STOCHASTIC ANALYSIS OF REAL AND VIRTUAL STORAGE IN THE SMART GRID

Jean-Yves Le Boudec,

joint work with
Nicolas Gast

Dan-Cristian Tomozei

I&C

EPFL

IEEE-Greencom keynote, Cyberspace, September 2012

1.

INTRODUCTION

Renewable but non dispatchable

Source: «Battle of the grids», Greenpeace, Report 2011.

- Wind and PV require some mechanisms to compensate non dispatchability

Renewable Methods to Compensate for Fluctuations of PV and Wind

Dispatchable renewables

Storage
Demand Response

2.

A MODEL OF DEMAND RESPONSE

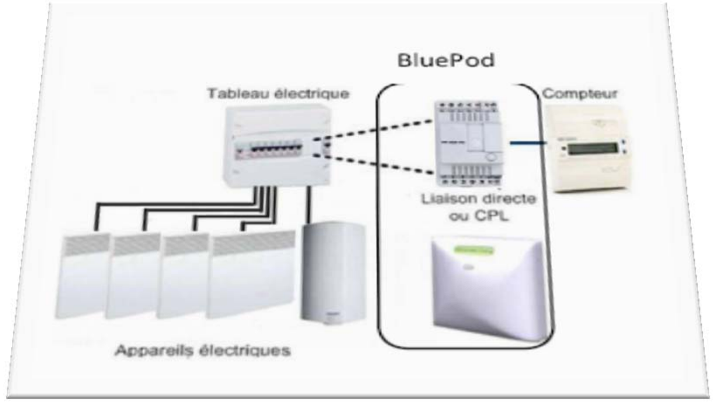
Le Boudec, Tomozei, *Satisfiability of Elastic Demand in the Smart Grid*, Energy 2011 and ArXiv.1011.5606

Demand Response

- = distribution network operator may interrupt / modulate power

- elastic loads support graceful degradation

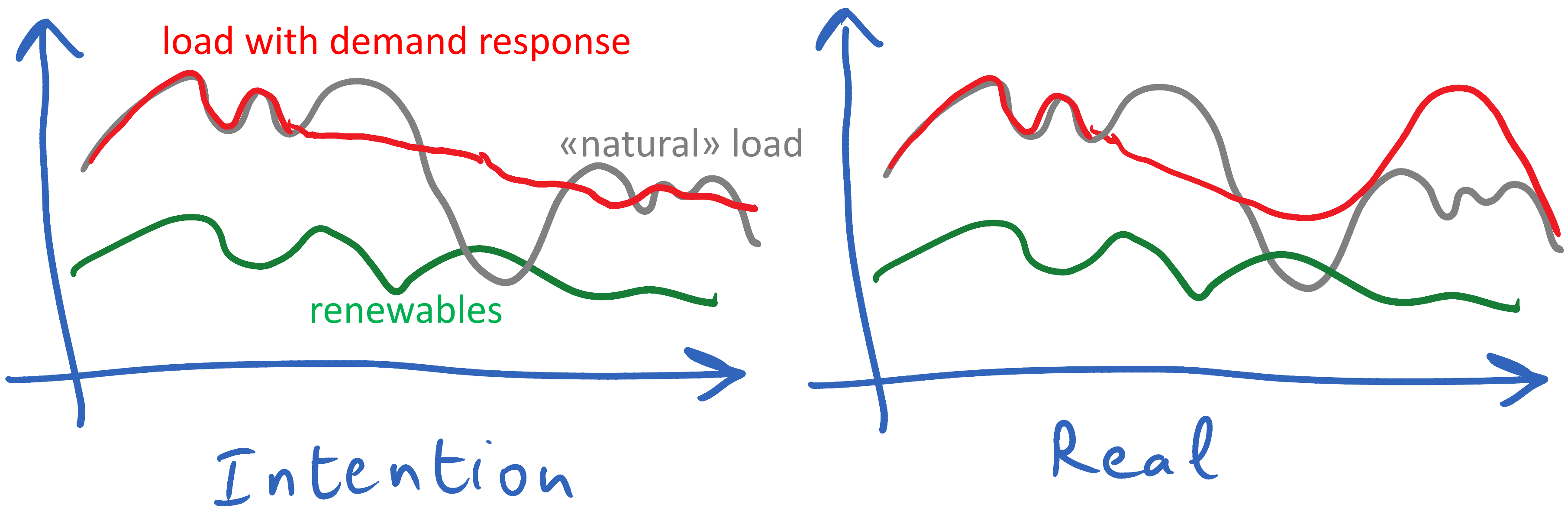
- Thermal load (Voltalis), washing machines (Romande Energie«commande centralisée»)
  e-cars



Voltalis Bluepod switches off thermal load for 60 mn

Issue with Demand Response: Grid Changes Load

- Widespread demand response may make load hard to predict



Our Problem Statement

- Does demand response work ?
  - Delays
  - Returning load
- **Problem Statement**
  Is there a control mechanism that can stabilize demand ?
- We make a macroscopic model of a transmission grid with large penetration of
  - demand response
  - Non dispatchable renewables
- We leave out for now the details of signals and algorithms

Starting Point: Macroscopic Model of Cho and Meyn [1], without Demand Response

Step 1: Day-ahead market

- Forecast demand: $D^f(t)$
- Forecast supply:
  $G^f(t) = D^f(t) + r_0$

nominal reserve

Step 2: Real-time market

- Actual demand
  $D^a(t) = D(t) + D^f(t)$
- Actual supply $G^a(t) =$
  $G(t-1) + G^f(t) + M(t)$

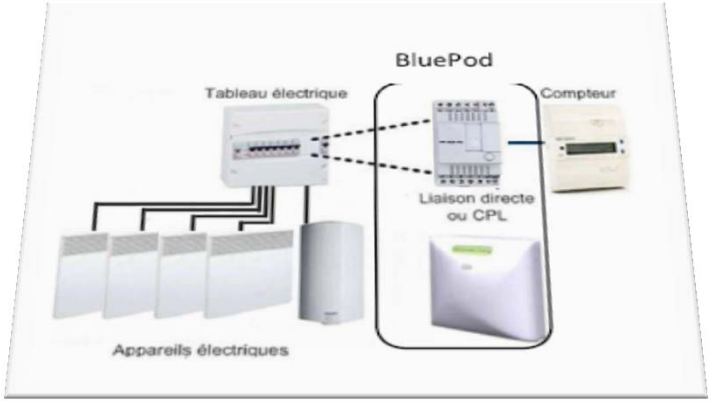
deterministic

random
(deviation from forecast)

control
(real time adjustement of Generation)

We add demand response to the model

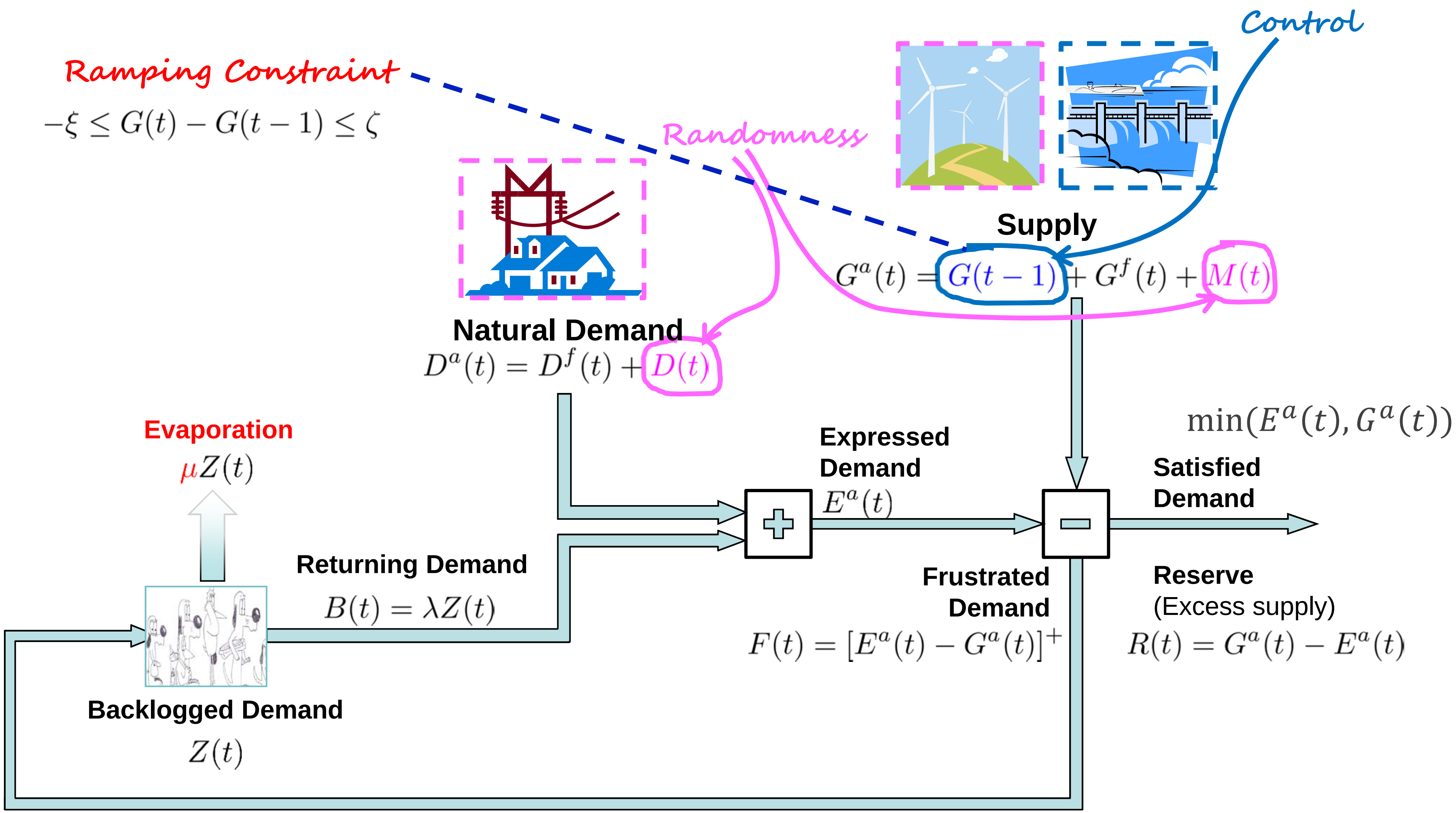
- We capture two effects of Demand Response
  - Some load is delayed
  - Returning load is modified



- We do not model the IT aspects
  - Operation of Demand response is instantaneous

    (but has delayed impact)

Our Macroscopic Model with Demand Response



Demand that was subject to demand response is later re-submitted

- Delay term

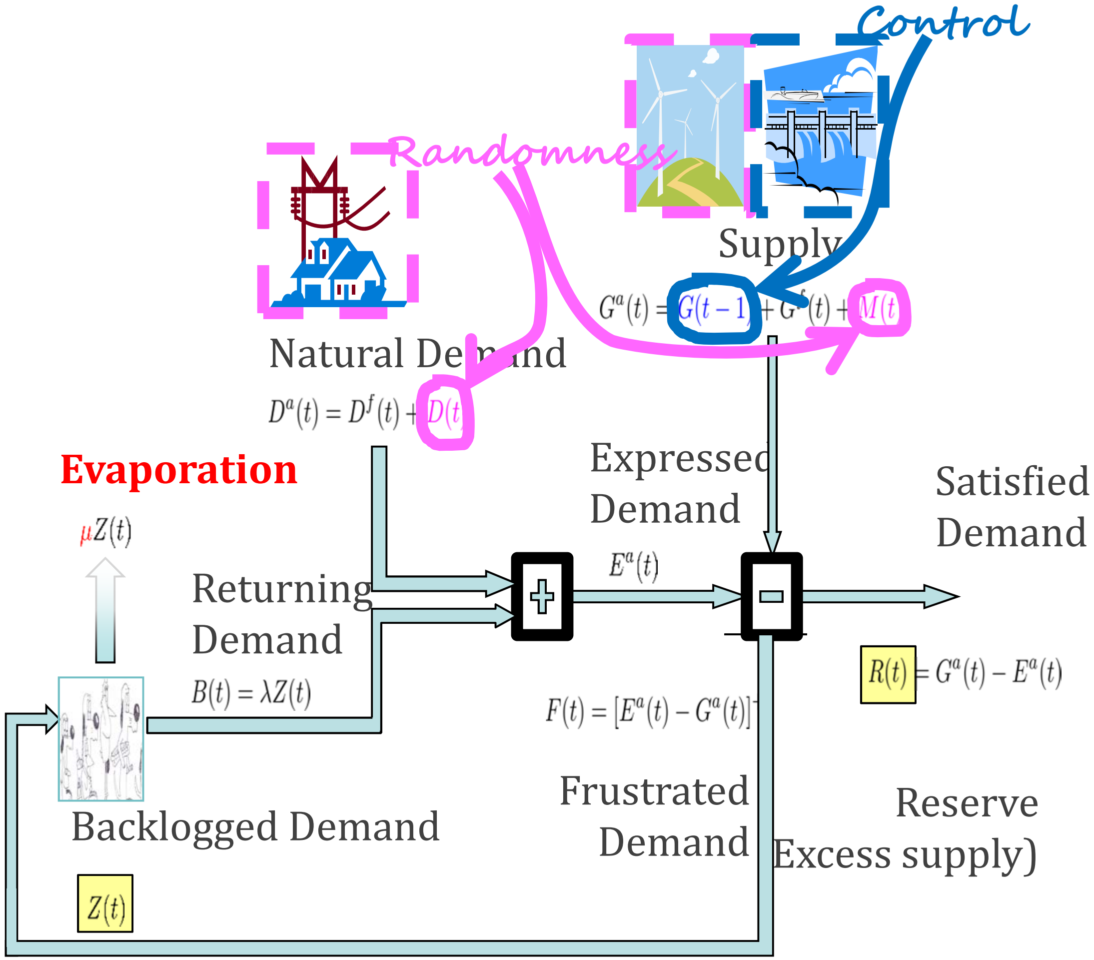
  $\lambda Z\ dt$

  $1/\lambda$ (time slots) is the average delay
- Update term (evaporation):

  $\mu Z\ dt$

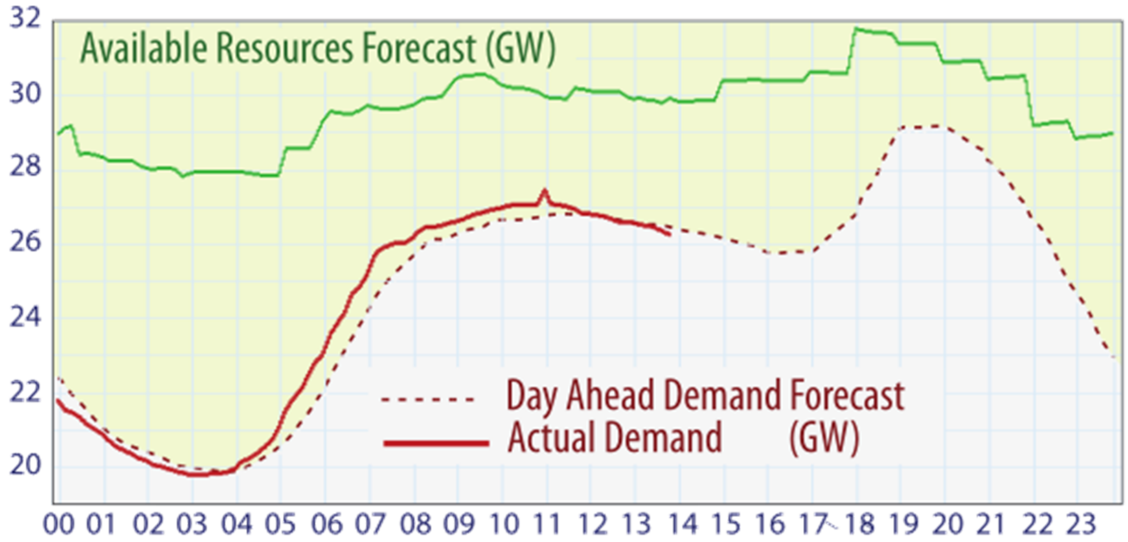
  with $\mu > 0$ or $\mu < 0$

  μ is the evaporation rate (proportion of lost demand per time slot)



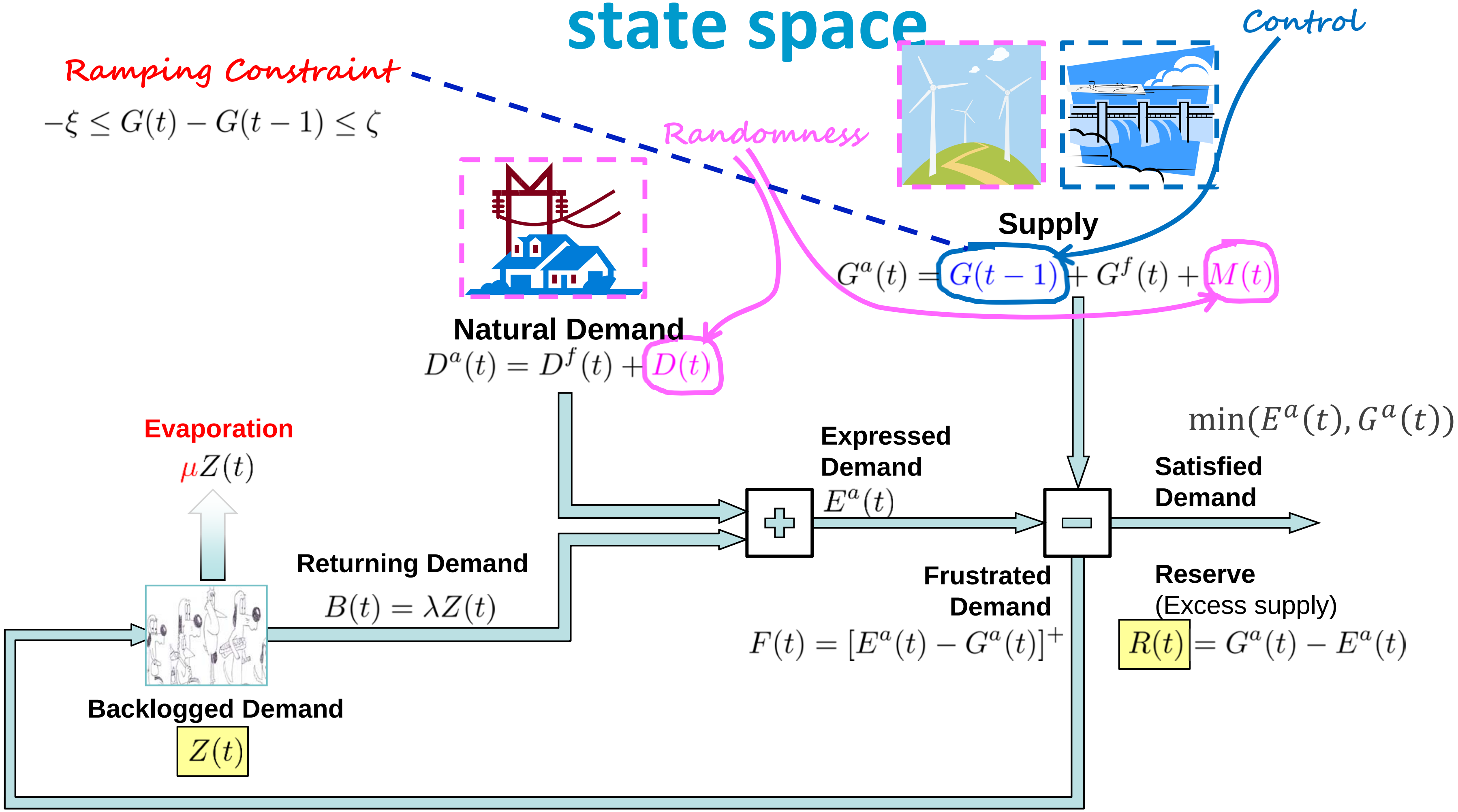
Deviations from Forecasts

- Assumption : $(M - D) = \mathrm{ARIMA}(0, 1, 0)$
  typical for deviation from forecast
  $$(M(t+1) - D(t+1)\,) - \big(M(t) - D(t)\big) \coloneqq N(t+1)$$
  $\sim iid$ with some finite variance



S. Meyn
"Dynamic Models and Dynamic Markets for Electric Power Markets"

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

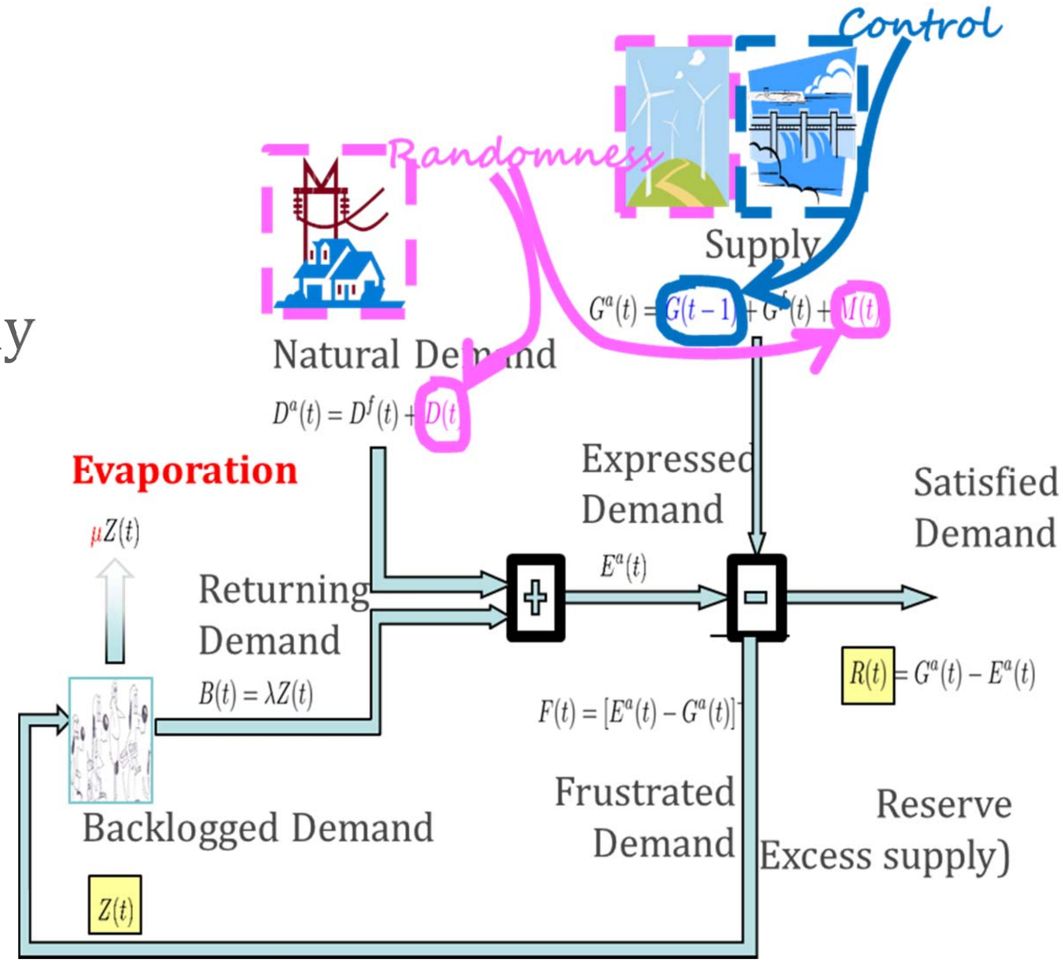


$$R(t) = G(t-1) - \lambda Z(t) + M(t) - D(t) + r_0$$
$$Z(t) = Z(t-1) - \lambda Z(t) - \mu Z(t) + \mathbb{1}_{\{R(t)<0\}}|R(t)|$$

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

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



Threshold Based Policies

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

Forecast supply is adjusted to forecast demand

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

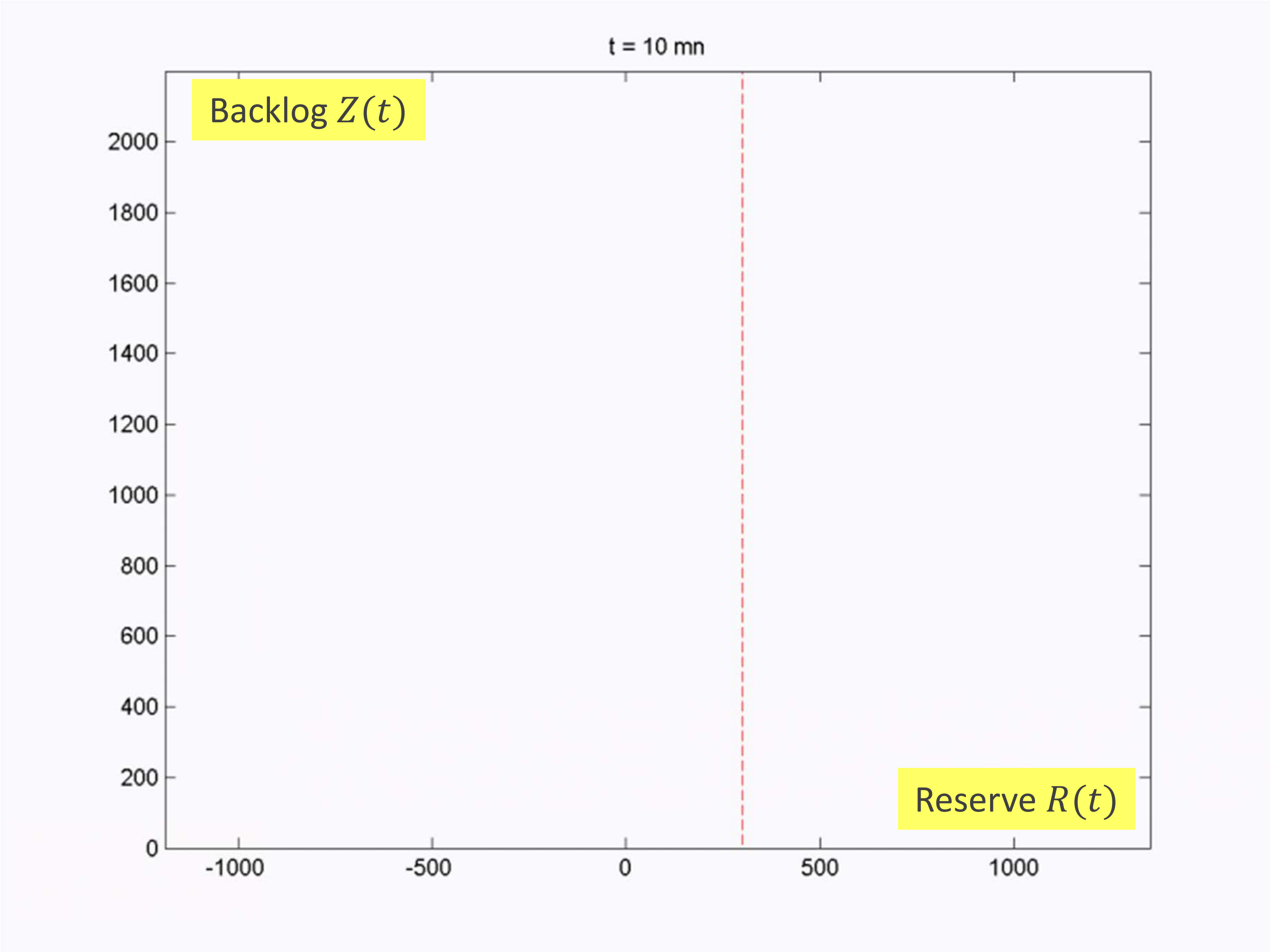
R(t) := reserve = excess of demand over supply

Threshold policy:

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

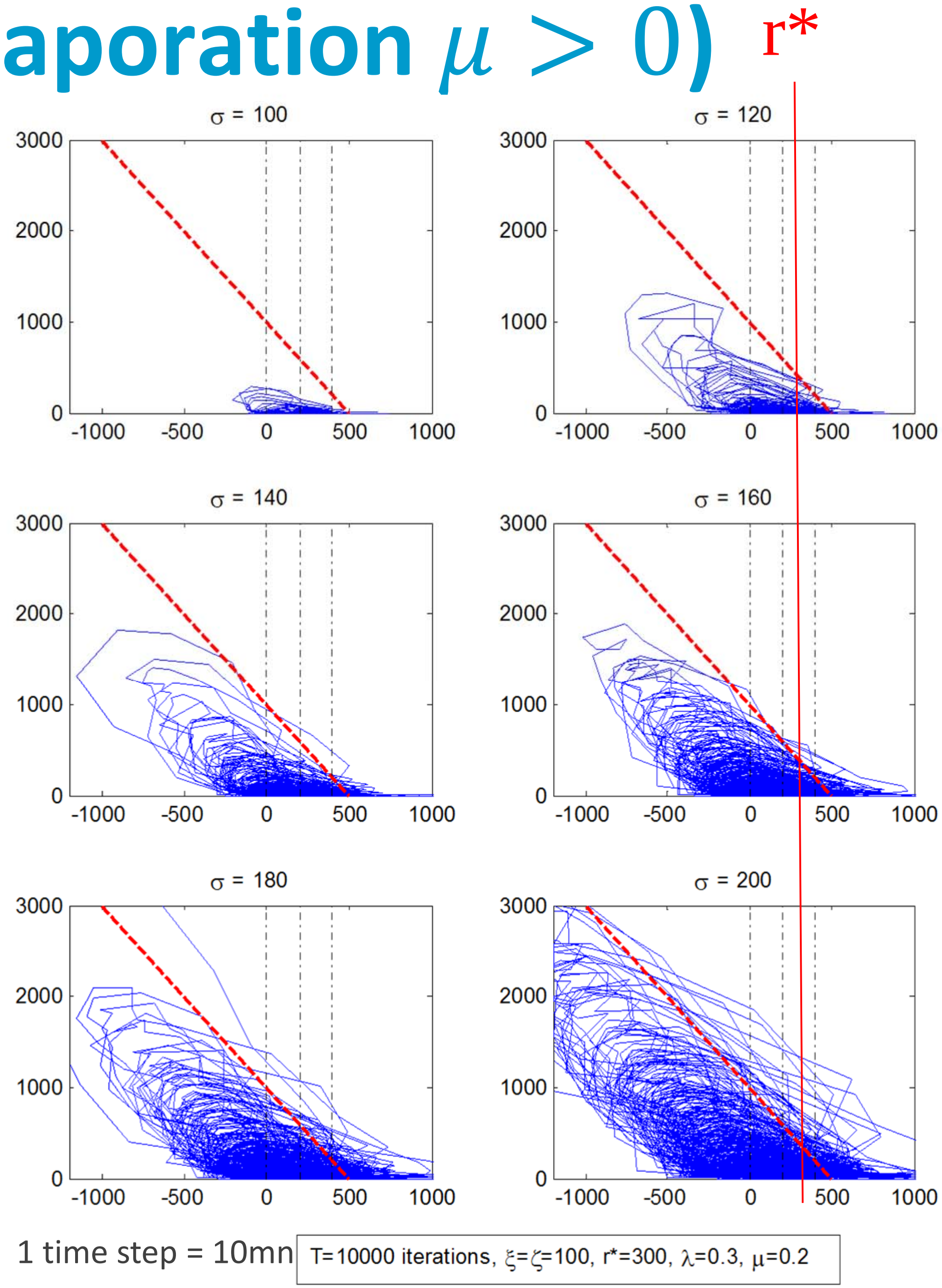
else decrease supply to come as close to r^* as possible (considering ramp down constraint)

Simulations (evaporation $\mu > 0$)

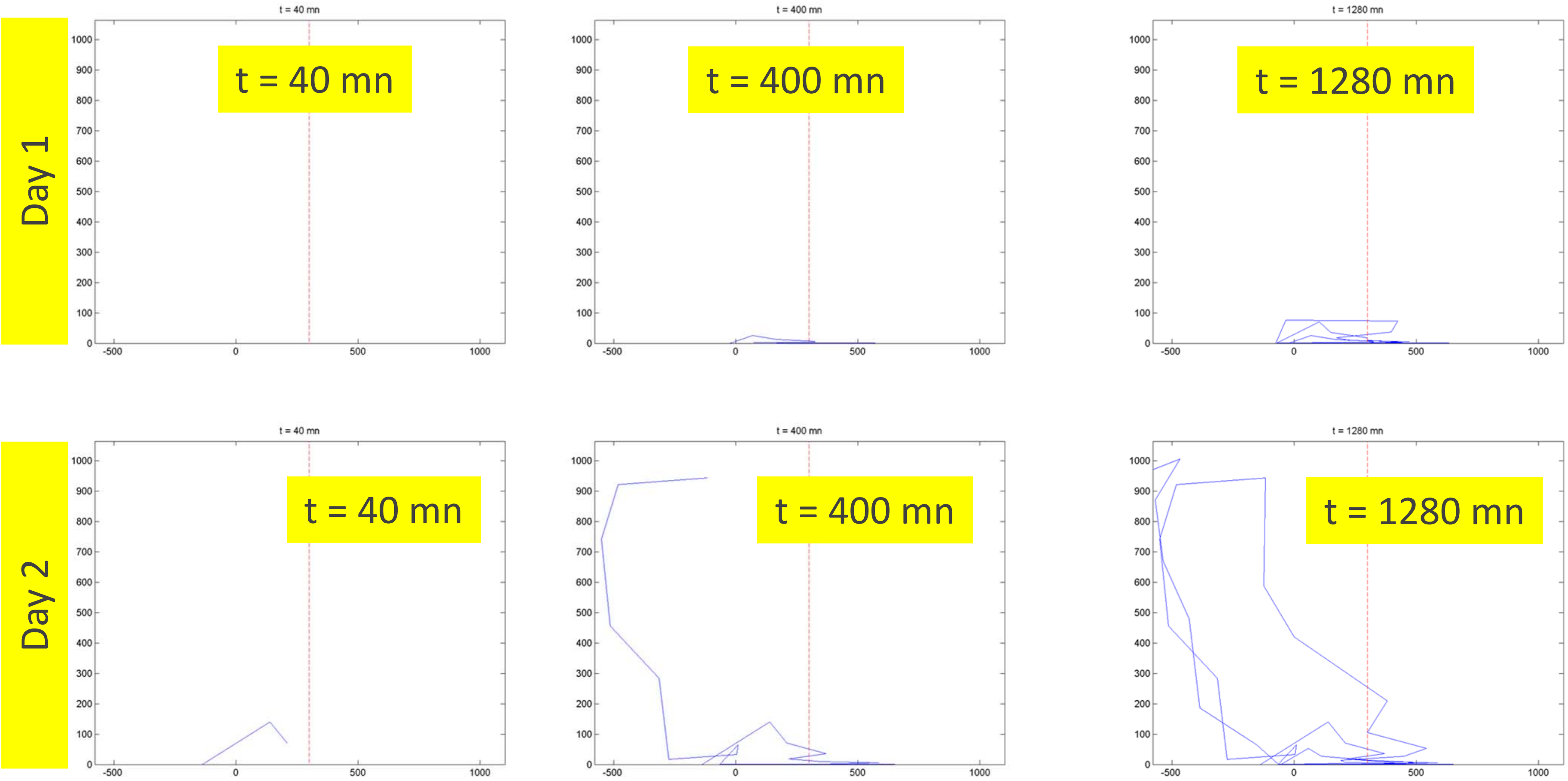


Simulations (evaporation $\mu > 0$)

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

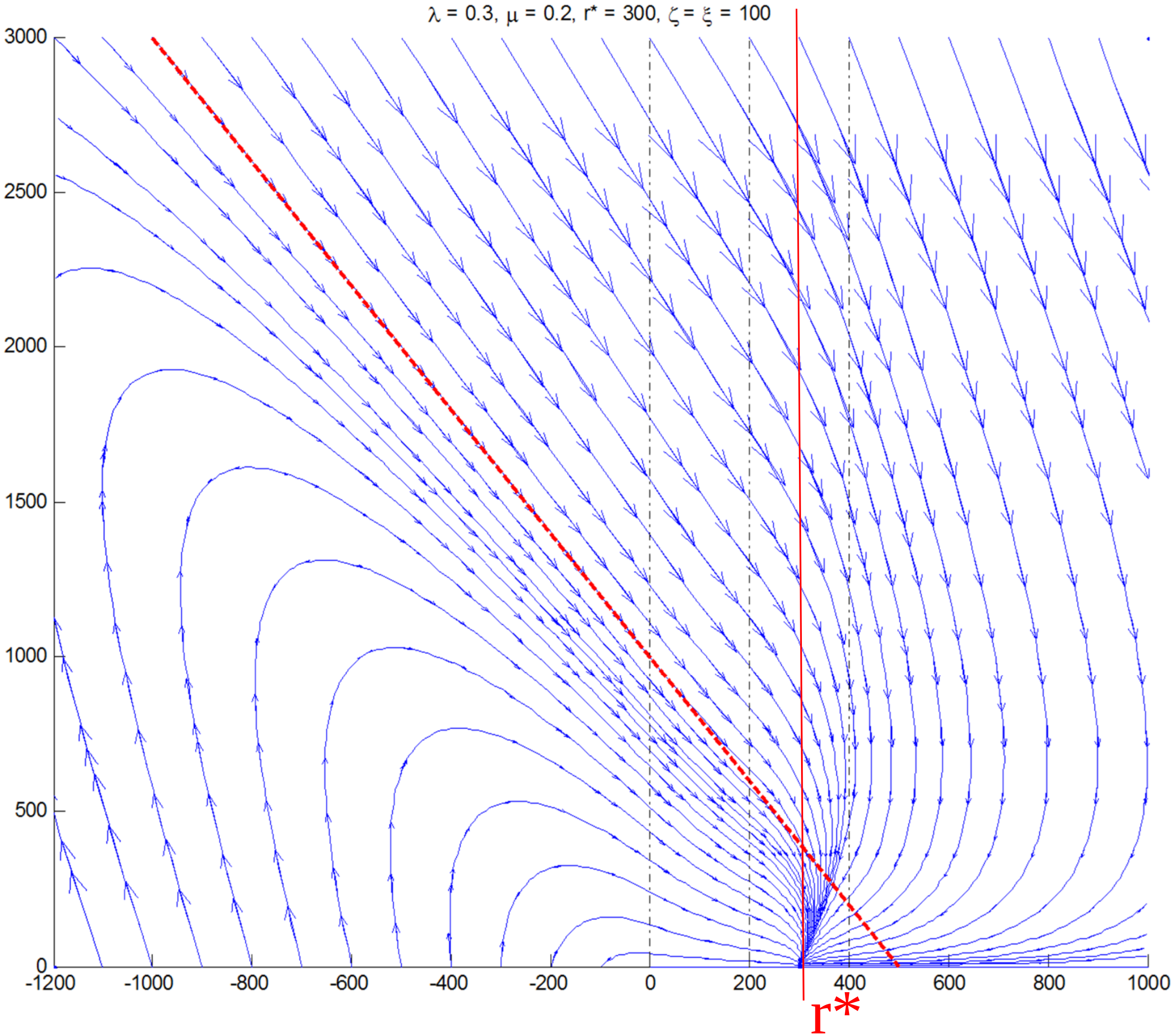


Large backlogs may occur within a day, at any time (when evaporation $\mu > 0$)

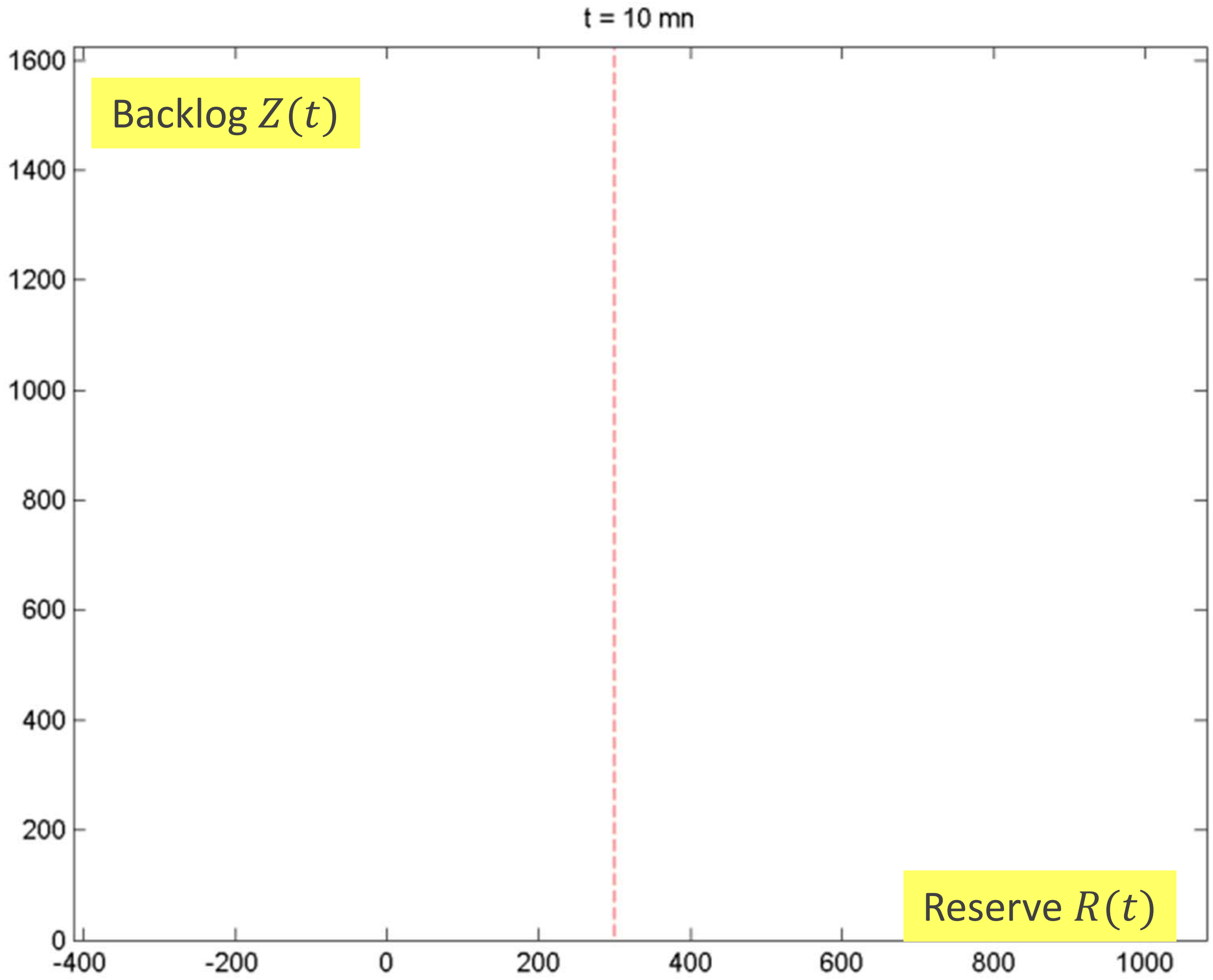


Typical delay $\frac{1}{\lambda}$ =30 mn, all simulations with same parameters as previous slide, $\sigma = 160$

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

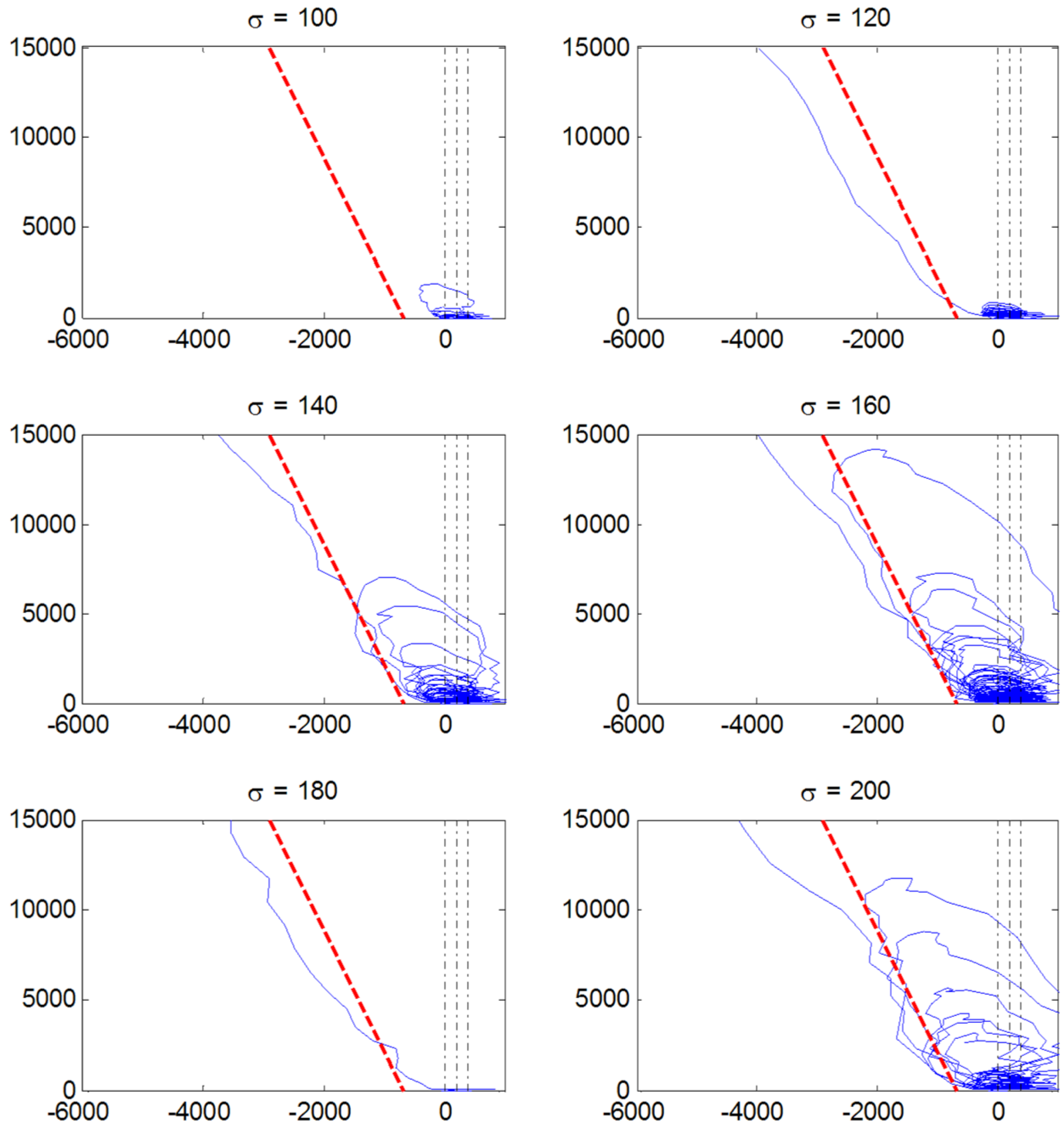


Simulations (evaporation $\mu < 0$)



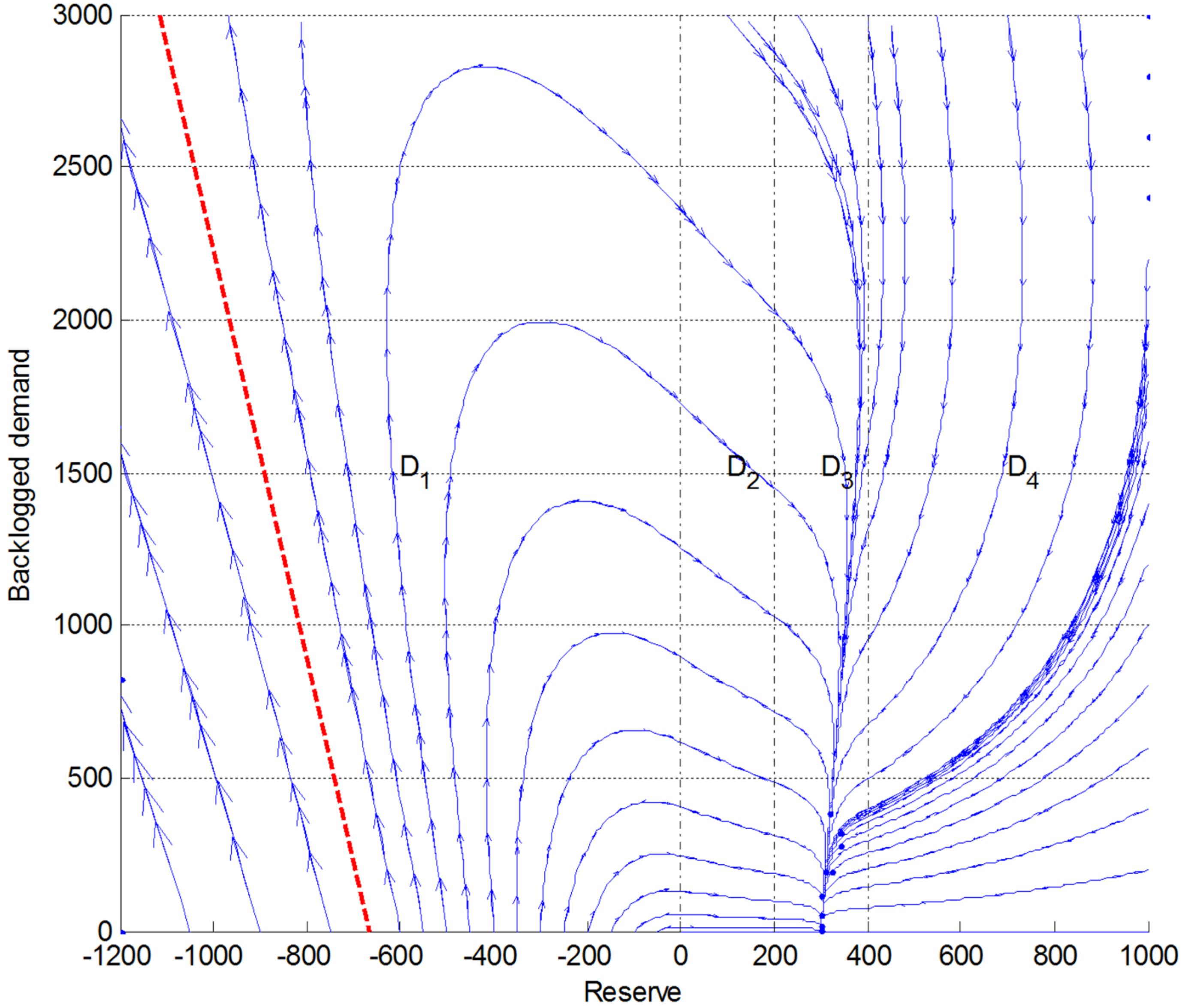
Simulations (evaporation $\mu < 0$)

- $\mu < 0$ 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

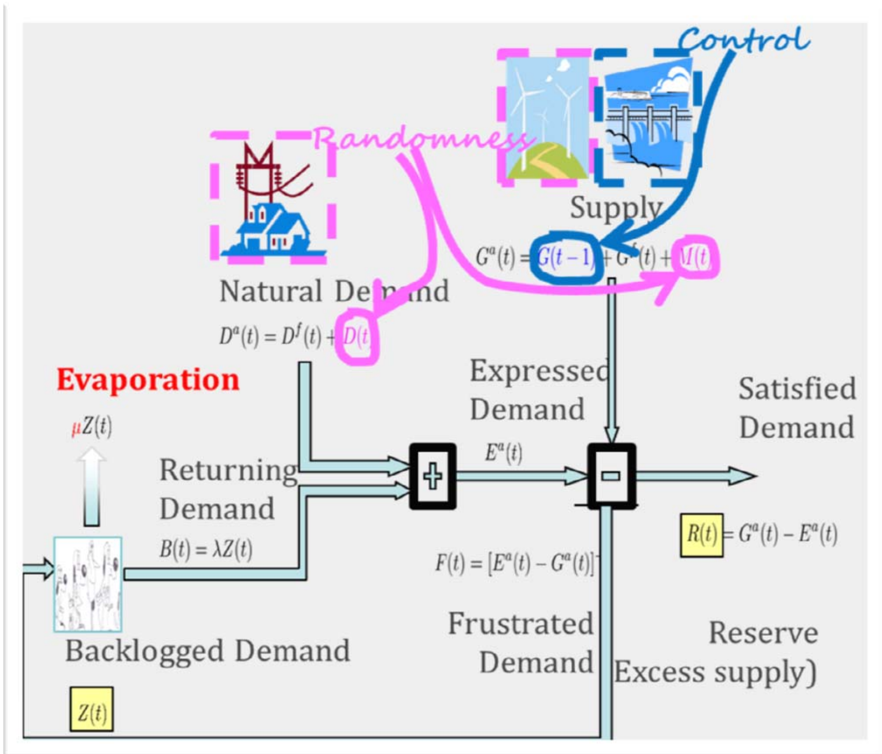


Findings : Stability Results

- 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



Evaporation

- *Negative* evaporation μ means: delaying a load makes the *returning load* larger than the original one.

- Could this happen ?

Q. Does letting your house cool down now imply
spending more heat in total compared to
keeping temperature constant ?

- $\neq$ return of the load:

Q. Does letting your house cool down now imply spending more heat later ?

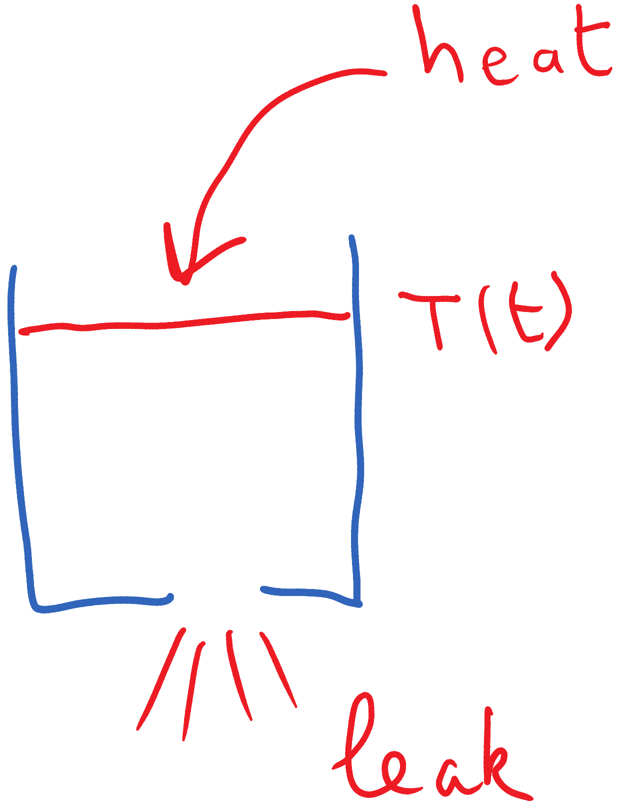
A. Yes
(you will need to heat up your house later -- delayed load)

- Assume the house model of [6]

heat provided to building

$$\boxed{d(t)\epsilon} = \boxed{K}(T(t) - \theta(t)) + \boxed{C}(T(t) - T(t-1))$$

leakiness　outside　inertia



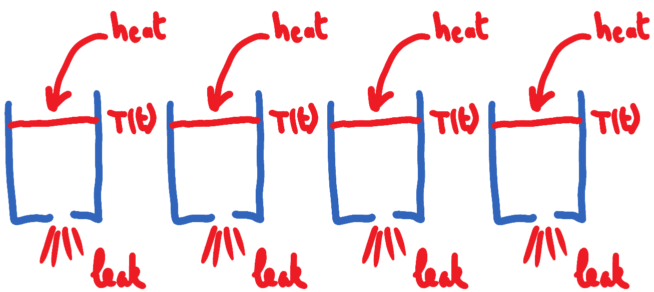
efficiency

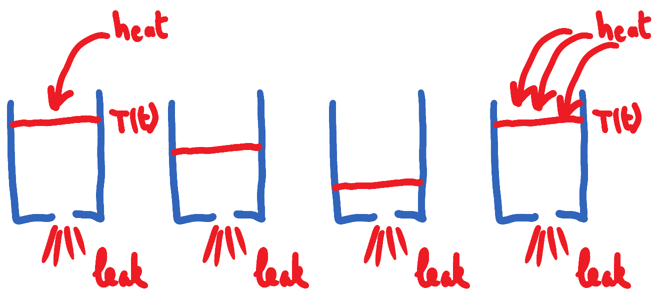
$$\epsilon \boxed{\sum_{t=1}^{\tau} d(t)} = K \sum_{t=1}^{\tau} \left(\boxed{T(t)} - \theta(t)\right) + C\left(T(\tau) - T(0)\right)$$

achieved t°

E, total energy provided

Scenario	***Optimal***	***Frustrated***
Building temperature	$T^*(t), t = 0 \dots \tau$	$T(t), t = 0 \dots \tau,$ $T(t) \leq T^*(t)$
Heat provided	$E^* = \frac{1}{\epsilon}\left(K \sum_{t=1}^{\tau} (T^*(t) - \theta(t)) + C(T^*(\tau) - T^*(0))\right)$	$E < E^*$



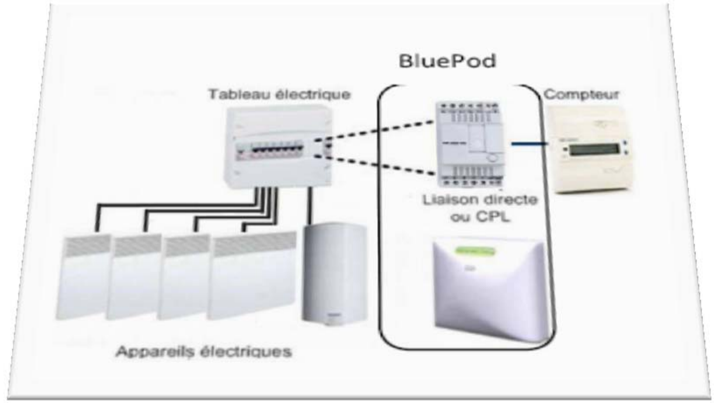


- **Q.** Does letting your house cool down now imply spending more heat in total compared to
keeping temperature constant ?
- ***A***. No, less heat

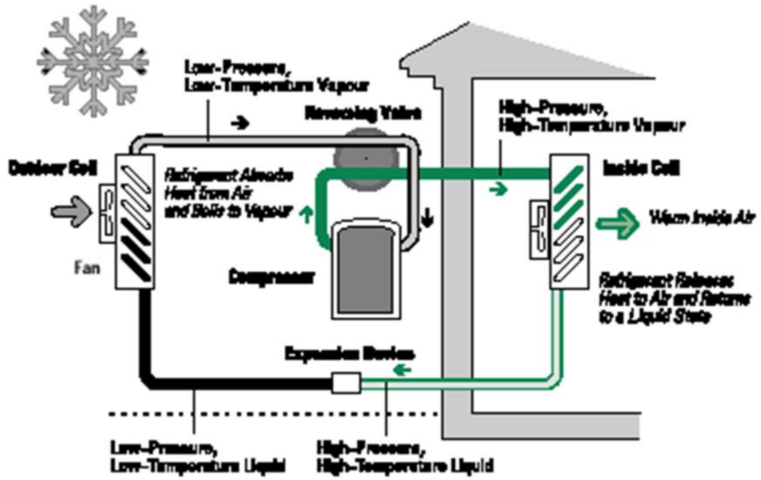
Findings

- Resistive heating system: evaporation is positive.

  This is why Voltalis bluepod is accepted by users



- If heat = heat pump, coefficient of performance ϵ may be variable negative evaporation is possible

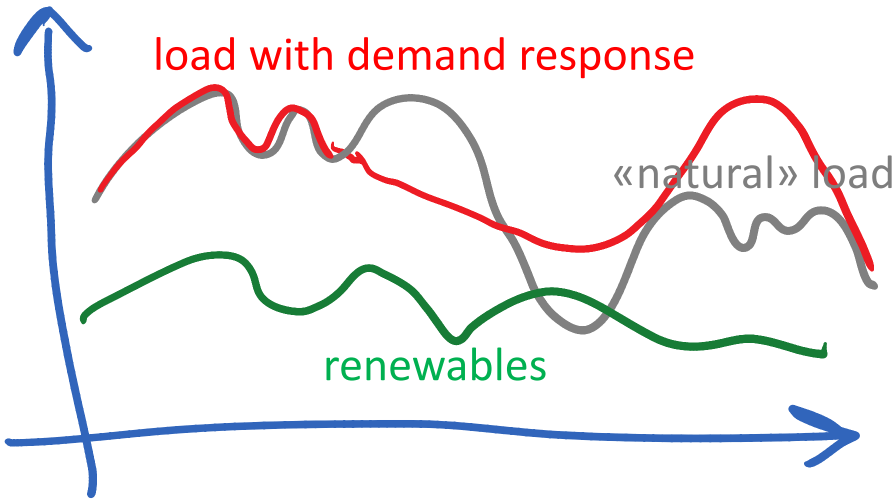


- Electric vehicle: delayed charge may have to be faster, less efficient, negative evaporation is possible

What this suggests about Demand Response:

- Negative evaporation makes system unstable
  Existing demand-response positive experience (with Voltalis/PeakSaver) might not carry over to other loads

- Model suggests that large backlogs are possible and unpredictible



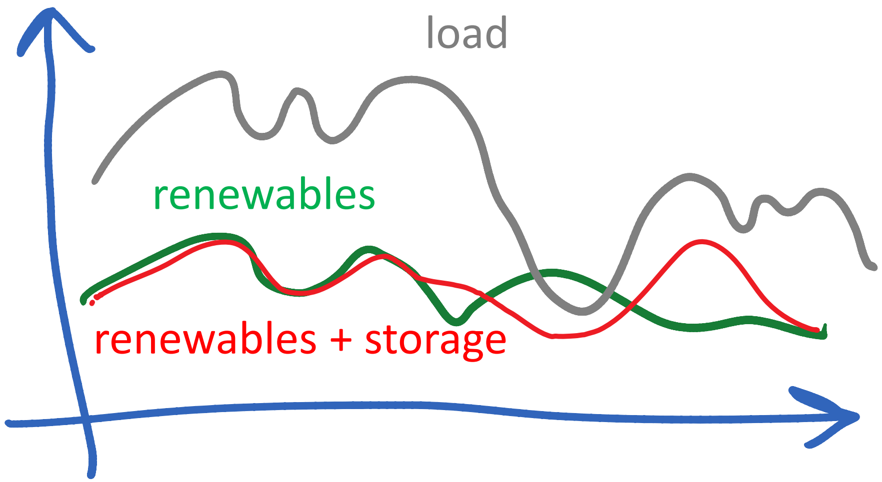
- Backlogged load is a new threat to grid operation
  Need to measure and forecast backlogged load

3.

USING STORAGE TO COPE WITH WIND VOLATILITY

Gast, Tomozei, Le Boudec. Optimal Storage Policies with Wind Forecast Uncertainties, *GreenMetrics 2012*

Storage



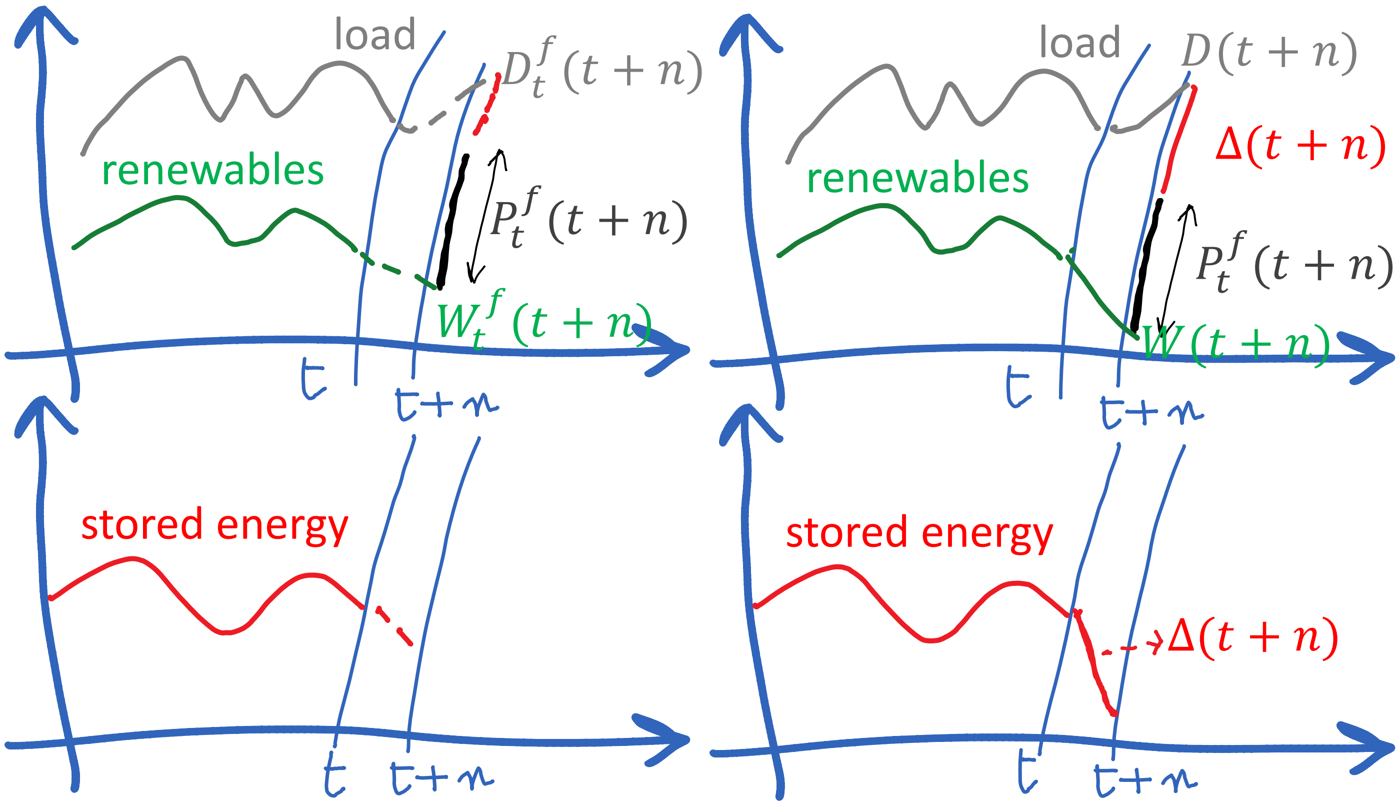
- Stationary batteries, pump hydro

  Cycle efficiency $\approx 70 - 80\%$

Operating a Grid with Storage

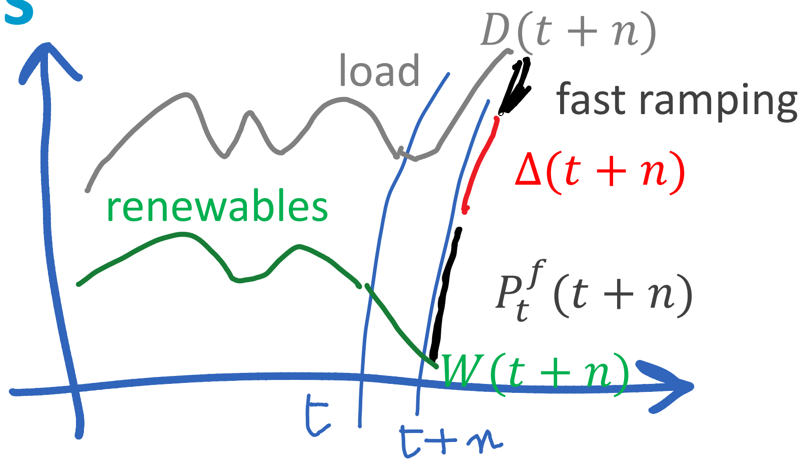
1a. Forecast load $D_t^f(t+n)$ and renewable suppy $W_t^f(t+n)$
1b. Schedule dispatchable production $W_t^f(t+n)$

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

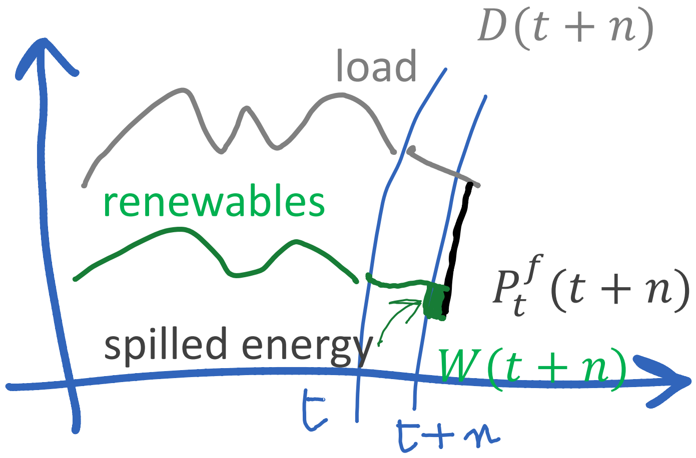


Full compensation of fluctuations by storage may not be possible due to power / energy capacity constraints

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



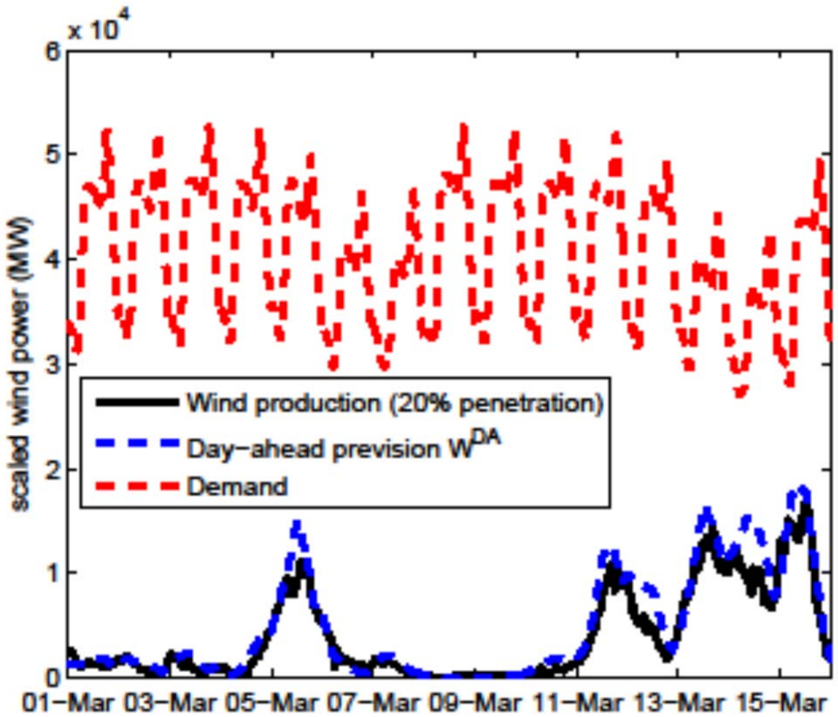
- Energy may be wasted when
  - Storage is full
  - Unnecessary storage (cycling efficiency < 100%)



- Control problem: compute dispatched power schedule $P_t^f(t+n)$ to minimize energy waste and use of fast ramping

Example: Wind data & forecasting

- Aggregate data from UK (BMRA data archive https://www.elexonportal.co.uk/)



- Demand perfectly predicted
- 3 years data
- Scale wind production to 20% (max 26GW)

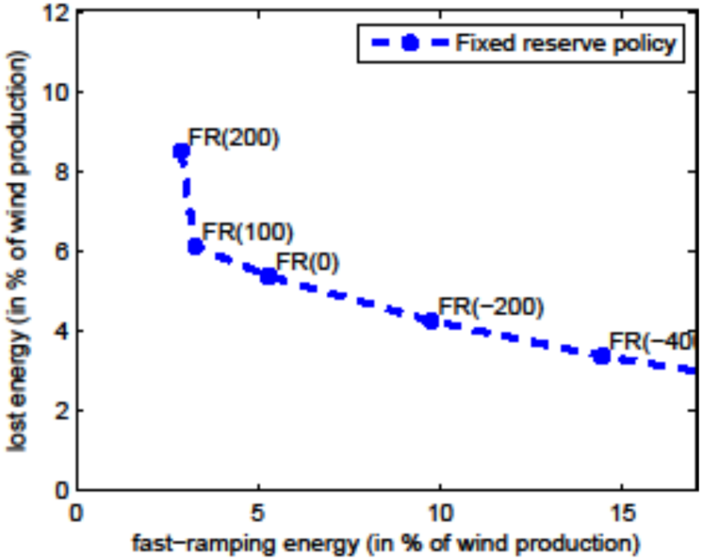
$$W(t) := \frac{\text{production}(t)}{\text{total wind capacity at time } t} \times 26\text{GW}.$$

- Relative error $\frac{\sum_t |W_t^f(t+n) - W(t+n)|}{\sum_t W(t)}$
- Day ahead forecast = 24%
- Corrected day ahead forecast = 19%

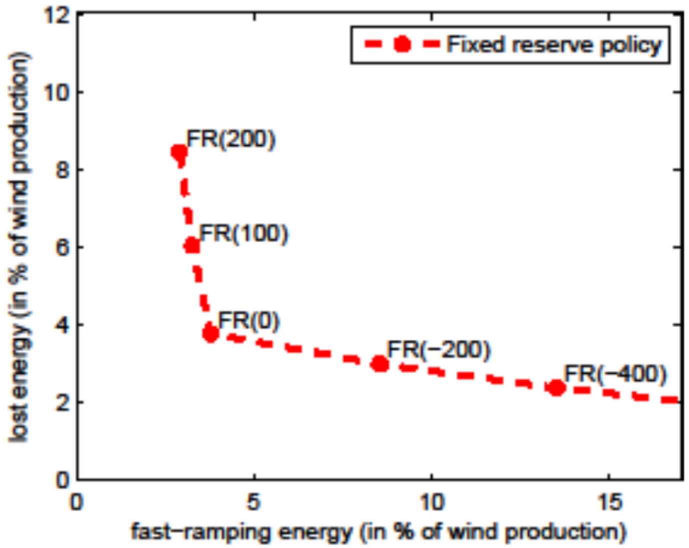
Example: The Fixed Reserve Policy

- Set $P_t^f(t+n)$ to $D_t^f(t+n) - W_t^f(t+n) + r^*$ where $r^*$is fixed (positive or negative)
- Metric: Fast-ramping energy used (x-axis)
  Lost energy (y-axis) = wind spill + storage inefficiencies

$B_{\max} = 100\text{GWh}, C_{\max} = D_{\max} = 2\text{GW}$



Efficiency $\eta = 0.8$



Efficiency $\eta = 1$

A lower bound

- Theorem. *Assume that the error* $e(t+n) = W(t+n) - W_t^f(t+n)$ *conditioned to* $\mathcal{F}_t$ *is distributed as* $\mathcal{E}$. *Then:*

  (i) $\bar{G} \geq \mathbb{E}[(\varepsilon+\bar{u})^-] - \mathrm{ramp}(\bar{u})$

  $\bar{L} \geq \mathbb{E}[(\varepsilon+\bar{u})^+] - \mathrm{ramp}(\bar{u})$

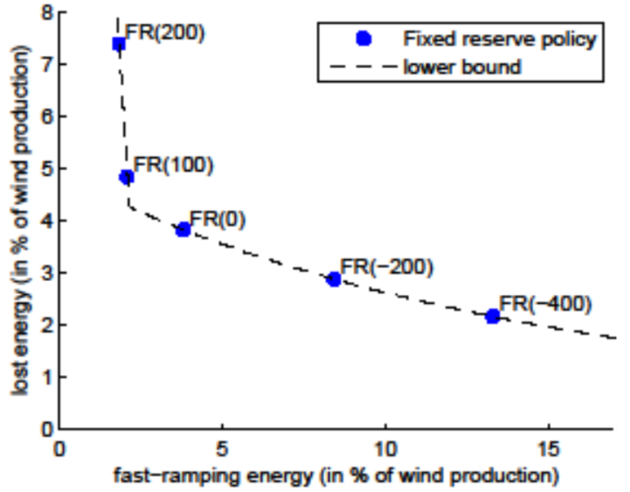
  where $\mathrm{ramp}(\bar{u}) := \mathbb{E}[\min(\eta(\varepsilon+\bar{u})^+, \eta C_{\max}, (\varepsilon+\bar{u})^-, D_{\max})]$

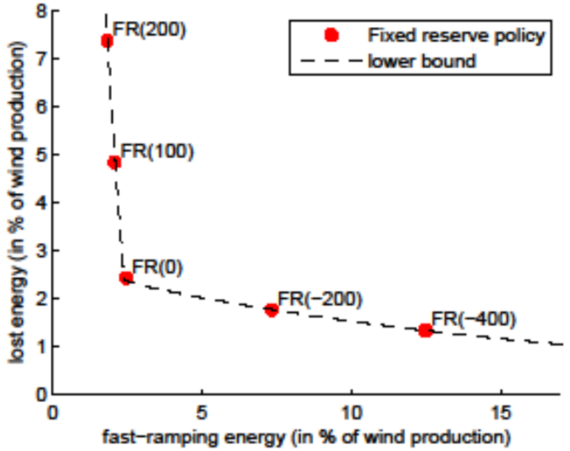
  (ii) The lower bound is achieved by the Fixed Reserve when storage capacity is infinite.

  - Depends on storage characteristics
    - Efficiency, maximum power (but not on size)
  - Assumption valid if prediction is best possible

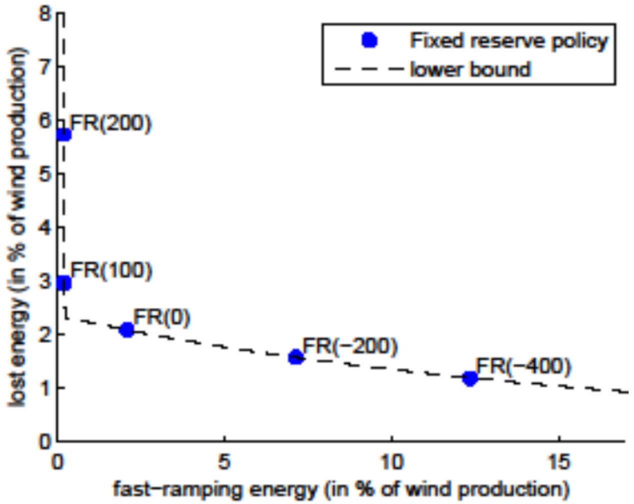
Lower bound is attained for $B_{\max} = 100\text{GWh}$

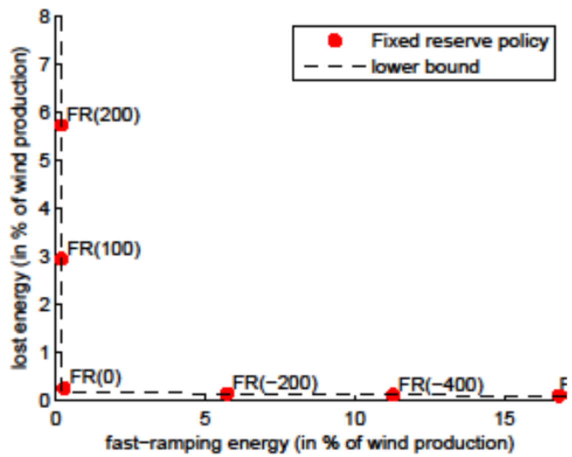
$C_{\max} = D_{\max} = 2\text{GW}$





$C_{\max} = D_{\max} = 6\text{GW}$



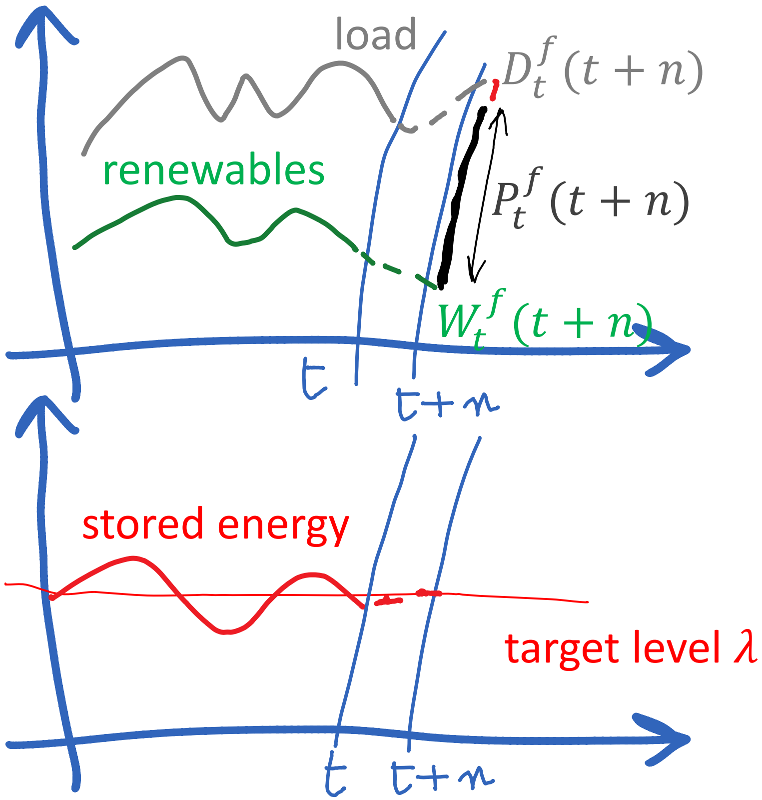


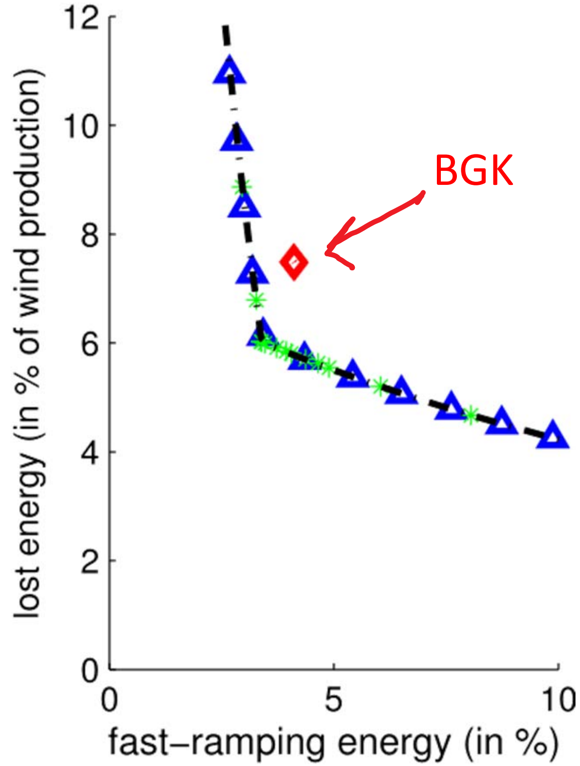
Efficiency $\eta = 0.8$

Efficiency $\eta = 1$

The BGK policy [Bejan, Gibbens, Kelly 2012]

- aims at keeping a constant level of stored energy

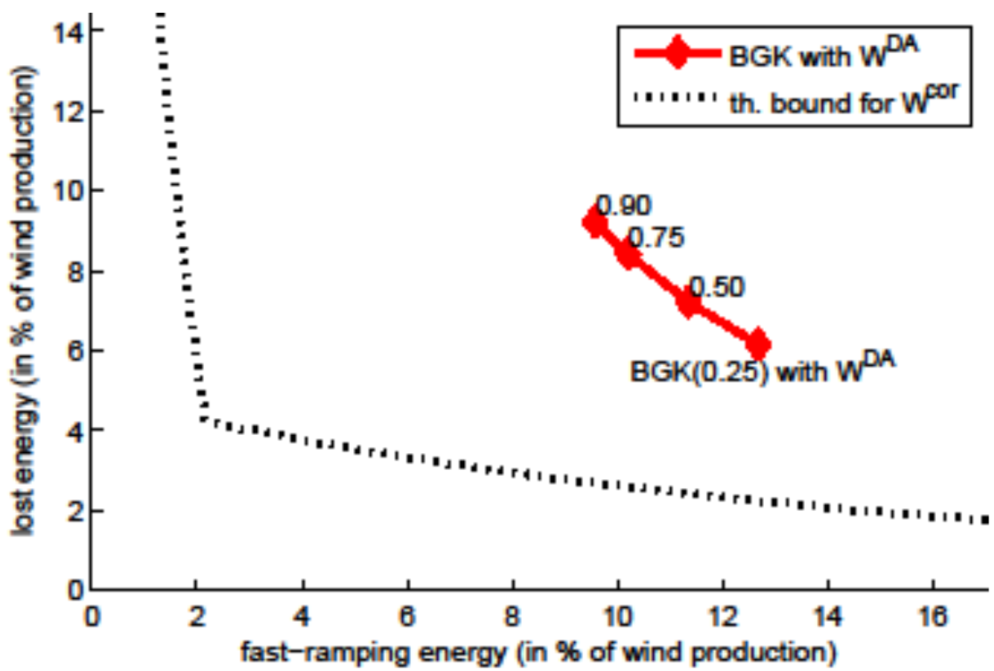




- Is moderately sub-optimal for large energy storage capacity

Small energy storage capacity?

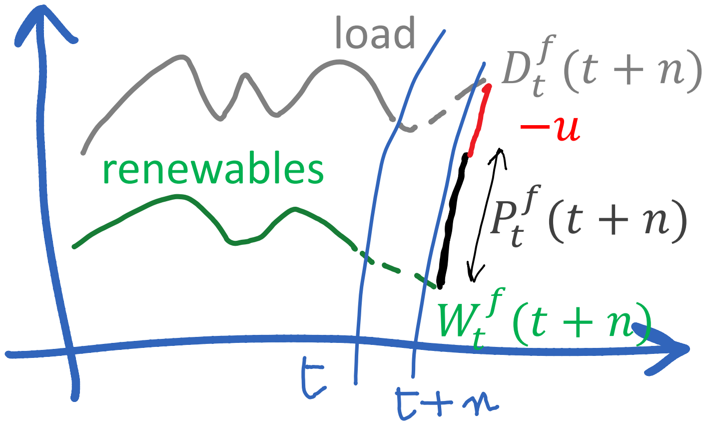
- BGK is far from lower bound – can one do better ?



$$B_{\max} = 5\text{GWh}, C_{\max} = D_{\max} = 2\text{GW} \qquad \eta = 0.8$$

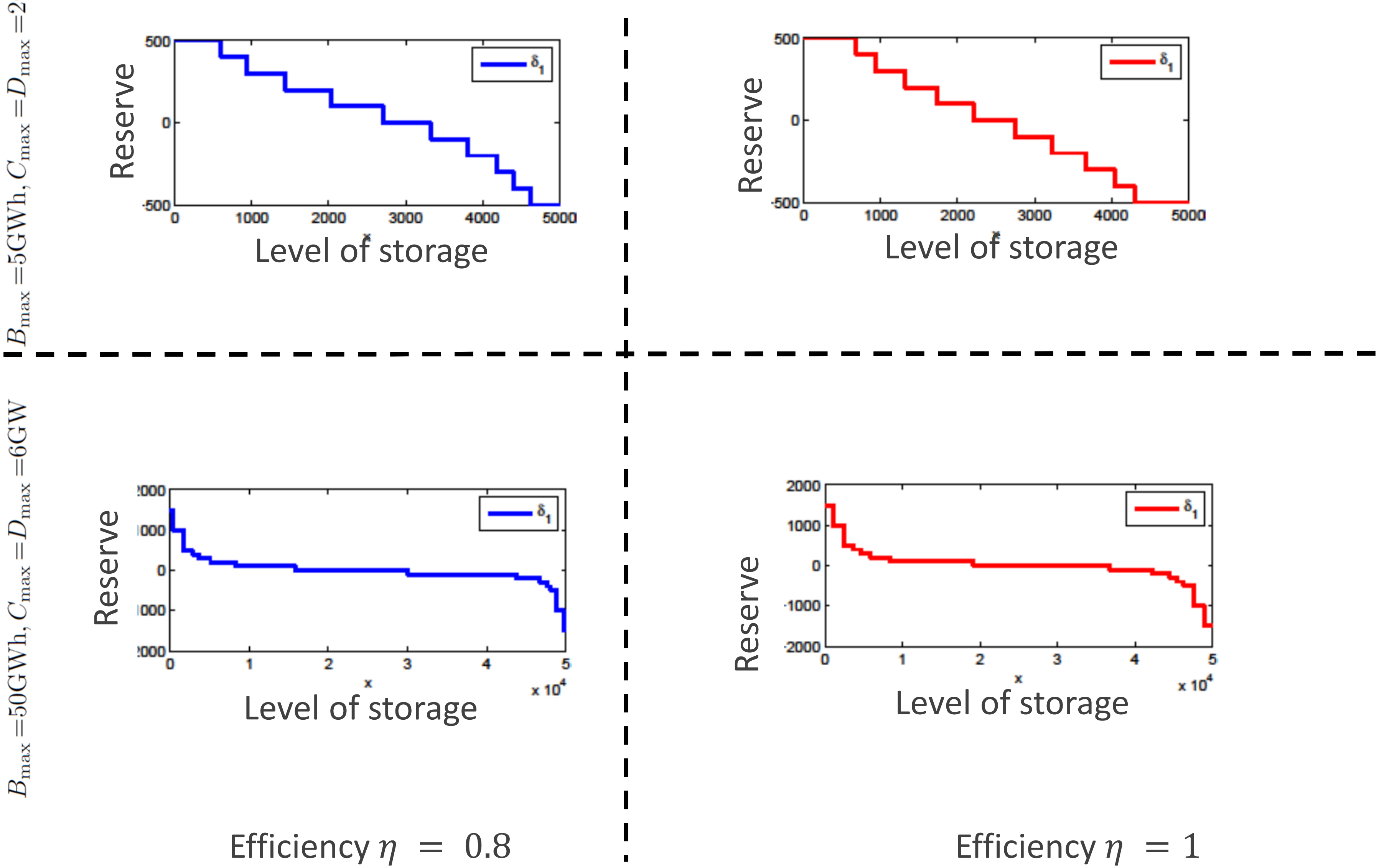
Scheduling Policies for Small Storage

- Fixed Reserve: $u = r^*$
- BGK: compute u so as to let storage level be close to nominal value λ
- Dynamic Reserve: compute u so as to minimize average anticipated cost
  - Solved using an MDP model and policy iteration



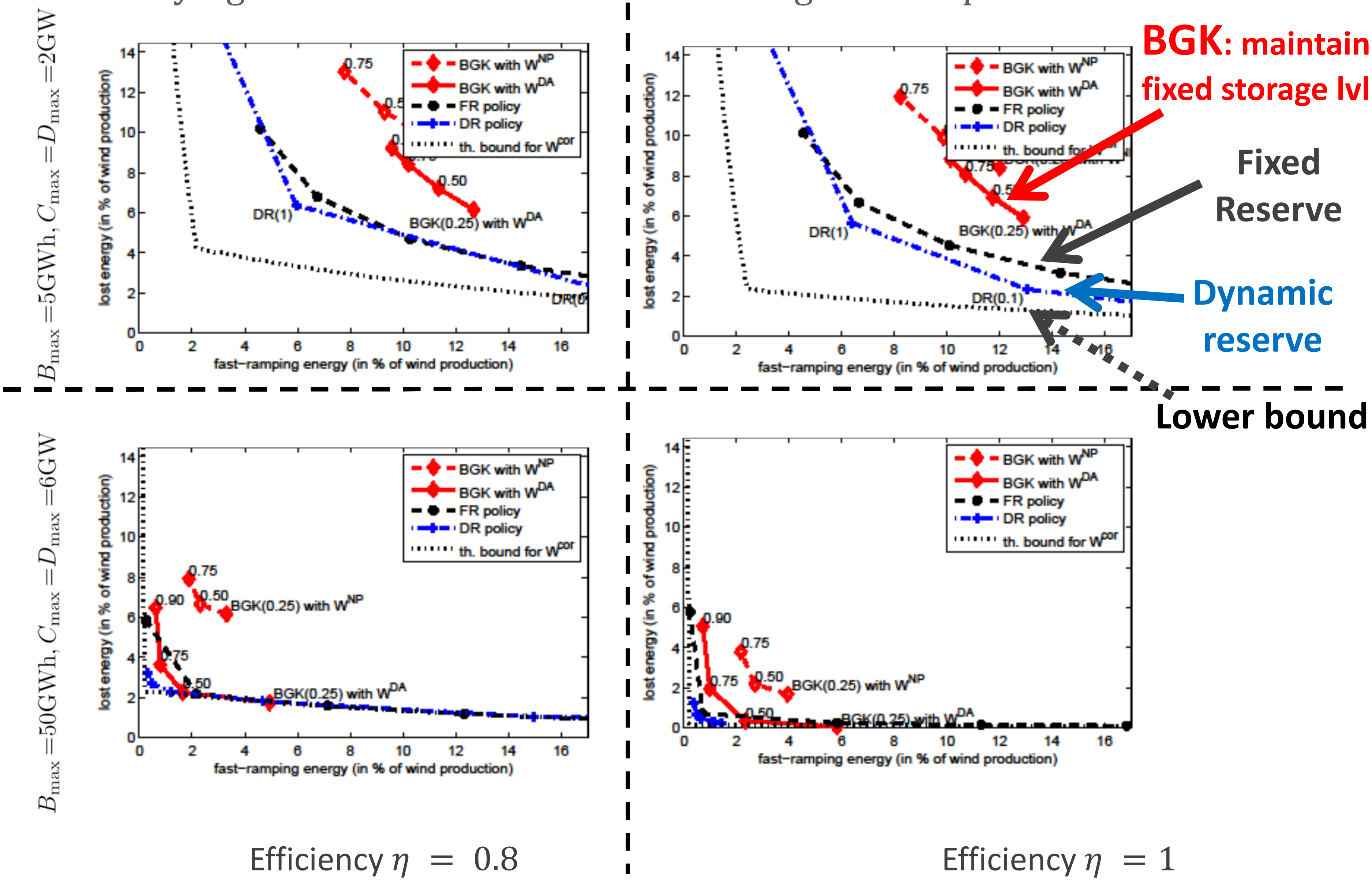
Dynamic Reserve uses a Control Law

- Effective algorithm to the Dynamic Reserve policy



The Dynamic Reserve policies outperform BGK

- Trying to maintain a fixed level of storage is not optimal



What this suggests about Storage

- (BGK policy:) Maintain storage at fixed level: not optimal
  - Worse for low capacity
  - There exist better heuristics

- Lower bound (valid for any type of policy)
  - depends on η and maximum power
  - Tight for large capacity (>50GWh)
  - Still gap for small capacity

- 50GWh and 6GW is enough for 26GW of wind

- Quality of prediction matters

Conclusion: Demand Response vs Storage

Demand Response

- Attractive (little capital investment)
- Unpredictable effects

Storage

- Capital investment
- Can be managed and understood

Questions ?

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

[2] Le Boudec, Tomozei, *Satisfiability of Elastic Demand in the Smart Grid,* Energy 2011 and ArXiv.1011.5606

[3] Le Boudec, Tomozei, *Demand Response Using Service Curves,* IEEE ISGT-EUROPE, 2011

[4] Le Boudec, Tomozei, *A Demand-Response Calculus with Perfect Batteries*, WoNeCa, 2012

[5] Papavasiliou, Oren - *Integration of Contracted Renewable Energy and Spot Market Supply to Serve Flexible Loads,* 18th World Congress of the International Federation of Automatic Control, 2011

[6] David MacKay, *Sustainable Energy – Without the Hot Air,* UIT Cambridge, 2009

[7] Bejan, Gibbens, Kelly, *Statistical Aspects of Storage Systems Modelling in Energy Networks.* 46th Annual Conference on Information Sciences and Systems, 2012, Princeton University, USA.