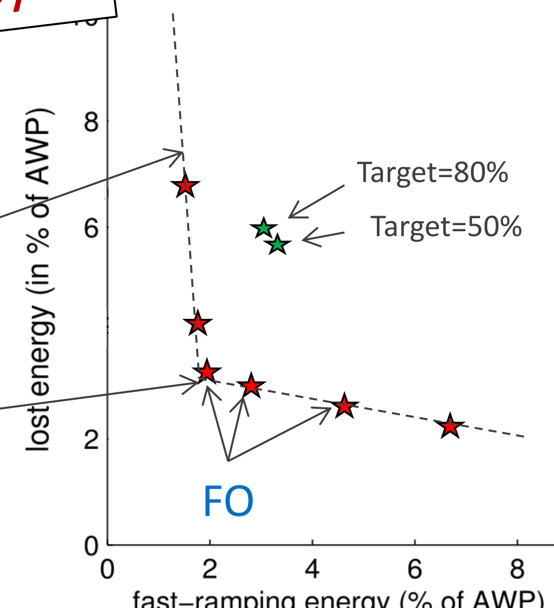
Problem solved for large capacity

- What about small / medium capacity?

- Uses distribution of error
- Fixed reserve is Pareto-optimal

(ℓ, g) curve : Lower bound

Optimal fixed offset $u = 2\%$ AWP



Scheduling Policies for Small Storage

- Dynamic offset policy:
  - choose offset as a function of forecasted storage level

- Stochastic optimal control (general idea)
  - Compute a value $V(B)$ of being at storage level B

$$u = \underset{u\,\in \text{offset}}{\text{arginf}}\ \mathbb{E}[\ \text{cost}\ (u) + V\big(\phi(b,u)\big)]$$

Expectation on possible errors

Instant cost (losses or fast-ramping energy)

Storage level at next time-slot

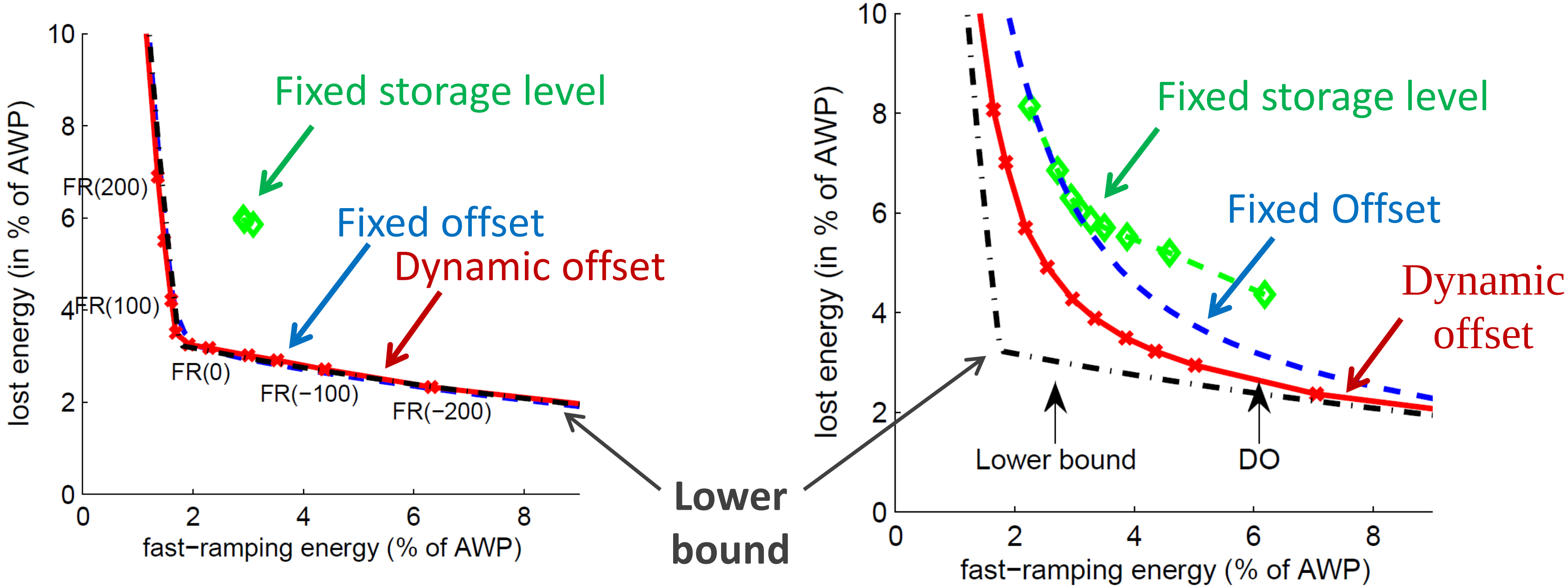
- Computation of V: depends on problem
  - Here: solution of a fixed point equation:

$$V(b) = g + \inf_{u\,\in \text{offset}} \mathbb{E}[\ \text{cost}\ (u) + V\big(\phi(b,u)\big)]$$

  - Approximate dynamic programming if state space is too large
  - Can be extended to more complicated state V(t,B,B',…)

Dynamic Offset outperforms other heuristics

- Large storage capacity (=20h of average production of wind energy)
  - Power = 30% of average wind power
- Small storage capacity (=3h of average production of wind energy)
  - Power = 30% of average wind power



- Fixed Offset & Dynamic offset are optimal
- DO is the best heuristic

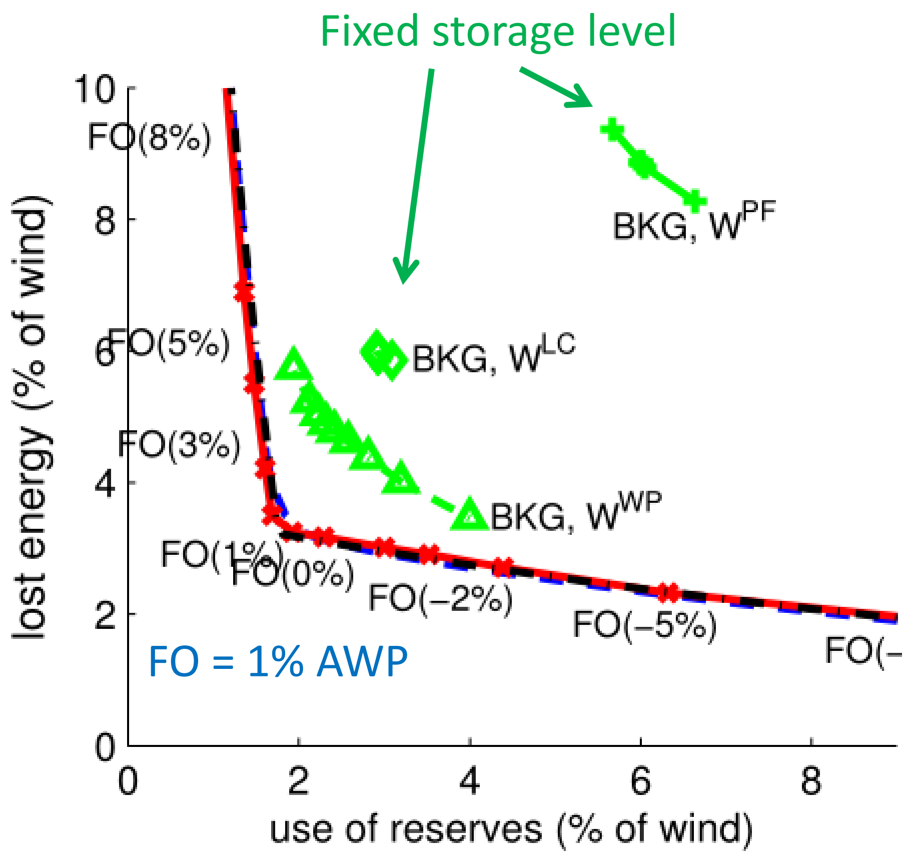
Maintaining storage at fixed level: not optimal

There exist better heuristics

Take Home Message

- For “large” (i.e. one day) storage, there is an optimal value of fixed offset reserve, which can be computed from forecast error statistics

- Can be used to dimension secondary reserve



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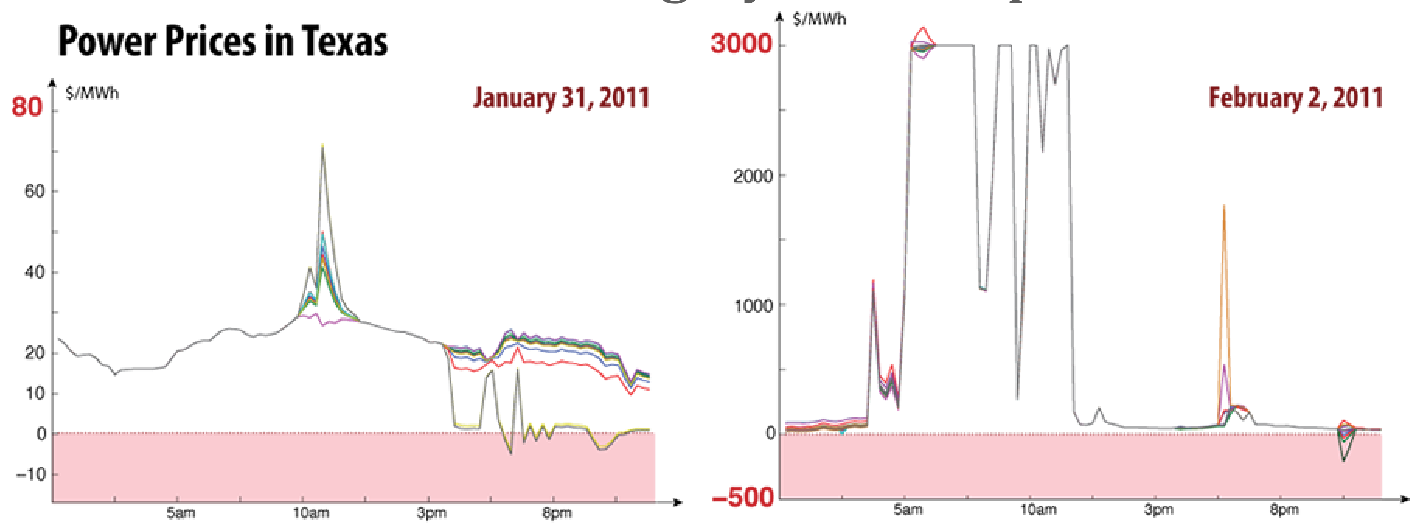
Real-time Market

- US Electricity markets are organized in two stages
  - Day-ahead (On-peak / off-peak)
  - Real-time (deviations from forecast)
- Europe wants to do the same

- Real-time markets exhibit highly volatile prices



- Efficiency or Market manipulation?

The first welfare theorem

- Impact of volatility on prices in real time market is studied by Meyn and co-authors: price volatility is expected

> Theorem (Cho and Meyn 2010). When dynamics (generation constraints) are taken into account:
> - Markets are efficient
> - Prices are never equal to marginal production costs.

- Efficiency or Market manipulation? : hard to distinguish

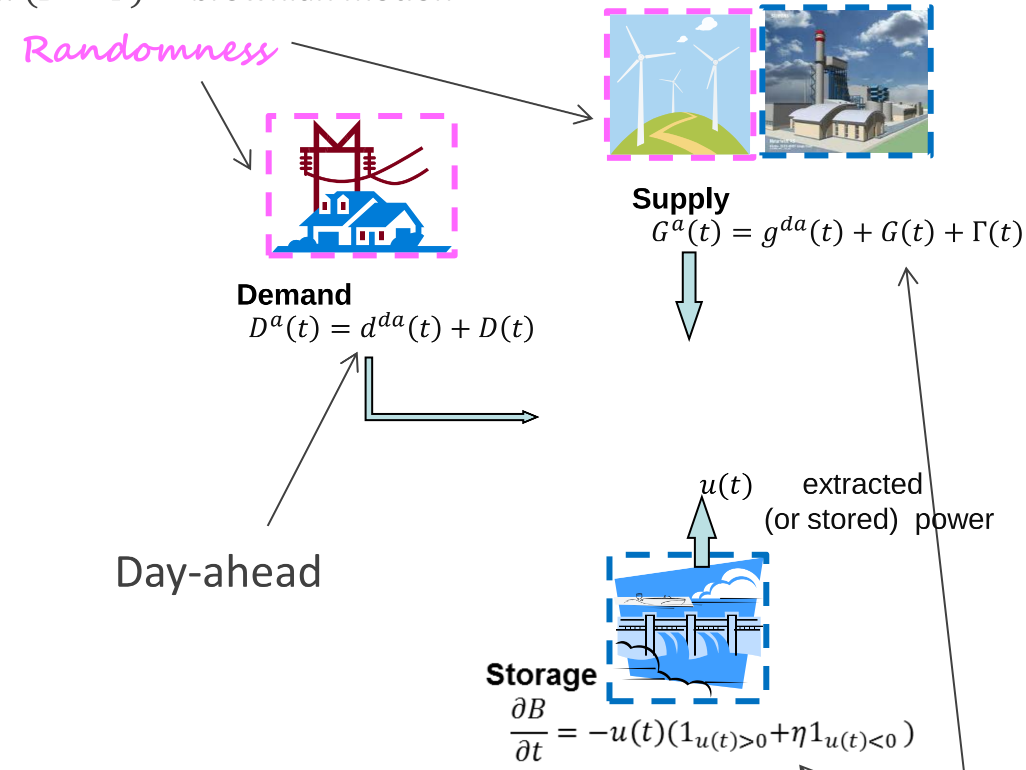
We add storage to the model

- Q1: Market implies socially optimal control (efficiency)?
  - Is there a price that dictates both generation scheduling and storage usage? (even when cycle efficiency < 100%?)
- Q2: what are the effects on prices?
- Q3: does it lead to socially optimal investments strategies?

[Cho and Meyn, 2010] I. Cho and S. Meyn *Efficiency and marginal cost pricing in dynamic competitive markets with friction*, Theoretical Economics, 2010

A Macroscopic Model of Real Time Market with Storage

H: $(D - \Gamma) \sim$ brownian motion



Control

Ramping Constraint

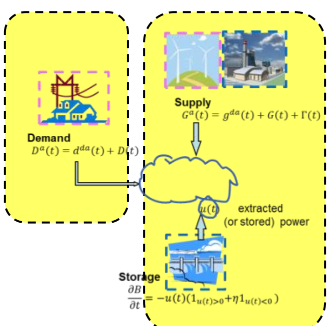
$-\xi \leq G(t) - G(t-1) \leq \zeta$

Storage cycle efficiency

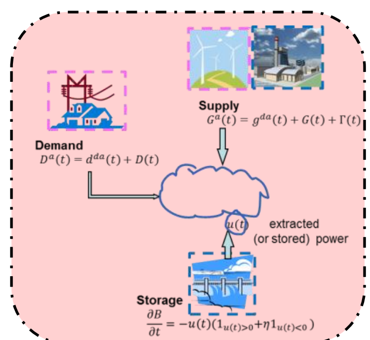
(E.g. $\eta = 0.8$)

Limited capacity

- Questions:

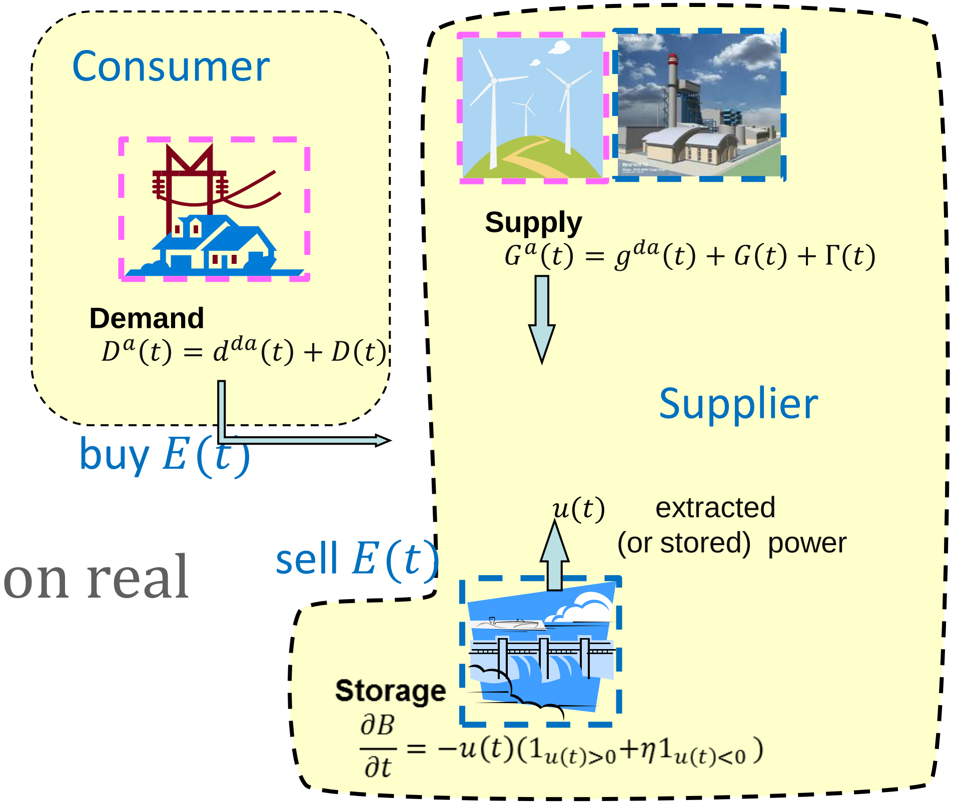


1. Competitive equilibria: definition and existence.



2. Relation to social planner's problem

Scenario A: Storage at Supplier



$P(t) =$ stochastic price process on real time market

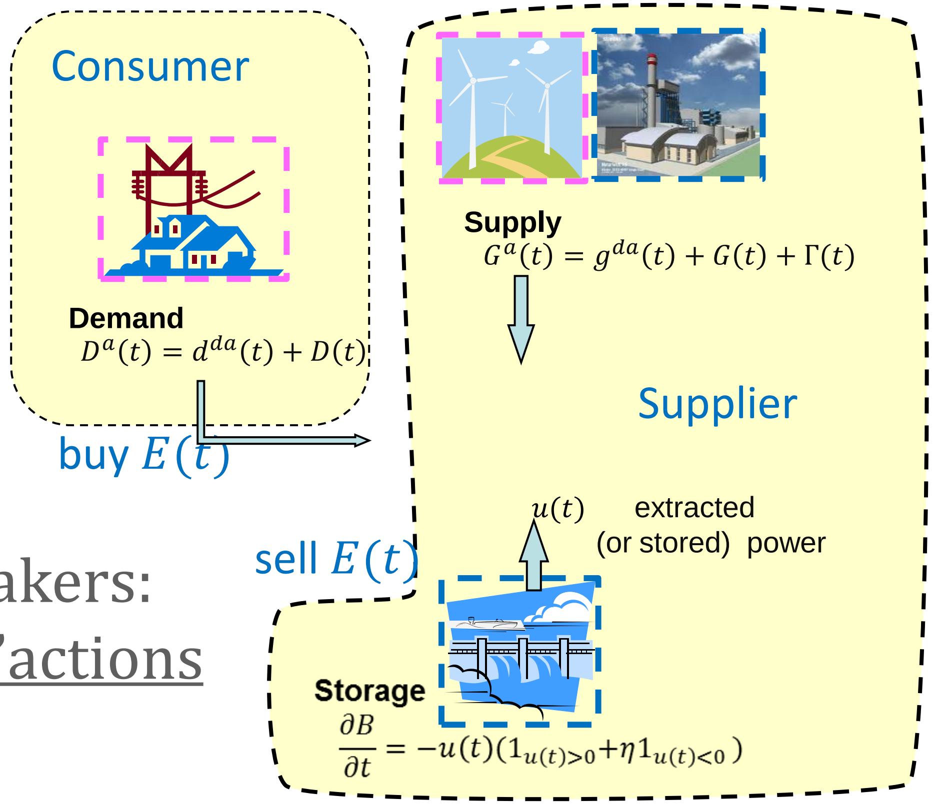
- Consumer's payoff

$$\underbrace{v\min(D^a(t), E(t) + g^{da}(t))}_{\text{satisfied demand}} - \underbrace{c^{bo}\left(D^a(t) - G^{da}(t) - -u(t)\right)^+}_{\text{Frustrated demand}} - \underbrace{P(t)E(t) - p^{da}(t)g^{da}(t)}_{\text{Price paid}}$$

- Supplier's payoff

$$= P(t)E(t) + p^{da}(t)g^{da}(t) - cG(t) - c^{da}g^{da}(t)$$

Definition of a competitive equilibrium



Assumption: agents are price takers:
<u>$P(t)$ does not depend on players'actions</u>

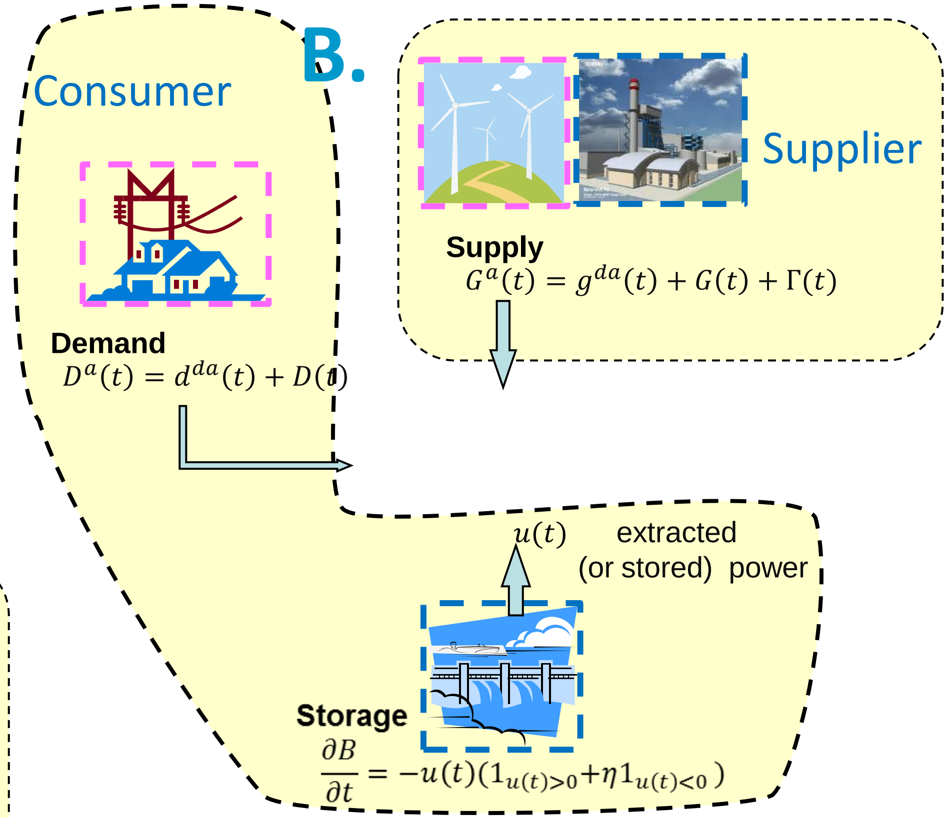
- (P, E, G, u) such that
  1. E maximizes welfare (= expected discounted payoff) of consumer
  2. E, G, u maximizes welfare of supplier (given friction constraints) for the same price process P
- Without storage, there exists such an equilibrium [Cho and Meyn 2010]

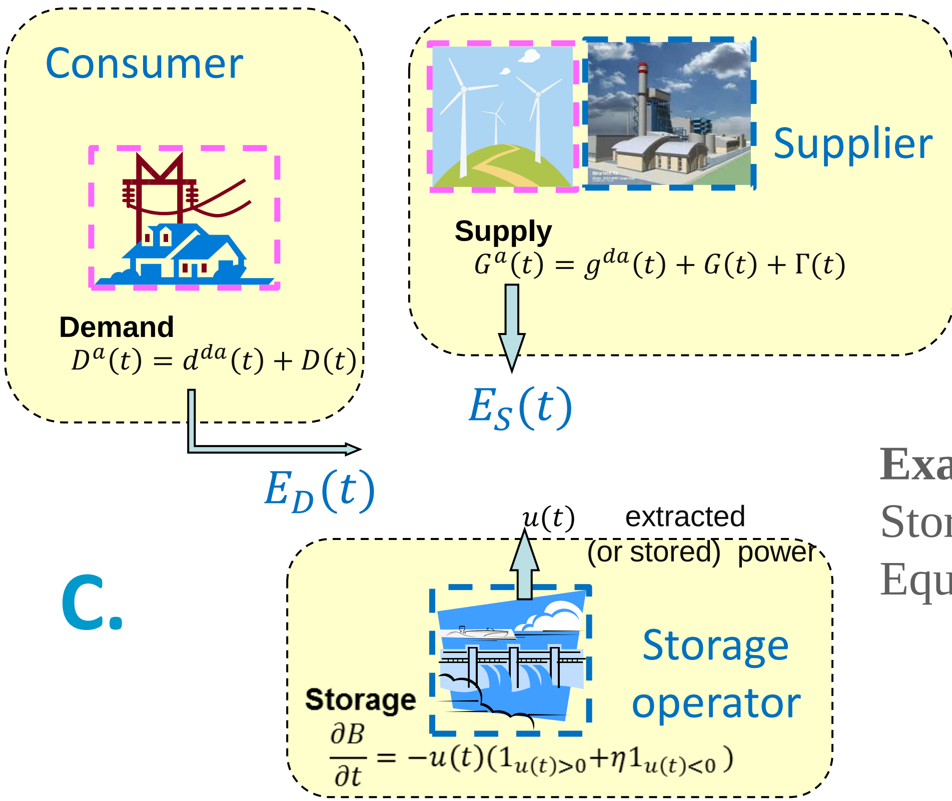
Other possible Storage owners

B. Storage at Consumer

C. Stand-alone storage operator

B.





C.

Example: Competitive equilibrium for scenario C:
Storage Operator's payoff $= u(t)P(t)$
Equilibrium: (P, E_D, E_S, G, u) such that

1. E_D maximizes consumer's welfare
2. E_S, G maximizes supplier's welfare
3. u maximizes storage op's welfare
4. $E_D(t) + u(t) = E_S(t)$

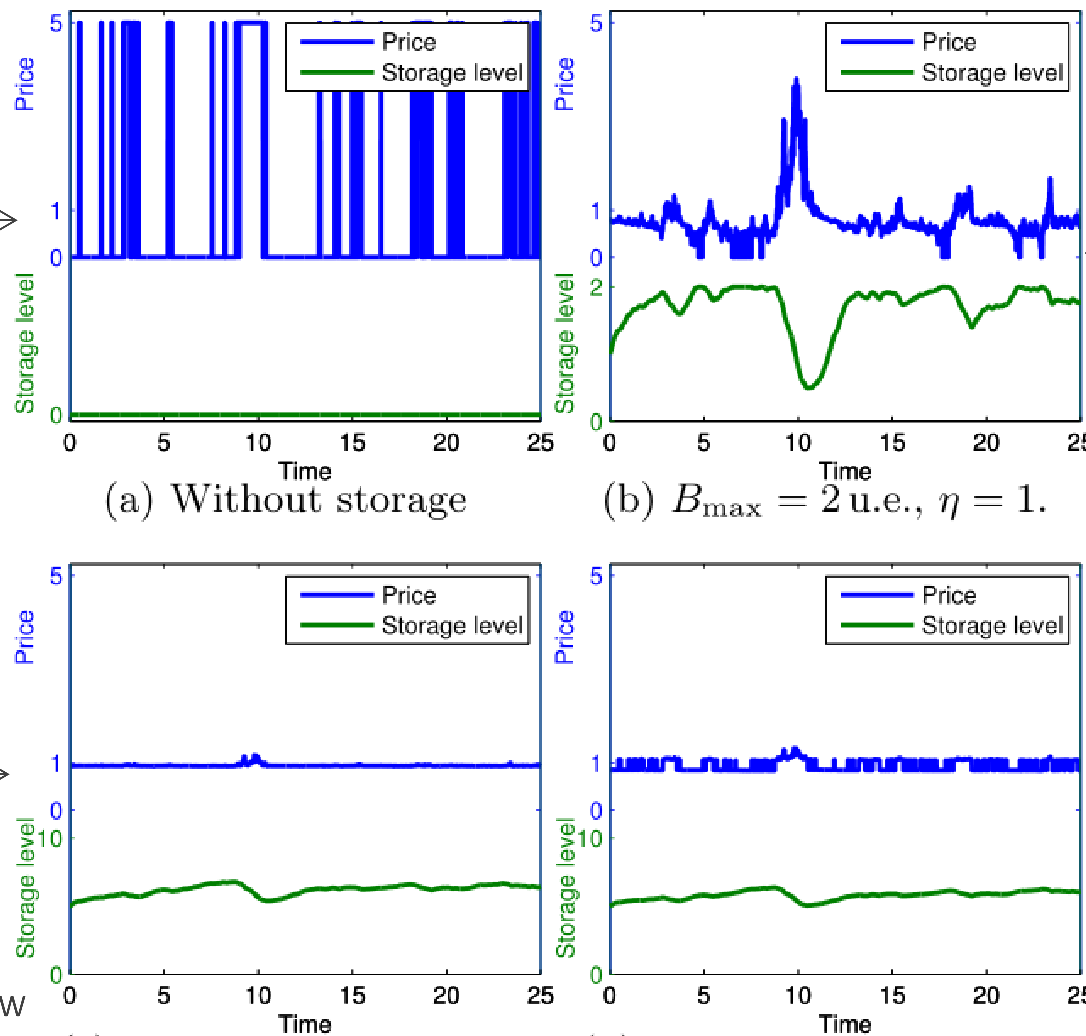
Dynamic Competitive Equilibria exist and are essentially the same for the 3 Scenarios [Theorem 3, Gast et al 2013]

No storage →

Small storage ←

Large storage $\eta = 1$ →

Large storage $\eta = 0.8$ ←



(a) Without storage

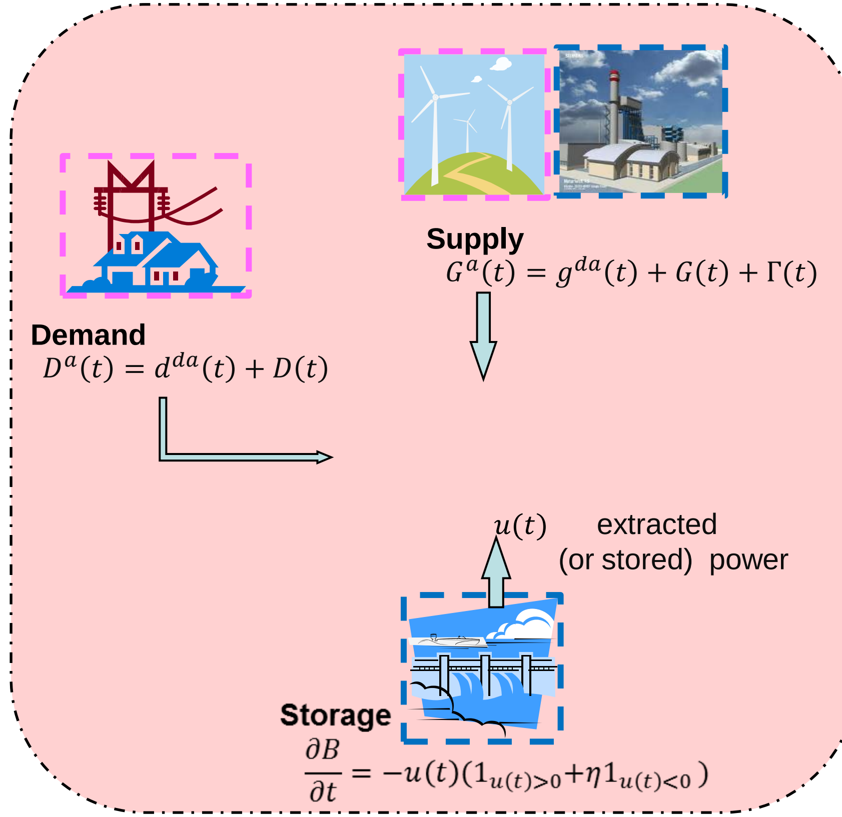
(b) $B_{\max} = 2$ u.e., $\eta = 1$.

(c) $B_{\max} = 10$ u.e., $\eta = 1$

(d) $B_{\max} = 10$ u.e., $\eta = 0.8$

1 u.e. = 360 MWh, 1 u.p .= 600 MW
σ^2= 0.6 GW2/h, ζ = 2GW/h
Cmax=Dmax= 3 u.p.

The social planner problem



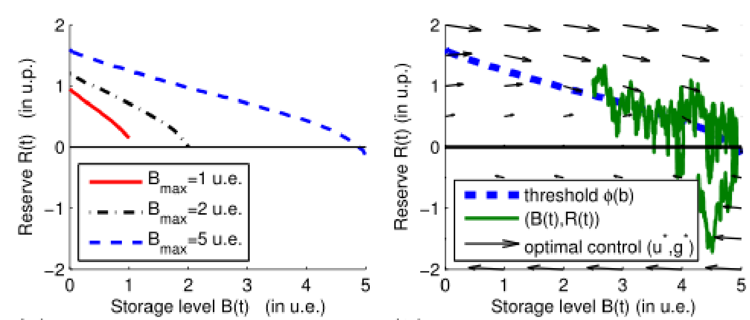
- The social planner wants to find G and u to maximize total expected discounted payoff

- Does not depend on storage owner

$$\underbrace{v \min(D^a(t), E(t) + g^{da}(t))}_{\text{satisfied demand}} - \underbrace{c^{bo}\left(D^a(t) - G^{da}(t) - -u(t)\right)^+}_{\text{Frustrated demand}} \underbrace{-cG(t) - c^{da} g^{da}(t)}_{\text{Cost of generation}}$$

- Let $R(t) := G^a(t) + u(t) - D^a(t)$

Optimal control is such that:
if $R(t) < \Phi(B(t))$ increase $G(t)$
if $R(t) > \Phi(B(t))$ decrease $G(t)$



The Social Welfare Theorem [Gast et al., 2013]

- Any dynamic competitive equilibrium for any of the three scenarios maximizes social welfare
  - The same price process controls optimally both the storage AND the production
- As storage grows, prices concentrate on the marginal production cost if $\eta = 1$
- If $\eta < 1$: discontinuity in R(t)=0
  - Bad for decentralized control

Cycle efficiency

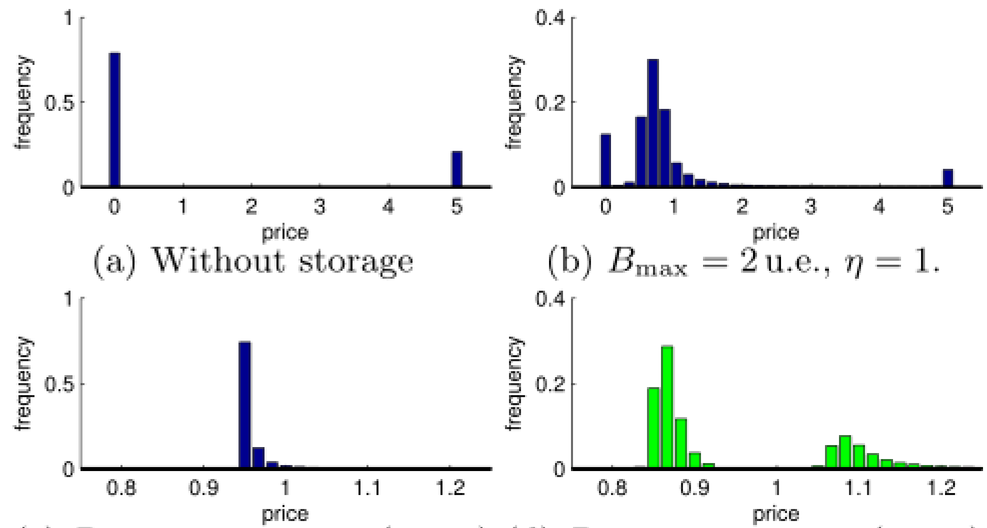
Overproduction that storage cannot store

$$P^{\star}(t) = \begin{cases} 0 \\ \eta \frac{\partial V}{\partial b}(R^{\star}(t), B^{\star}(t)), \\ \frac{\partial V}{\partial b}(R^{\star}(t), B^{\star}(t)), \\ v + c^{bo}, \end{cases}$$

Storage compensates fluctuations

Prices are *dynamic* Lagrange multipliers

Underproduction that storage cannot satisfy



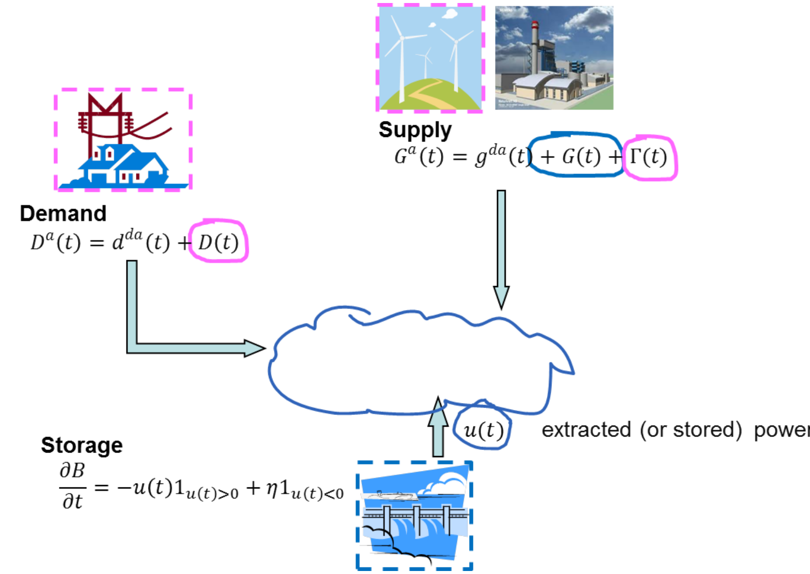
(a) Without storage (b) $B_{\max} = 2$ u.e., $\eta = 1$.

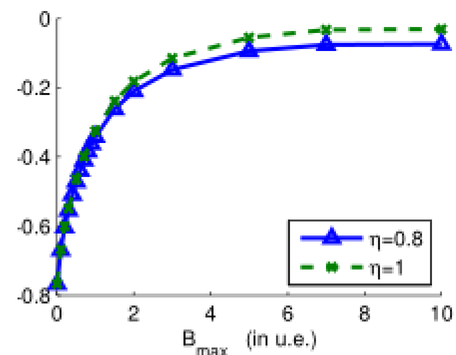
(c) $B_{\max}$=10 u.e., η=1 (zoom) (d) $B_{\max}$=10ue, η=0.8(zoom)

Figure 6: Steady-state distribution of prices for various storage energy capacities $B_{\max}$. For $B_{\max}$ = 10 u.e., we zoom on c=1 to compare $\eta = 0.8$ and $\eta = 1$.

The Invisible Hand of the Market may not be optimal

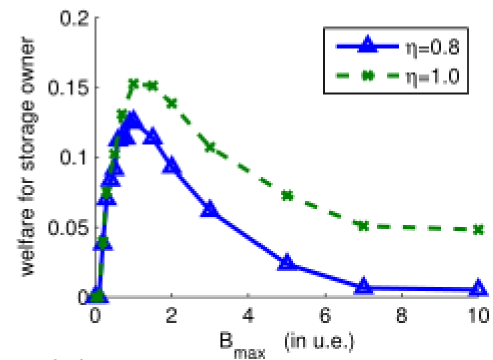
- Any dynamic competitive equilibrium for any of the three scenarios maximizes social welfare
- However, this assumes a given storage capacity.
- Is there an incentive to install storage ?
  - No, stand alone operators or consumers have no incentive to install the optimal storage





(b) $C_{\max} = 3\,\mathrm{u.p.}$

Expected social welfare



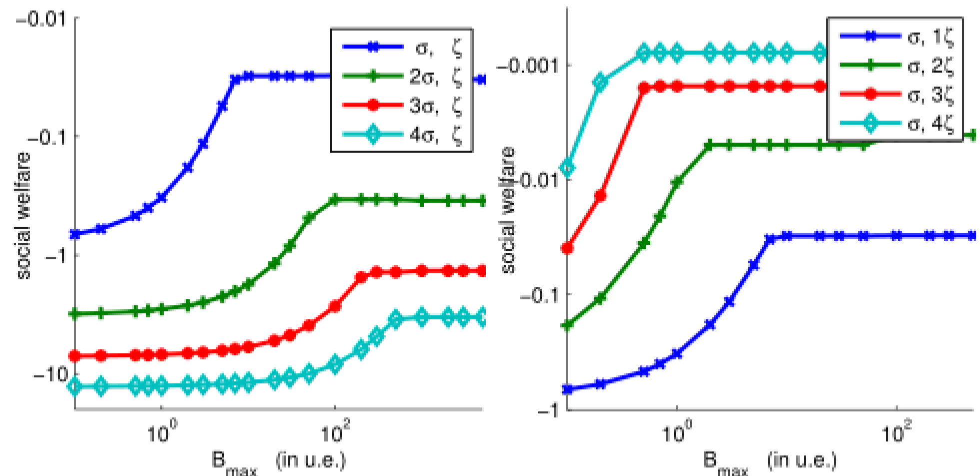
(b) $C_{\max} = D_{\max} = 3\,\mathrm{u.p.}$

Expected welfare of stand alone operator

Can lead to market manipulation
(undersize storage and generators)

Scaling laws and optimal storage sizing

- (steepness) being close to social welfare requires the optimal storage capacity



(a) Fixed ζ (b) Fixed σ

- optimal storage capacity scales like $\frac{\sigma^4}{\zeta^3}$!

(σ is ≈proportional to the installed renewable capacity)

Bad news for renewables

(similar situation in Spain: for each 1MW of wind turbines, 1MW of gaz turbines in build!)

- increase volatility and rampup capacity by x = increase storage by x

What this suggests about storage :

- with a free and honest market, storage can be operated by prices
  - But prices are still volatile when $\eta < 1$
- however, there may not be enough incentive for storage operators to install the optimal storage size
- perhaps preferential pricing should be directed towards storage as much as towards PV

- Multi temporal-scales are inherent to electricity networks
  - Joint scheduling is essential

- Limitation of the model / future work
  - Oligopolistic setting
  - Network constraints and distributed storage

Thank You !

- [Cho and Meyn, 2010] I. Cho and S. Meyn *Efficiency and marginal cost pricing in dynamic competitive markets with friction*, Theoretical Economics, 2010
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