REAL-TIME STORAGE AND DEMAND MANAGEMENT

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,
joint work with

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INTRODUCTION

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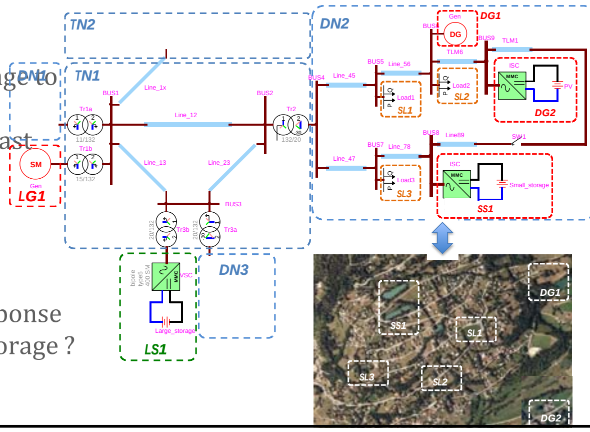
Storage and Demand Response can be used to mitigate volatility of renewables

- Motivation: Swiss Nanotera S^3grid (M. Kayal, M. Paolone) use of storage in active distribution network as in [Bianchi et al, 2012]
- In this talk:
  1. can we use storage to compensate for renewable forecast errors ?
  2. can we control storage with prices ?
  3. can demand response substitute for storage ?



1.

USING STORAGE TO COPE WITH RENEWABLE VOLATILITY

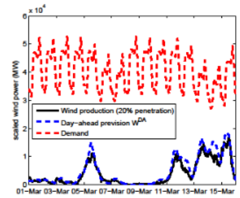
[Bejan et al 2012] Bejan, Gibbens, Kelly, “Statistical aspects of storage systems modelling in energy networks,” 46th Annual Conference on Information Sciences and Systems 2012

[Gast et al 2012] Gast, Tomozei, Le Boudec. “Optimal Storage Policies with Wind Forecast Uncertainties”, *GreenMetrics 2012*

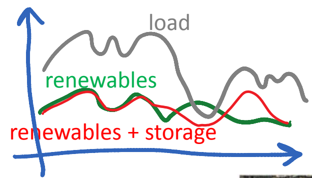
[Gast et al 2013] Gast, Tomozei, Le Boudec. “Optimal Energy Storage Policies with Renewable Forecast Uncertainties ”, *submitted, 2013*

Production scheduling w. forecasts errors

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



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



Pump hydro, Cycle efficiency ≈ 80%

- Compare two approaches
  1. Deterministic approach
     - try to maintain storage level at e.g. ½ of its capacity using updated forecasts
  2. Stochastic approach
     - Use statistics of past errors.

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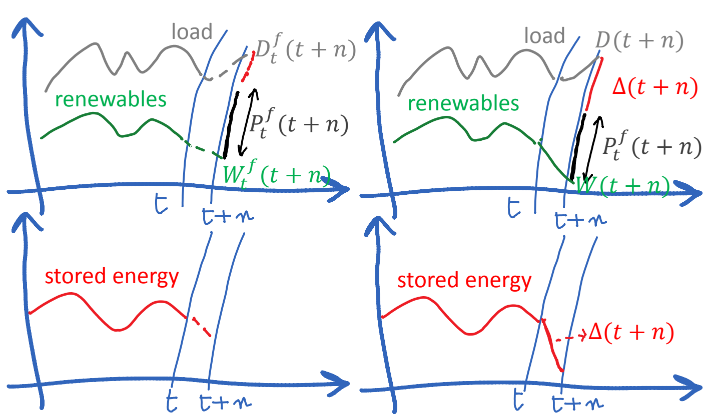
Production scheduling with delays

1a. Forecast load $D_t^f(t+n)$ and renewable suppy $W_t^f(t+n)$
1b. Schedule dispatchable production $P_t^f(t+n)$

2. Compensate deviations from forecast by charging / discharging Δ from storage



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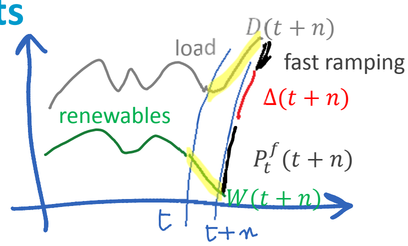
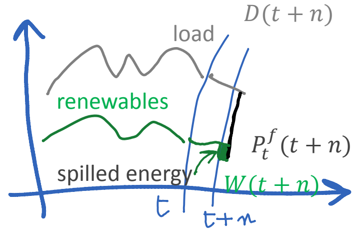
Full compensation of fluctuations by storage may not be possible due to power / energy capacity constraints

- Fast ramping energy source (CO_2 rich) is used when storage is not enough to compensate fluctuation
- Energy may be wasted when
  - Storage is full
  - Unnecessary storage (cycling efficiency < 100%)
- Control problem: compute dispatched power schedule $P_t^f(t+n)$ to minimize energy waste and use of fast ramping





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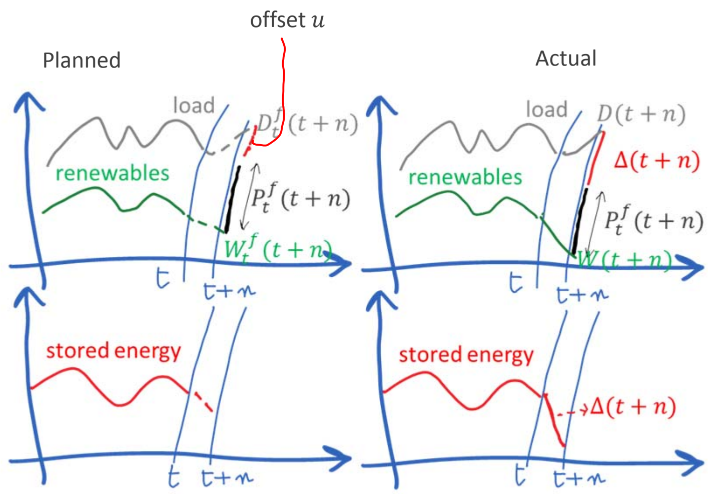
Example of scheduling policy: Fixed Offset

- Fixed Offset policy:
  $u > 0$ means excess production (expect to store)
  $u < 0$ means deficit of production (expect to draw from storage)



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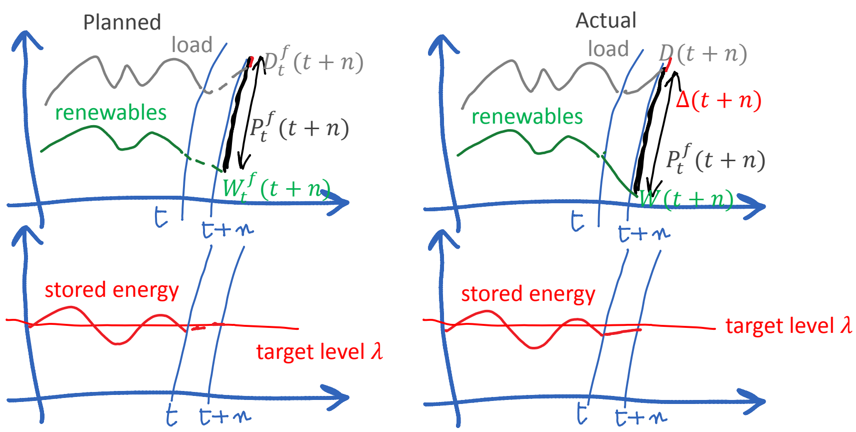
Example of scheduling policy: Fixed Level

- target a fixed storage level (e.g. $\lambda = \frac{1}{2}$ Max)
- [Bejan et al 2012]



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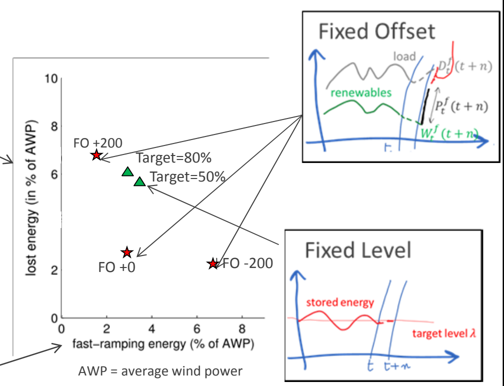
Metric and performance (large storage)

- 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

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%

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

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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 $f(u) := \min\left(\eta\mathbb{E}\left[\min\left((\varepsilon+u)^+, C_{\max}\right)\right], \mathbb{E}\left[\min\left((\varepsilon+u)^-, D_{\max}\right)\right]\right)$

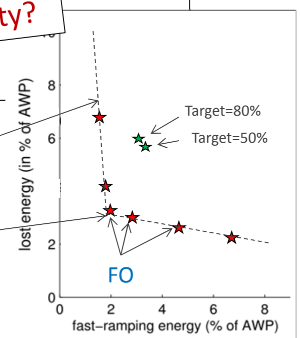
- **Theorem.** *If the forecast error is distributed as ε Then:*
  1. (ℓ, g) is a **lower bound**: for any policy π, there exists u such that:
     $\bar{G}^{\pi}(T) \geq g(u) - \frac{B_{\max}}{T}$ $\bar{L}^{\pi}(T) \geq \ell(u) - \frac{B_{\max}}{T}$
  2. **FO is optimal for large storage**: if t… B_δ,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

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

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

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:
    $$V(b) = g + \inf_{u\,\in \text{offset}} \mathbb{E}[\,\text{cost}\,(u) + V(\phi(b,u))]$$
  - Approximate dynamic programming if state space is too large
  - Can be extended to more complicated state V(t,B,B',…)

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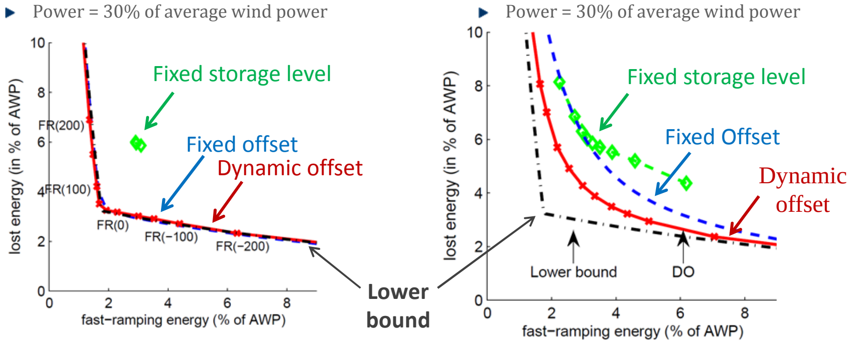
Dynamic Offset outperforms other heuristics

- **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



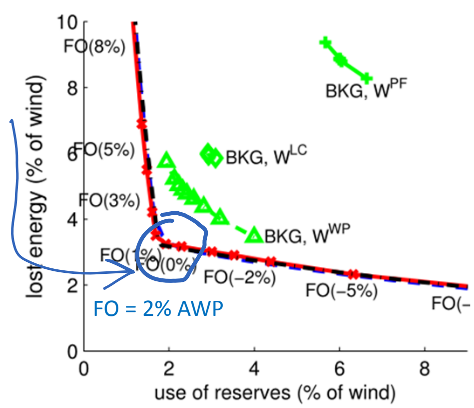
- Fixed Offset & Dynamic offset are optimal
- DO is the best heuristic

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

2.

PRICES AND STORAGE IN REAL-TIME ELECTRICITY MARKETS

[Gast et al 2013] Gast, Le Boudec, Proutière, Tomozei, “Impact of Storage on the Efficiency and Prices in Real-Time Electricity Markets”, ACM e-Energy 2013, Berkeley, May 2013

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Storage and Real Time Prices

- Impact of volatility on prices in real time market is studied by Meyn and co-authors, e.g.
  [Cho and Meyn, 2010] I. Cho and S. Meyn *Efficiency and marginal cost pricing in dynamic competitive markets with friction,* Theoretical Economics, 2010
- We add storage to the model
- Q1: how does storage impact volatility ? what is the required storage capacity ?
- Q2: does the market provide optimal control ?

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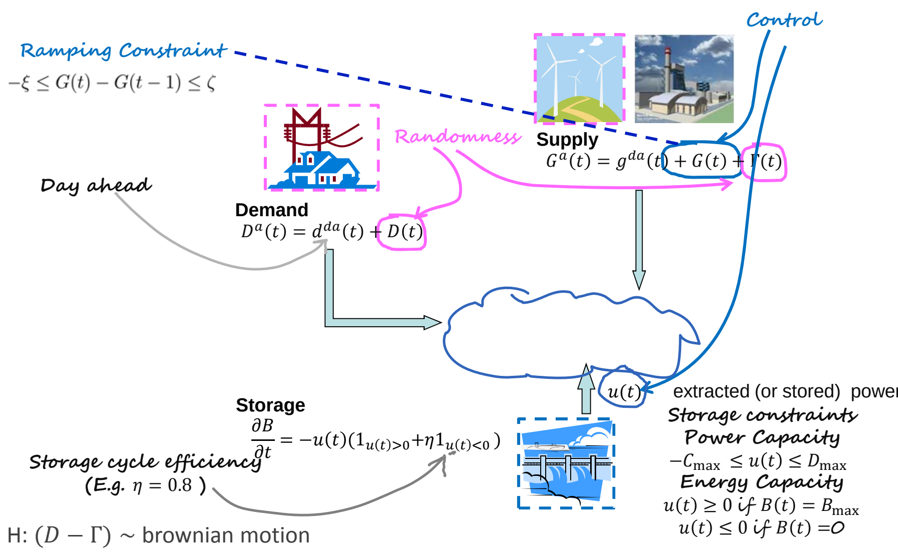
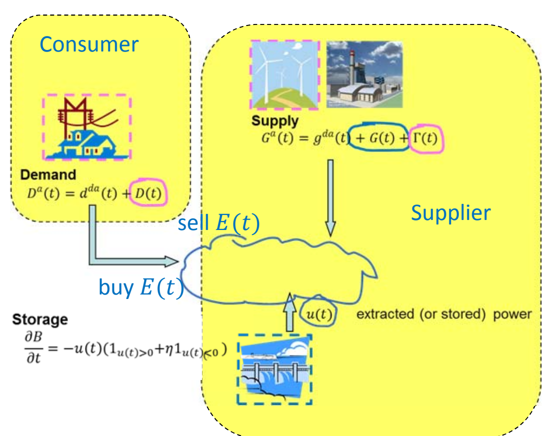
A Macroscopic Model of Real Time Market with Storage
Extension of [Cho and Meyn 2010]



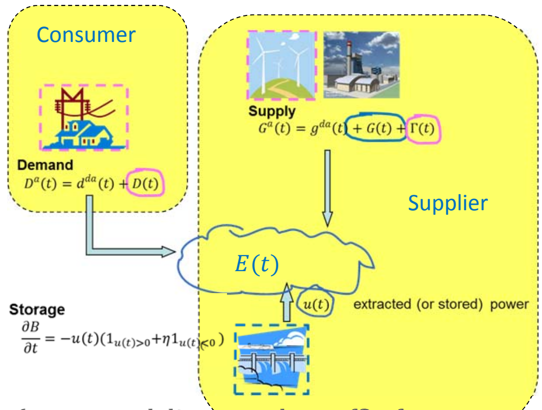
H: $(D - \Gamma) \sim$ brownian motion

Scenario A: Storage at Supplier



- Consumer's payoff
  $$= \underbrace{v\big(D^a(t) \wedge [E(t) + g^{da}(t)]\big)}_{\text{satisfied demand}} - c^{bo}\underbrace{\big(D^a(t) - E(t) - g^{da}(t)\big)^+}_{\text{frustrated demand}}$$
  $$- P(t)E(t) - p^{da}(t)g^{da}(t)$$
- Supplier's payoff
  $$= P(t)E(t) + p^{da}(t)g^{da}(t) - cG(t) - c^{da}g^{da}(t)$$
- $P(t) =$ stochastic price process on real time market

Definition of a Dynamic Competitive Equilibrium (Storage at Supplier) [Cho and Meyn 2010]



- (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]

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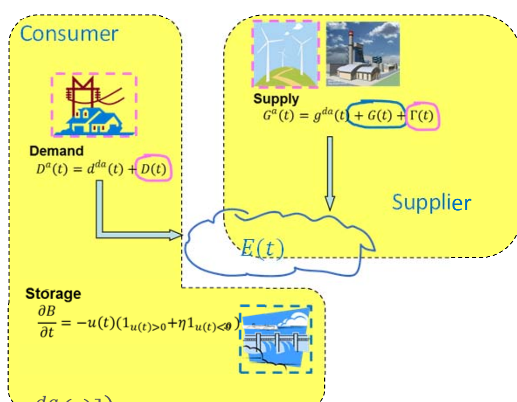
Scenario B: Storage at Consumer



- Consumer's payoff
  $$= v\big(D^a(t) \wedge [E(t) + u(t) + g^{da}(t)]\big)$$
  $$- c^{bo}\big(D^a(t) - E(t) - u(t) - g^{da}(t)\big)^+ - P(t)E(t) - p^{da}(t)g^{da}(t)$$
- Supplier's payoff
  $$= P(t)E(t) + p^{da}(t)g^{da}(t) - cG(t) - c^{da}g^{da}(t)$$
- Dynamic Competitive Equilibrium: (P, E, G, u) such that
  1. E, u maximizes consumer's welfare
  2. E, G maximizes supplier's welfare for the same price process P

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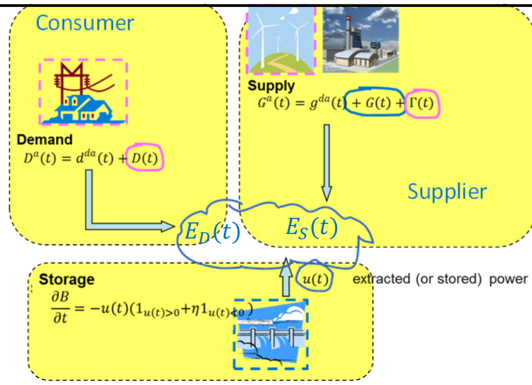
Scenario C: Stand-Alone Storage Operator



- Consumer's payoff
  $= v\big(D^a(t) \wedge [E_D(t) + g^{da}(t)]\big) - c^{bo}\big(D^a(t) - E_D(t) - g^{da}(t)\big)^+ - P(t)E_D(t)$
  $- p^{da}(t)g^{da}(t)$
- Supplier's payoff $= P(t)E_S(t) + p^{da}(t)g^{da}(t) - cG(t) - c^{da}g^{da}(t)$
- Storage Op's payoff $= u(t)P(t)$
- Dynamic Competitive 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. $E_D(t) + u(t) = E_S(t)$ for the same price process P

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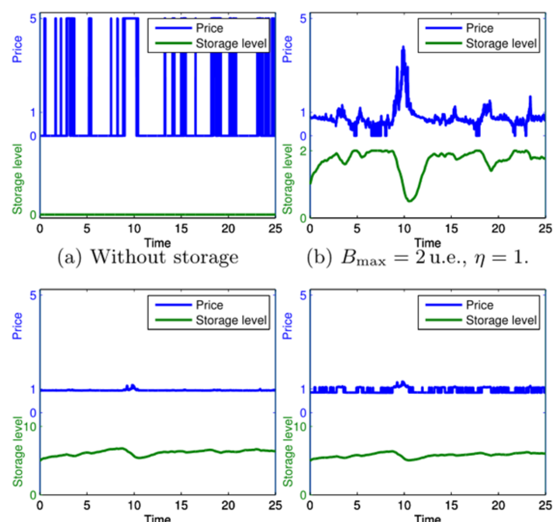
Dynamic Competitive Equilibria exist and are essentially the same for the 3 Scenarios [Theorem 3, Gast et al 2013]

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



(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., $\eta = 0.8$

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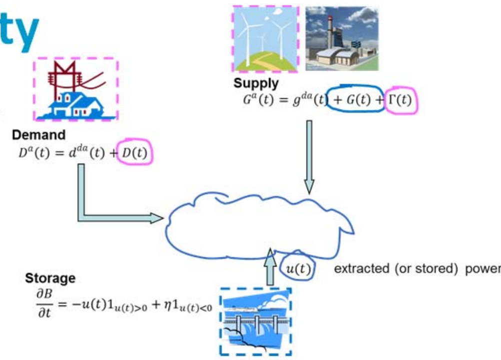
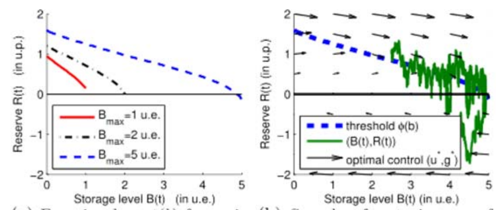
Social Optimality

- Assume a social planner wants to maximize total payoff
- Total payoff is same for all 3 scenarios and is independent of price process $P(t)$
- Structure of optimally social control G, u

Let $R(t) := \Gamma(t) + G(t) - D(t) + r^{da}$

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





(a) Function $b \mapsto \phi(b)$ for various values of the storage energy capacity $B_{\max}$.

(b) Sample of a trajectory of the optimal reserve and storage processes. $B_{\max} = 5$ u.e.

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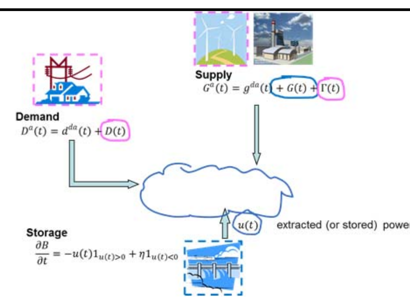
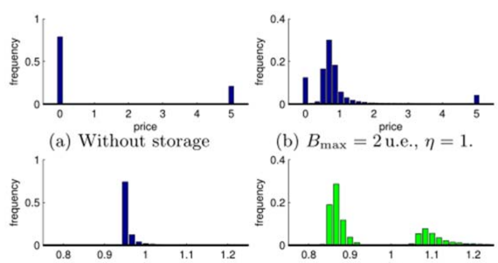
The Social Welfare Theorem [Gast et al., 2013]

- Any dynamic competitive equilibrium for any of the three scenarios maximizes social welfare





(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 $\eta = 1$.

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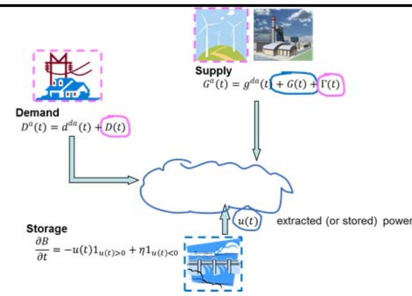
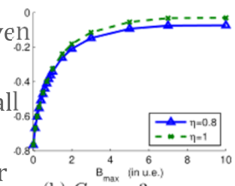
The Invisible Hand of the Market may not be optimal

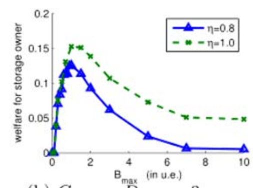


- Any dynamic competitive equilibrium for any of the three scenarios maximizes social welfare
- However, this assumes a given storage capacity.
- Is there an incentive to install storage ?
- No, stand alone operators or consumers have no incentive to install the optimal storage



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

Expected social welfare

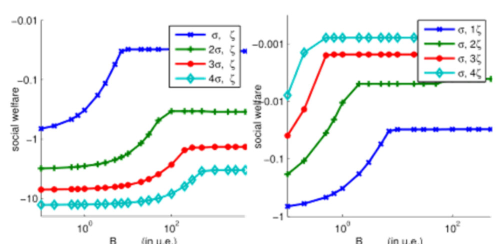


(b) $C_{\max} = D_{\max} = 3$ u.p.

Expected welfare of stand alone operator

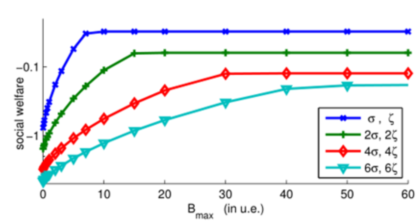
Scaling Laws

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



(a) Fixed ζ (b) Fixed σ

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

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3.

A MODEL OF REAL TIME DEMAND RESPONSE

[Le Boudec and Tomozei 2013] Le Boudec, Tomozei, "Stability of a stochastic model for demand-response", *Stochastic Systems 2013*, also available at http://infoscience.epfl.ch/record/185991

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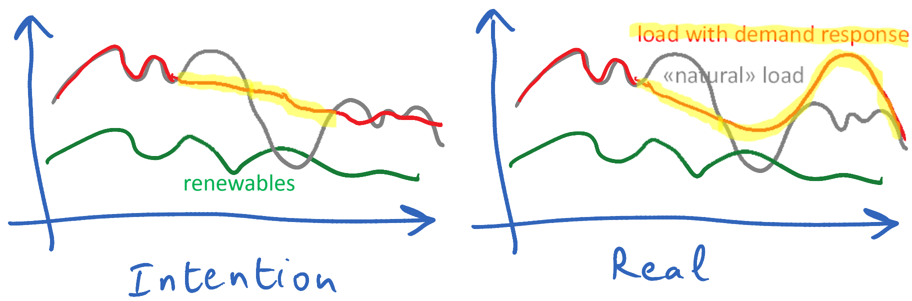
Issue with Demand Response: Grid Changes Load

- Widespread demand response may make load hard to predict



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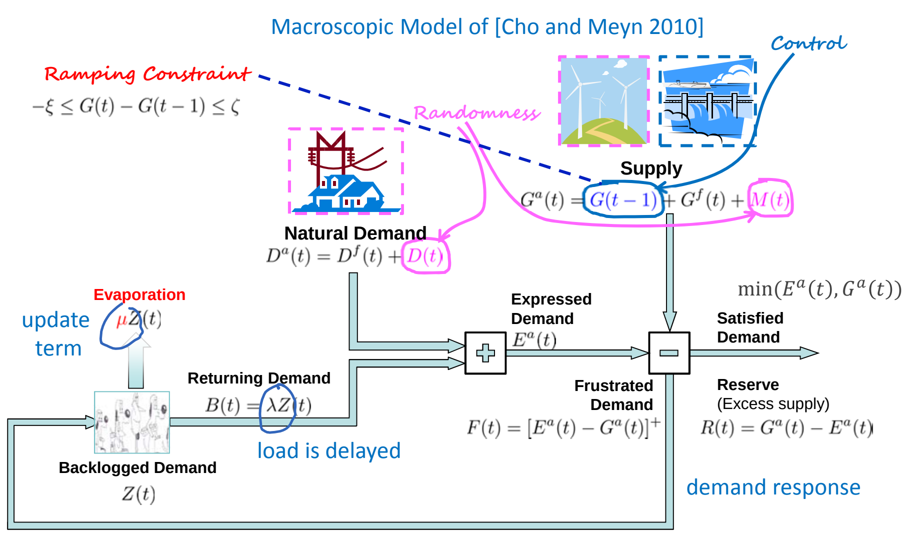
A Macroscopic Model of Demand Response



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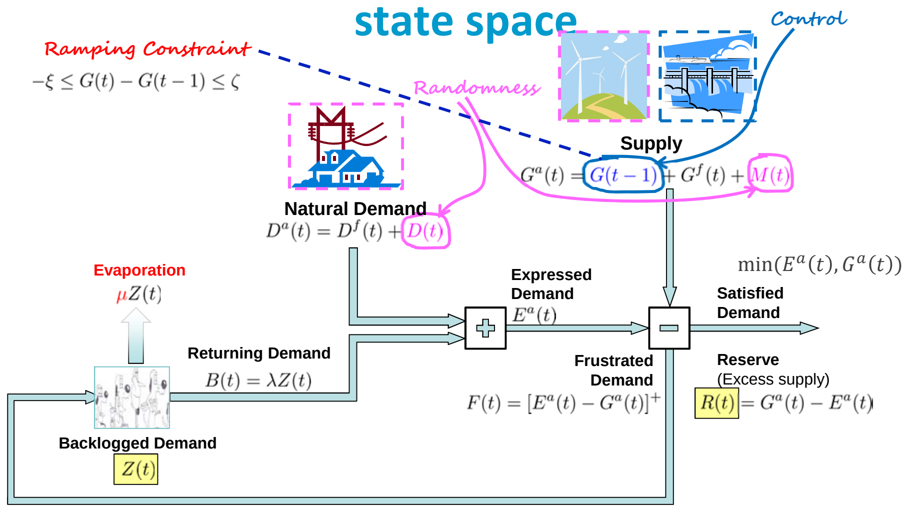
We obtain a 2-d Markov chain on continuous state space



$$R(t) = G(t-1) - \lambda Z(t) + M(t) - D(t) + r_0$$
$$Z(t) = Z(t-1) - \lambda Z(t) - \mu Z(t) + \mathbb{1}_{\{R(t)<0\}}|R(t)|$$

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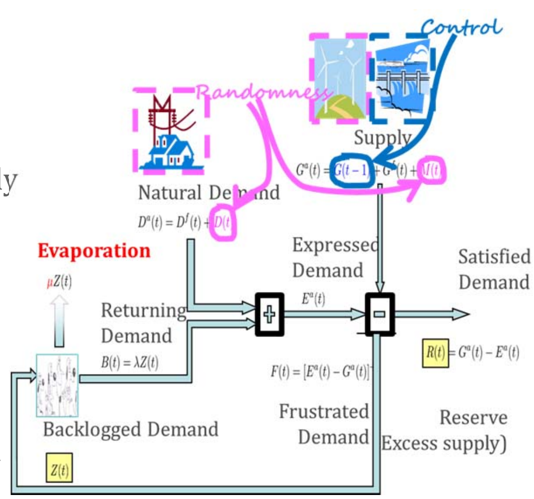
The Control Problem

- **Control variable:**
  $G(t-1)$
  production bought one time slot ago in real time market
- Controller sees only supply $G^a(t)$ and expressed demand $E^a(t)$
- **Our Problem:**
  keep backlog $Z(t)$ stable
- Ramp-up and ramp-down constraints
  $\xi \le G(t) - G(t-1) \le \zeta$



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Threshold Based Policies

$G^f(t) = D^f(t) + r_0$

Forecast supply is adjusted to forecast demand

$R(t) = G^a(t) - E^a(t)$

R(t) := reserve = excess of demand over supply

Threshold policy:

if $R(t) < r*$ increase supply to come as close to r^*as possible (considering ramp up constraint)

else decrease supply to come as close to r^*as possible (considering ramp down constraint)

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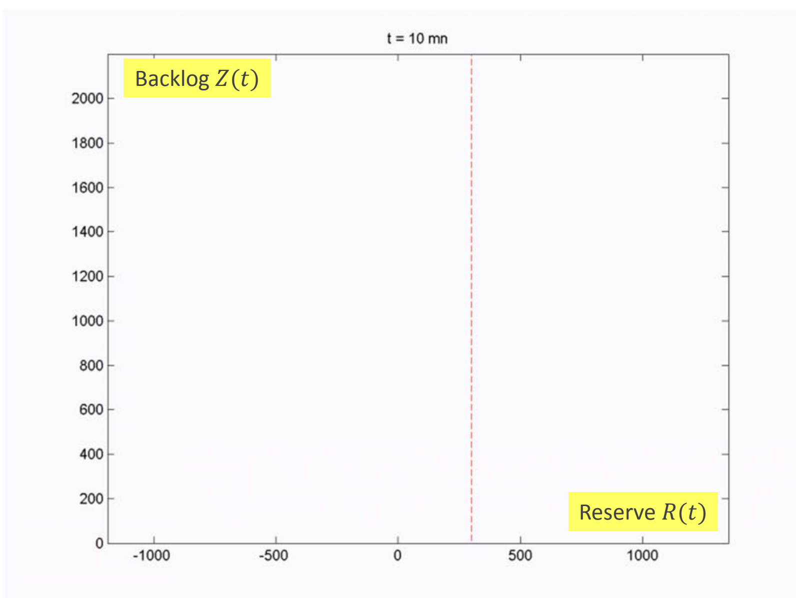
Simulations (evaporation $\mu > 0$)



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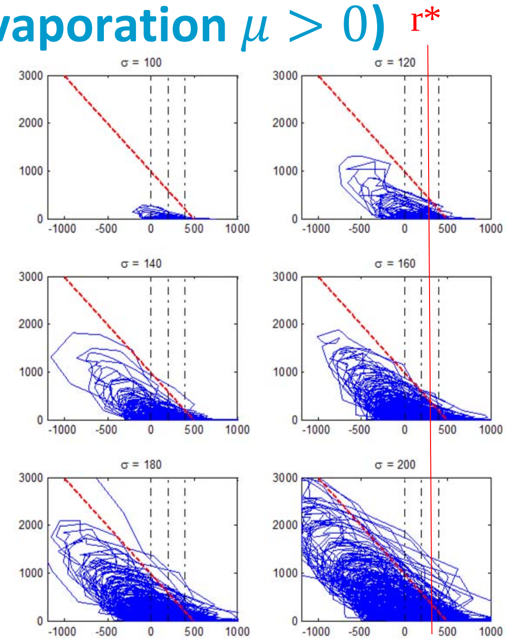
Simulations (evaporation $\mu > 0$)

- $\mu > 0$ means returning load is, in average, less
- Large excursions into negative reserve and large backlogs are typical and occur at random times



1 time step = 10mn

T=10000 iterations, $\xi=\zeta=100$, $r^*=300$, $\lambda=0.3$, $\mu=0.2$

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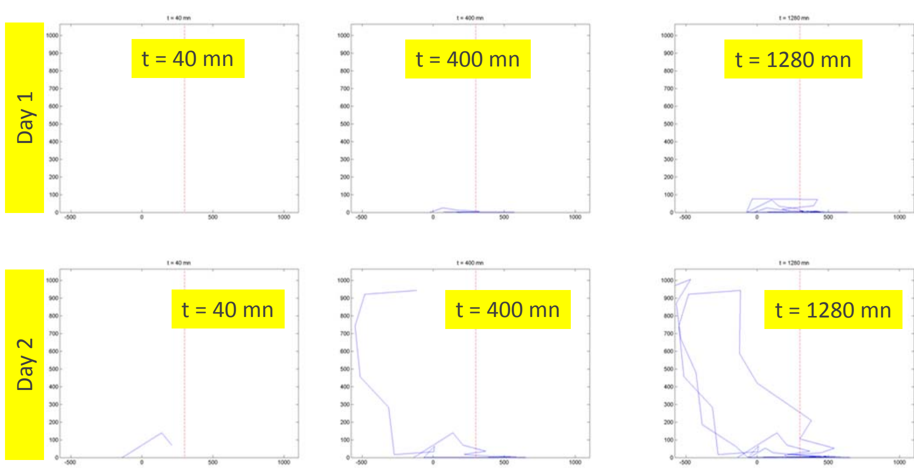
Large backlogs may occur within a day, at any time (when evaporation $\mu > 0$)



Typical delay $\frac{1}{\lambda}$ =30 mn, all simulations with same parameters as previous slide, $\sigma = 160$

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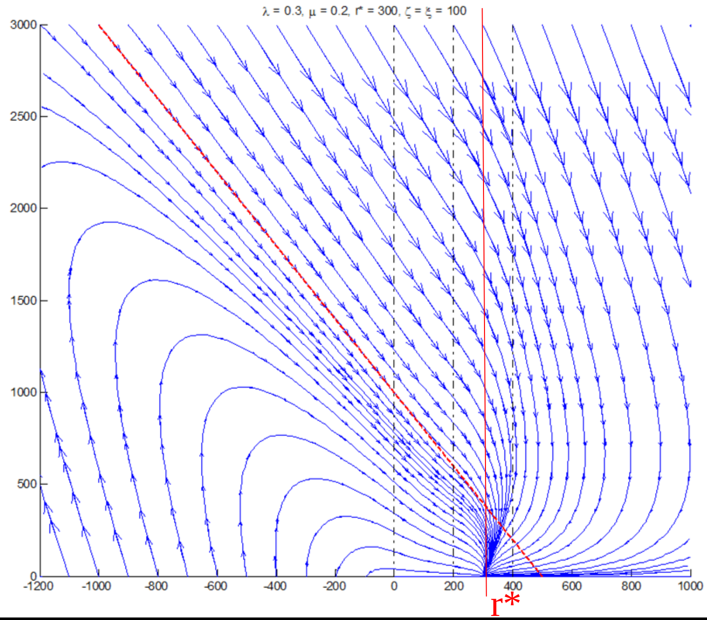
ODE Approximation ($\mu > 0$) explain large excursions into positive backlogs



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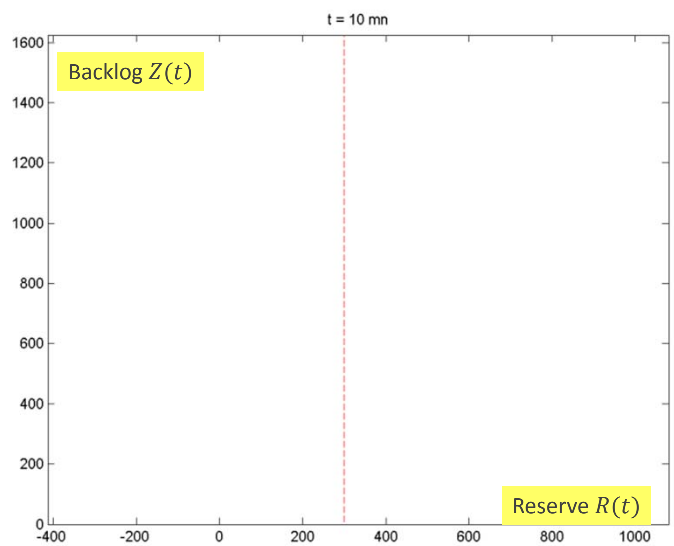
Simulations (evaporation $\mu < 0$)



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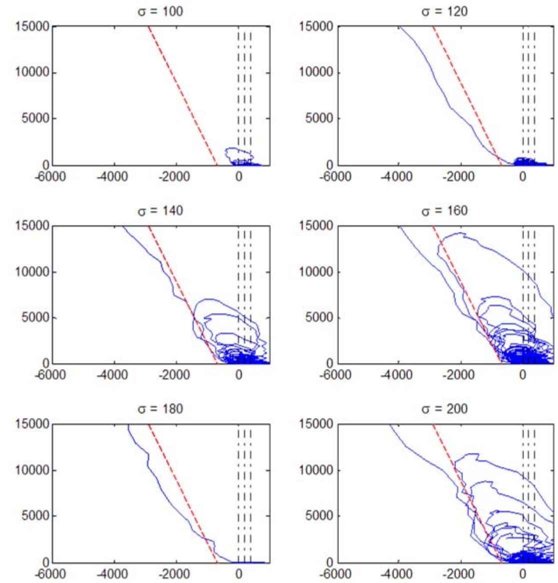
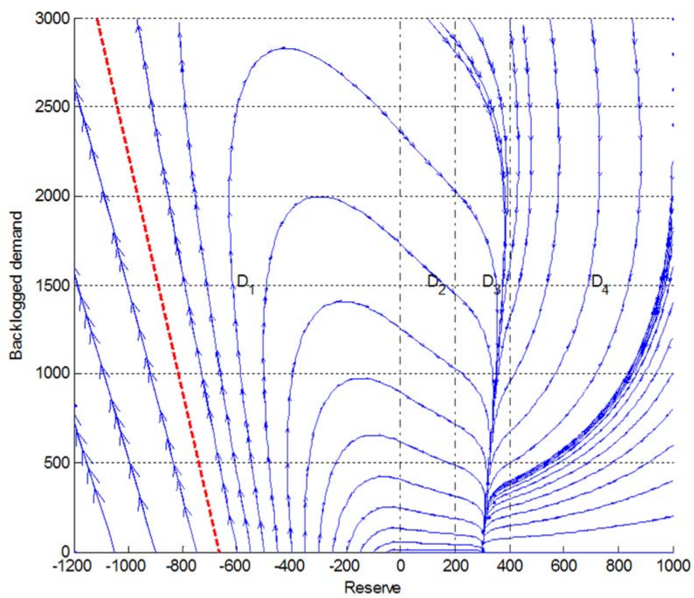
Simulations (evaporation $\mu < 0$)

- $\mu < 0$ means returning load is, in average, more
- Backlog grows more rapidly



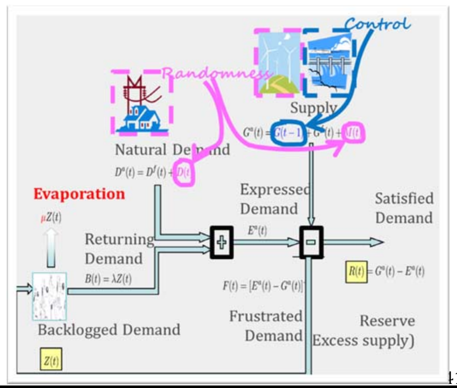
$\xi = \zeta = 100, \mu = -0.15, r^* = 300$ 1 time step = 10mn

ODE Approximation ($\mu < 0$) shows backlog is unstable



Findings : Stability Results

- If evaporation μ is positive, system is stable (ergodic, positive recurrent Markov chain) for any threshold $r*$
- If evaporation μ is negative, system unstable for any threshold $r*$
- Delay does not play a role in stability
- Nor do ramp-up / ramp down constraints or size of reserve



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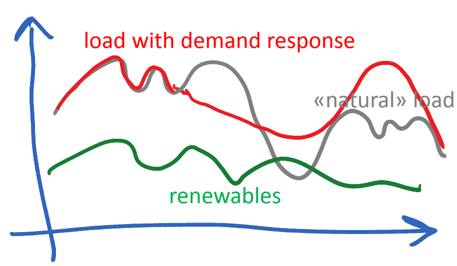
What this suggests about Demand Response:

- Positive evaporation is essential
  occurs with thermal loads, might not always occur for all load
- Model suggests that large backlogs are possible and unpredictible



- Backlogged load is a new threat to grid operation
  Need to measure and forecast backlogged load

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Thank You !

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