STOCHASTIC ANALYSIS OF REAL AND VIRTUAL STORAGE IN THE SMART GRID

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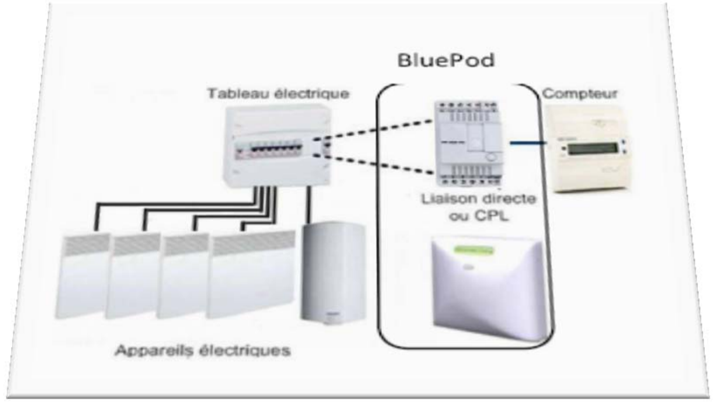
1.

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

Our Problem Statement

- Does demand response work ?
  - Delays
  - Returning load
- **Problem Statement**
  Is there a control mechanism that can stabilize demand ?
- We leave out for now the details of signals and algorithms

Macroscopic Model of Cho and Meyn [1], non elastic demand, mapped to discrete time

Step 1: Day-ahead market

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

control

deterministic

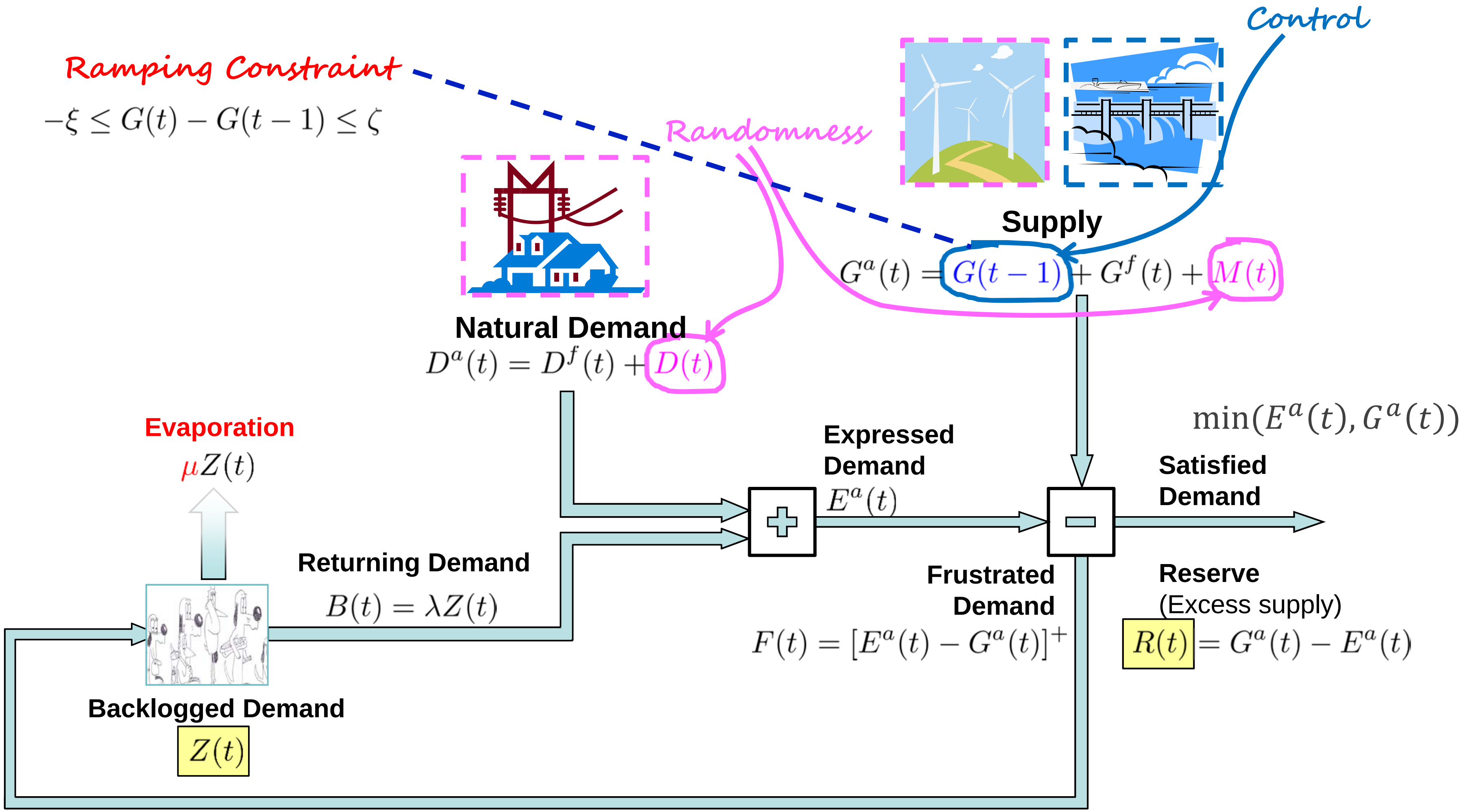
Step 2: Real-time market

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

random

- We now add the effect of elastic demand / flexible service
  Some demand can be «frustrated» (delayed)

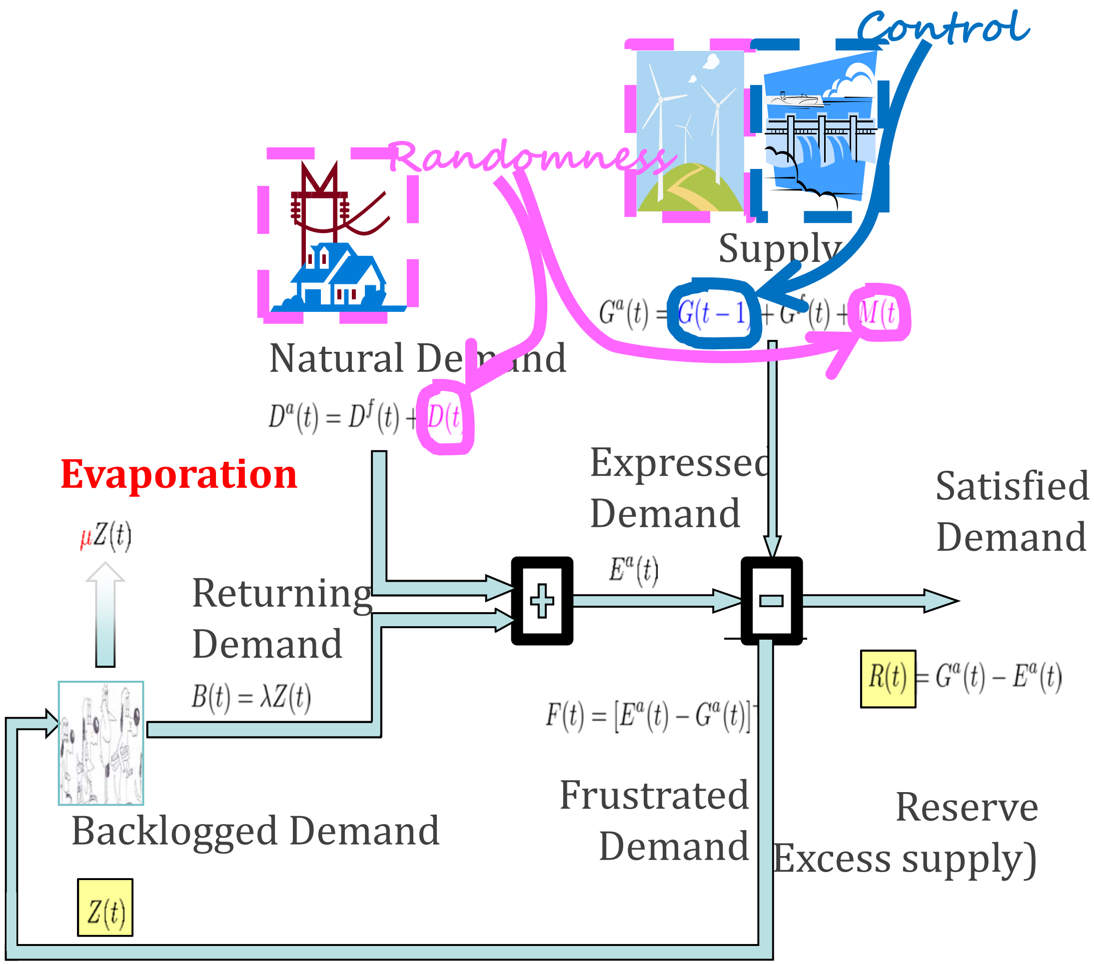
Our Macroscopic Model with Elastic Demand



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

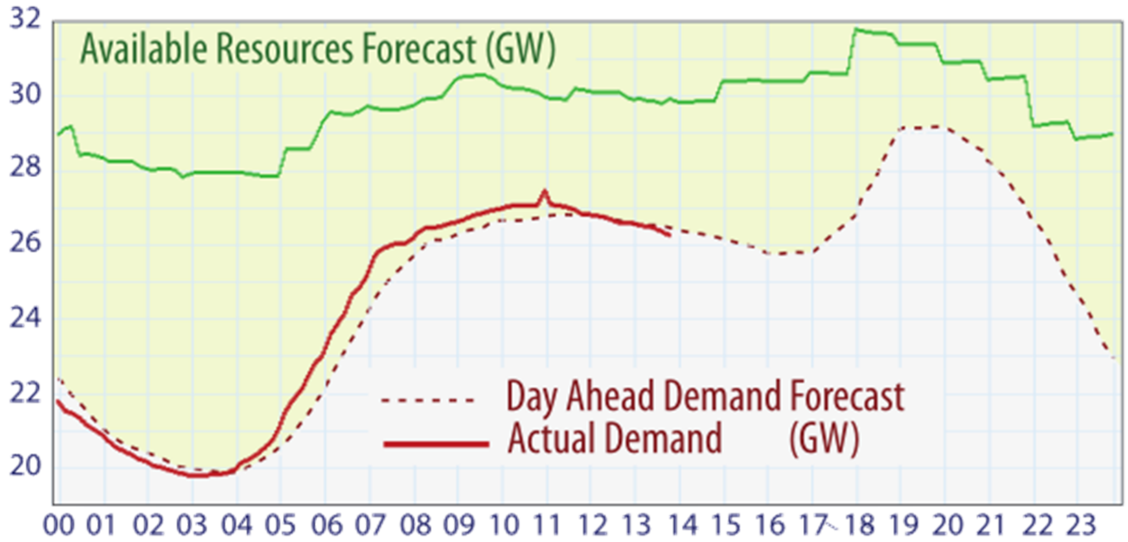
Backlogged Demand

- We assume backlogged demand is subject to two processes: update and re-submit
- Update term (evaporation): $\mu Z\, dt$ with $\mu > 0$ or $\mu < 0$ μ is the evaporation rate (proportion lost per time slot)
- Re-submission term $\lambda Z\, dt$ $1/\lambda$ (time slots) is the average delay



Macroscopic Model, continued

- Assumption : $(M - D) = \mathrm{ARIMA}(0, 1, 0)$
  typical for deviation from forecast
  $\big(M(t+1) - D(t+1) - M(t) - D(t)\big) := N(t+1) \sim N(0, \sigma^2)$



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

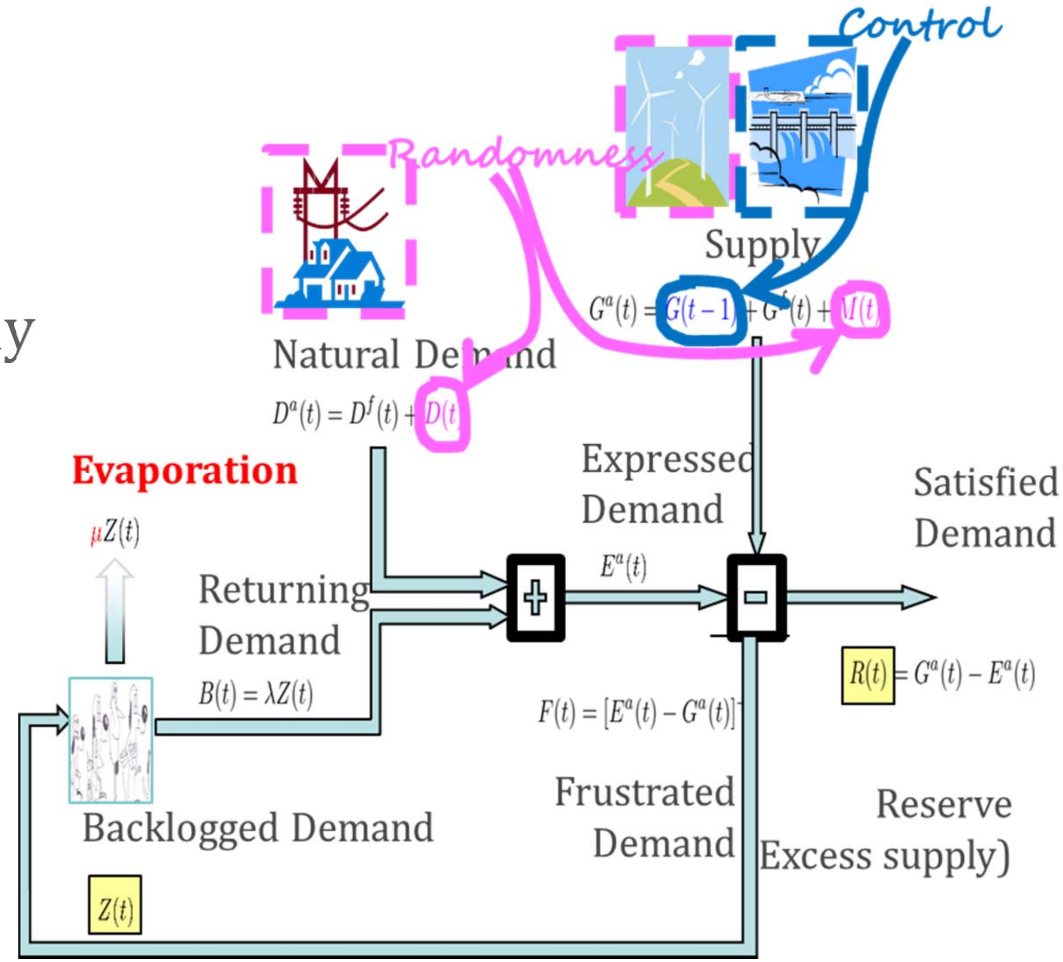
- 2-d Markov chain on continuous state space

$$
\begin{aligned}
R(t+1) &= R(t) + \Delta G(t) + N(t+1) - \lambda[Z(t+1) - Z(t)] \\
Z(t+1) &= (1 - \lambda - \mu)Z(t) + \mathbb{1}_{\{R(t)<0\}}R(t)
\end{aligned}
$$

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

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



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

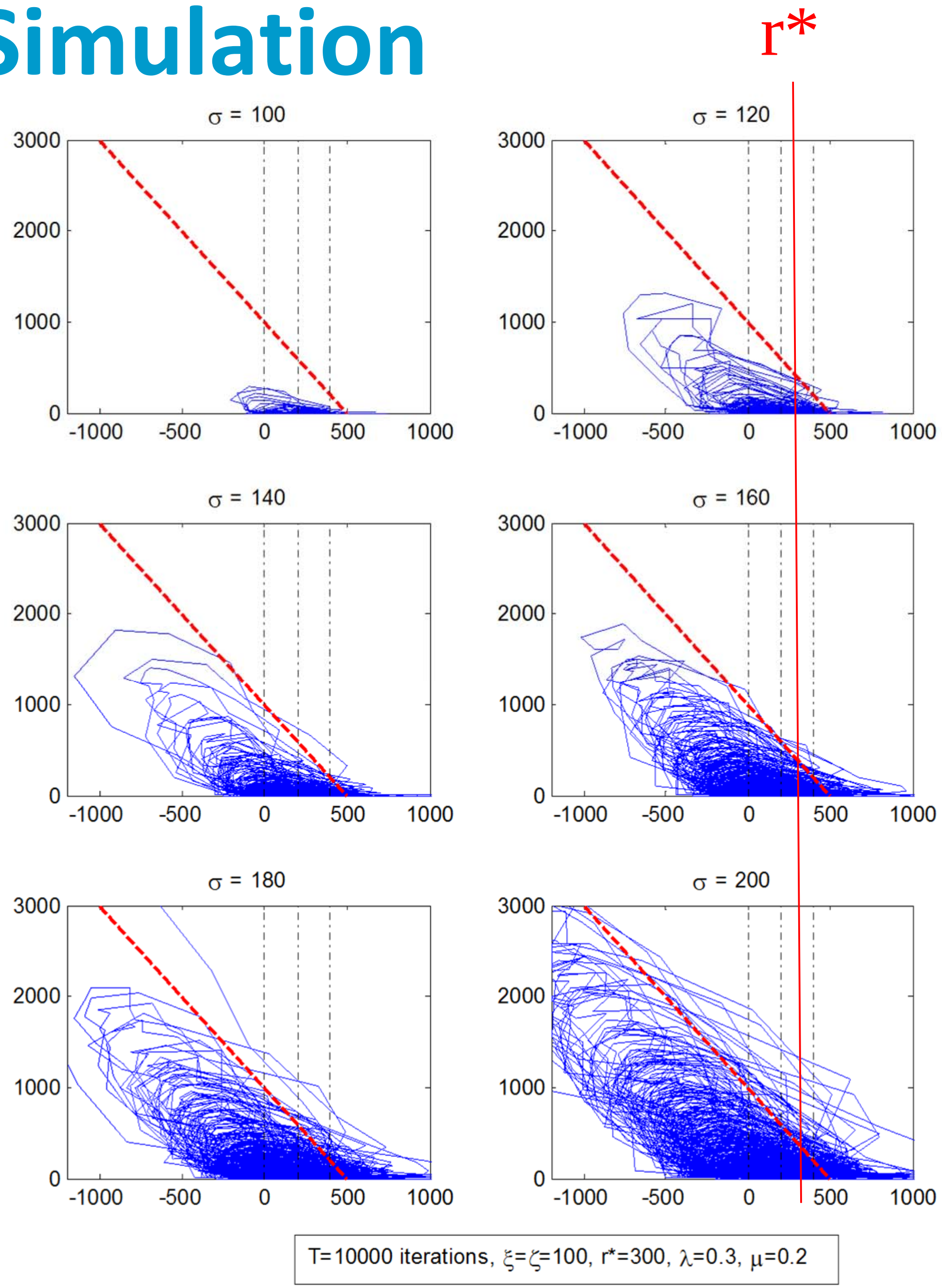
Threshold policy:

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

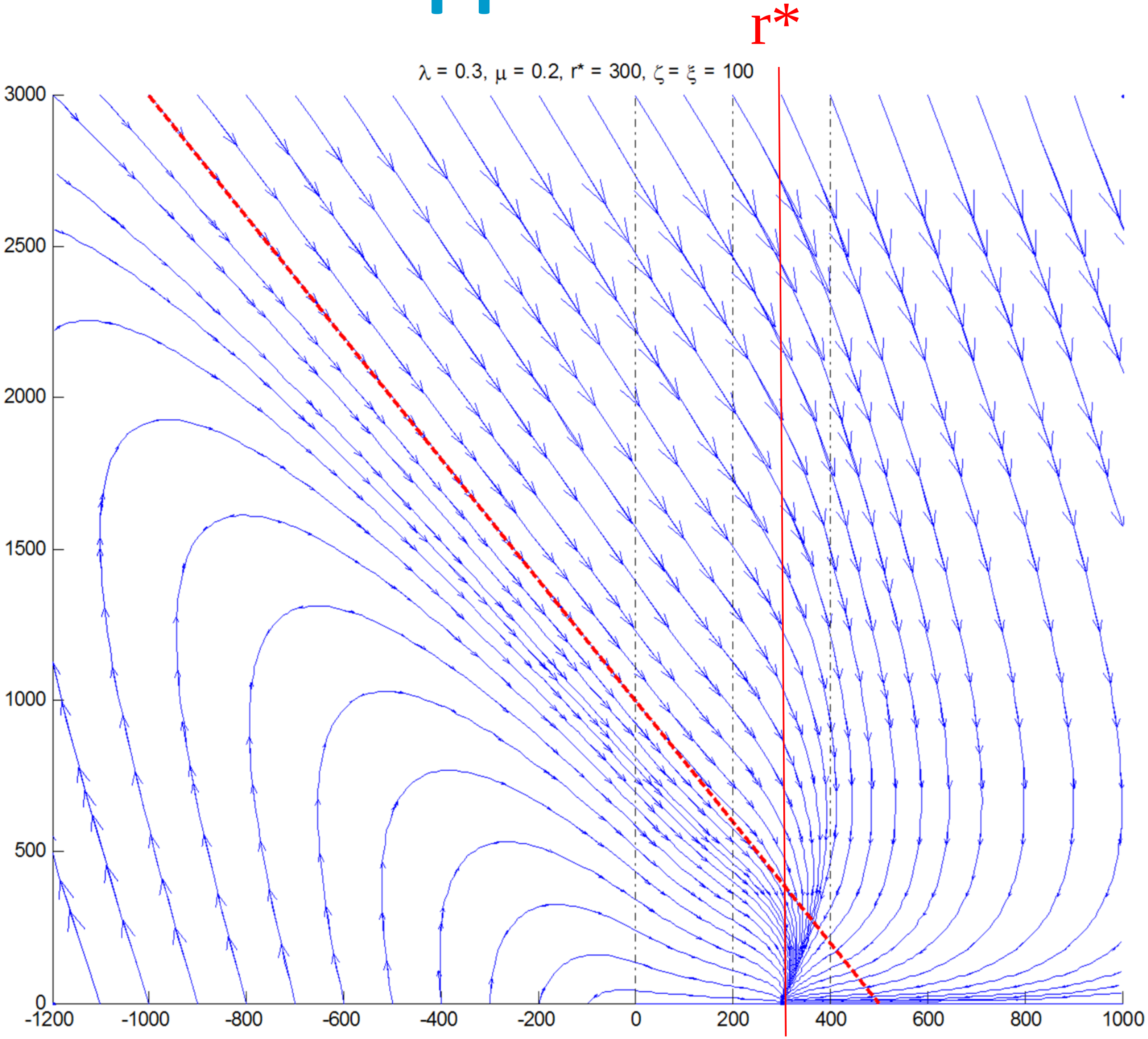
else decrease supply to come as close to r^*as possible (considering ramp down constraint)

Simulation

- Large excursions into negative reserve and large backlogs are typical



ODE Approximation

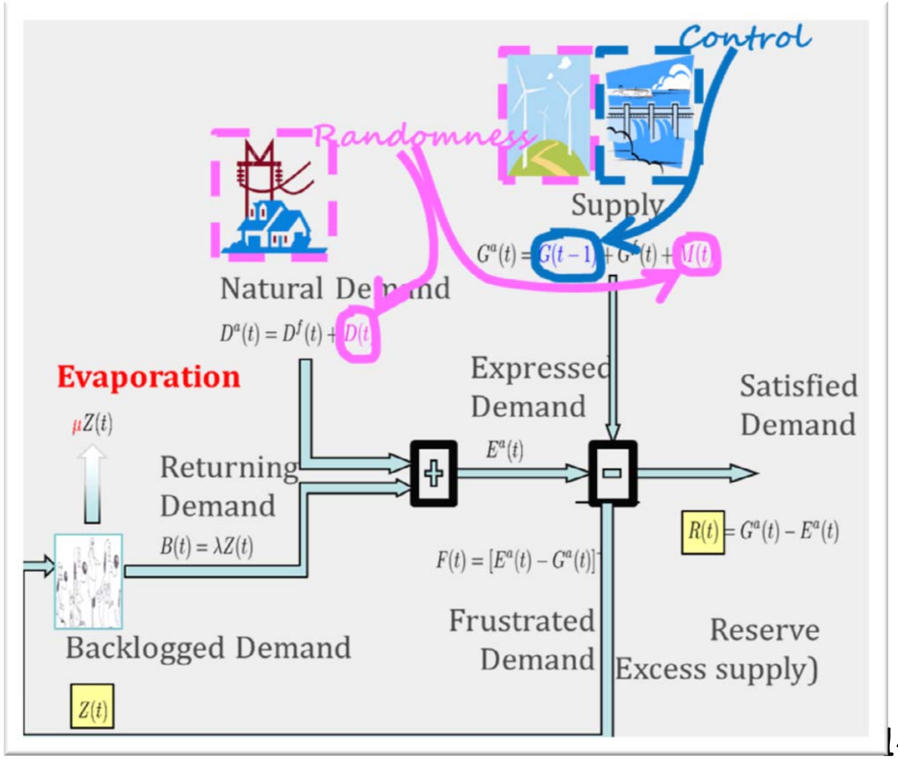


Findings : Stability Results

- 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°

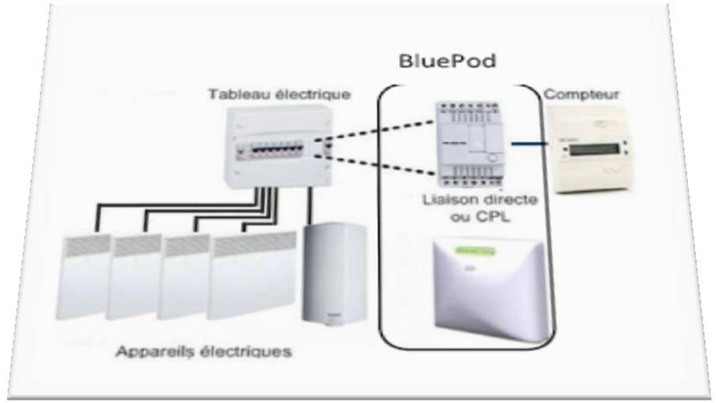
E, total energy provided

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

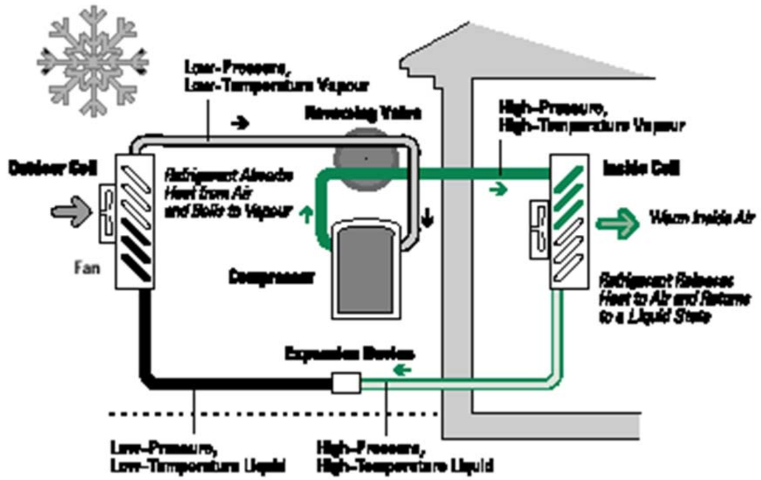
Findings

- 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

Conclusions

- A first model of demand response with volatile demand and supply

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

2.

COPING WITH WIND VOLATILITY

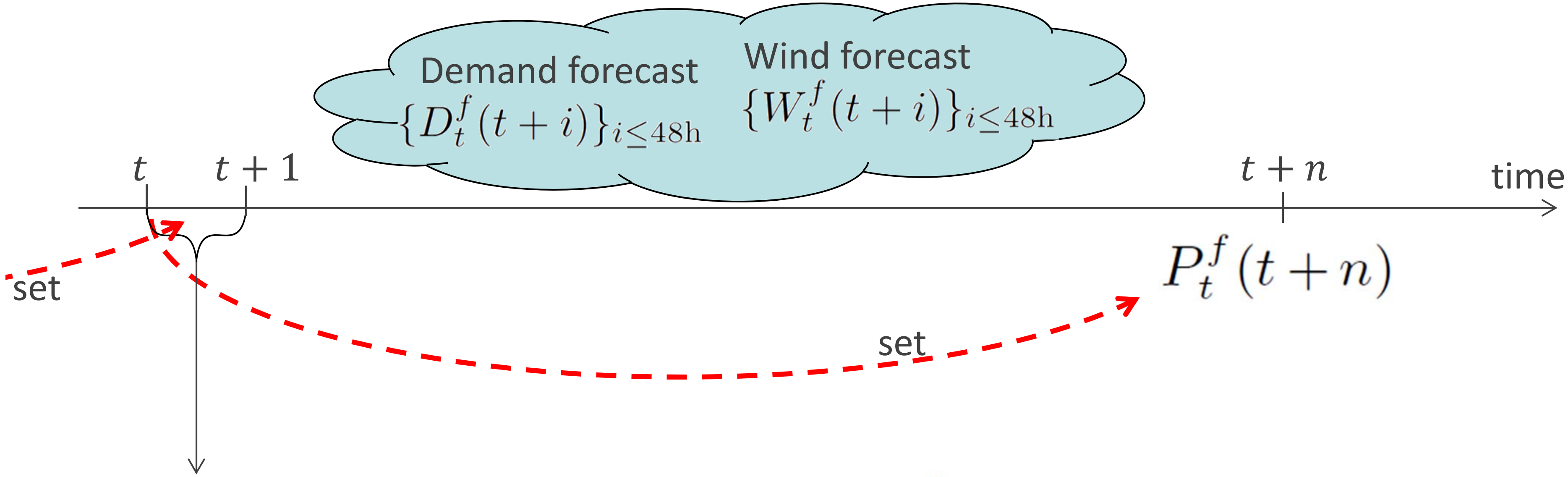
Gast, Tomozei, Le Boudec. Optimal Storage Policies with Wind Forecast Uncertainties, *GreenMetrics 2012*

Problem Statement

- Model
  - 20% wind penetration + prediction
  - Schedule P(t+n)
  - Imperfect storage (80% efficiency)

- Questions:
  - Optimal storage size
  - Lower bound when efficiency < 100%.
  - Scheduling policies with small storage

Storage Model, from [Bejan, Gibbens Kelly 2011]



- Mismatch: $\Delta(t) := D(t) - W(t) - P_{t-n}^f(t).$

  To compensate the mismatch:

  1. Storage system

     Power constraints

     $$B(t+1) = \begin{cases} \max(B - \min(\Delta, D_{\max}), 0) & \text{if } \Delta \geq 0, \quad \text{(discharge)} \\ \min(B + {\color{red}\eta} \min(-\Delta, C_{\max}), B_{\max}) & \text{if } \Delta < 0. \quad \text{(charge)} \end{cases}$$

     Efficiency of cycle (~70-80%)

     Capacity constraints

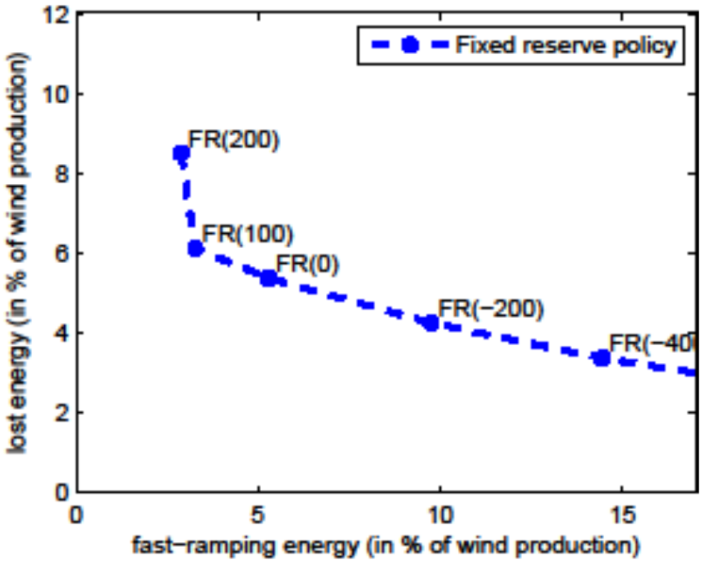
  2. Fast-ramping generation (gas) / Loss

Basic scheduling policy & metrics

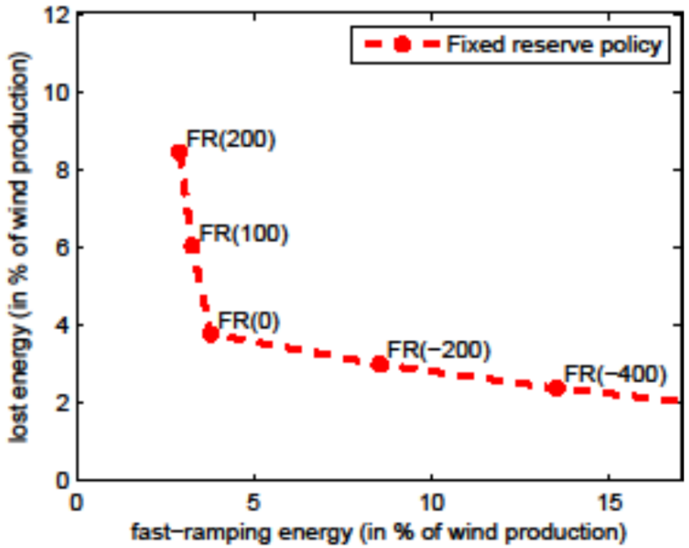
- Mismatch: $\Delta(t) := D(t) - W(t) - P^f_{t-n}(t).$
- Basic schedule: $P^f_t(t+n) := D^f_t(t+n) - W^f_t(t+n) + u^f_t(t+n)$

- Ex: **fixed reserve** $u^f_t(t+n) = x$
- Metric: Fast-ramping energy used (x-axis)
  Lost energy (y-axis) = wind spill + storage inefficiencies

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



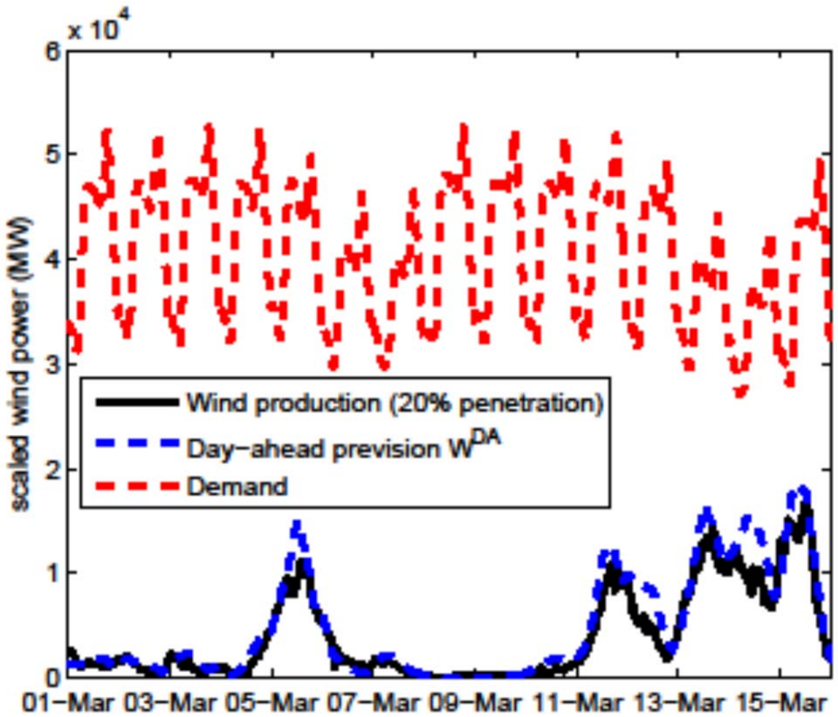
$\eta = 0.8$



$\eta = 1$

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%

- Key parameter: prediction error $e(t+n) = W(t+n) - W_t^f(t+n)$

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

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

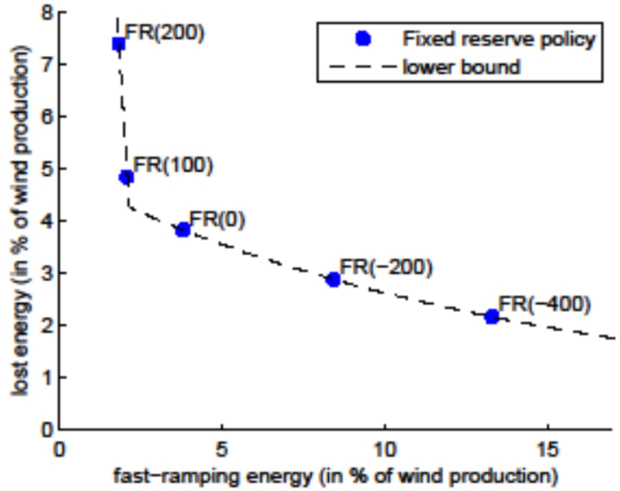
  where $\mathrm{ramp}(\bar{u}) := \mathbb{E}[\min(\eta(\varepsilon + \bar{u})^+, \eta C_{\max}, (\varepsilon + \bar{u})^-, D_{\max})]$

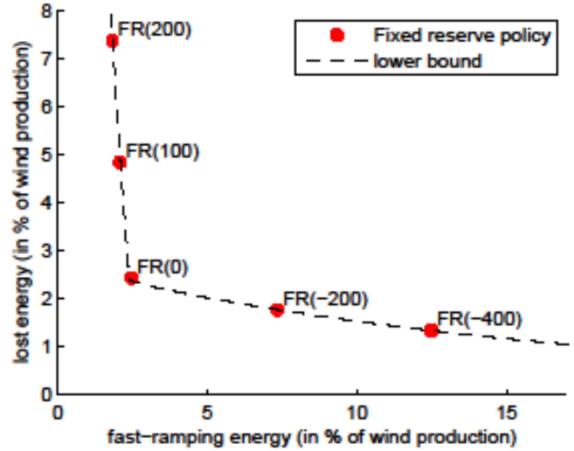
  (ii) The lower bound is achieved by the Fixed Reserve when storage capacity is infinite.

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

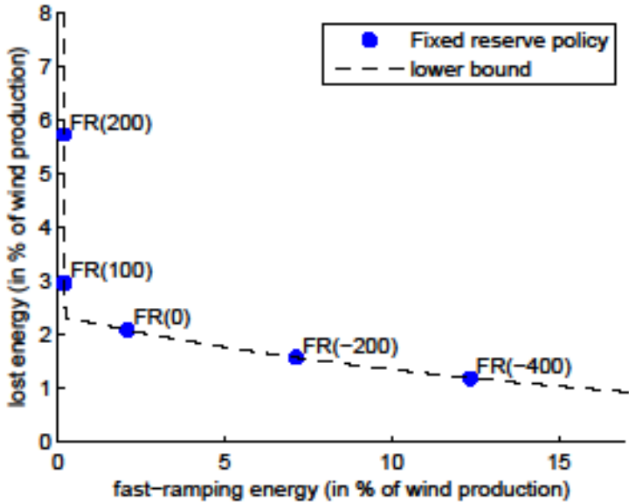
Lower bound is attained for $B_{\max} = 100\mathrm{GWh}$

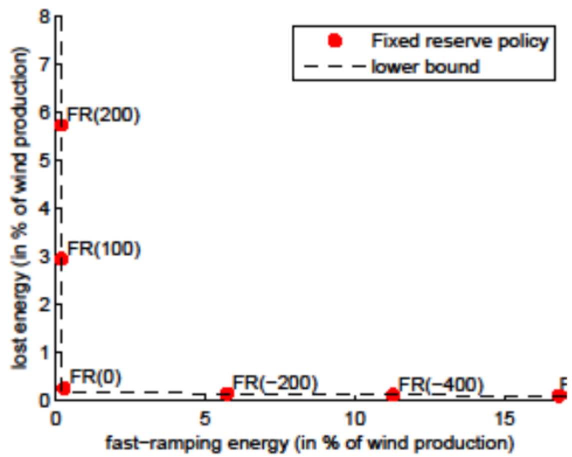
$C_{\max} = D_{\max} = 2\mathrm{GW}$





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





$\eta = 0.8$

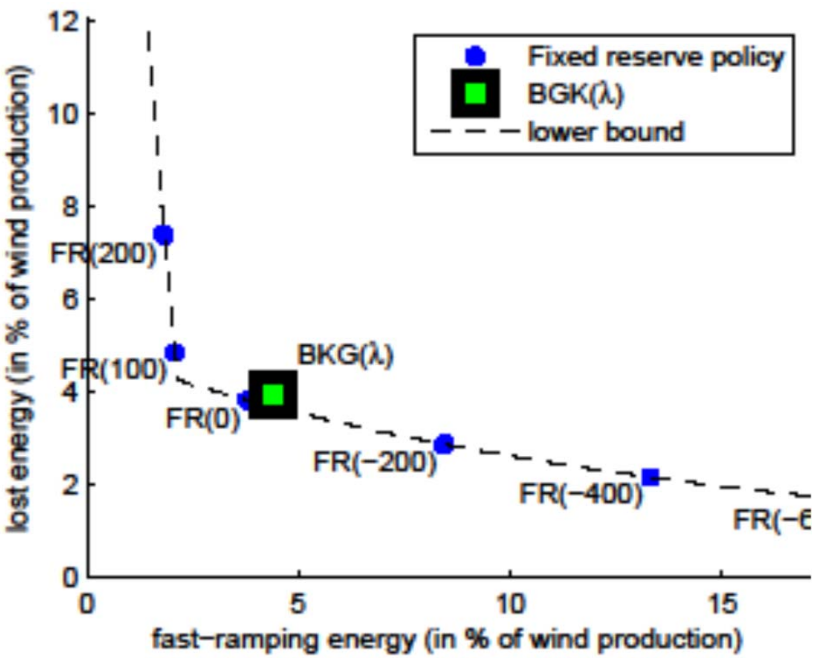
$\eta = 1$

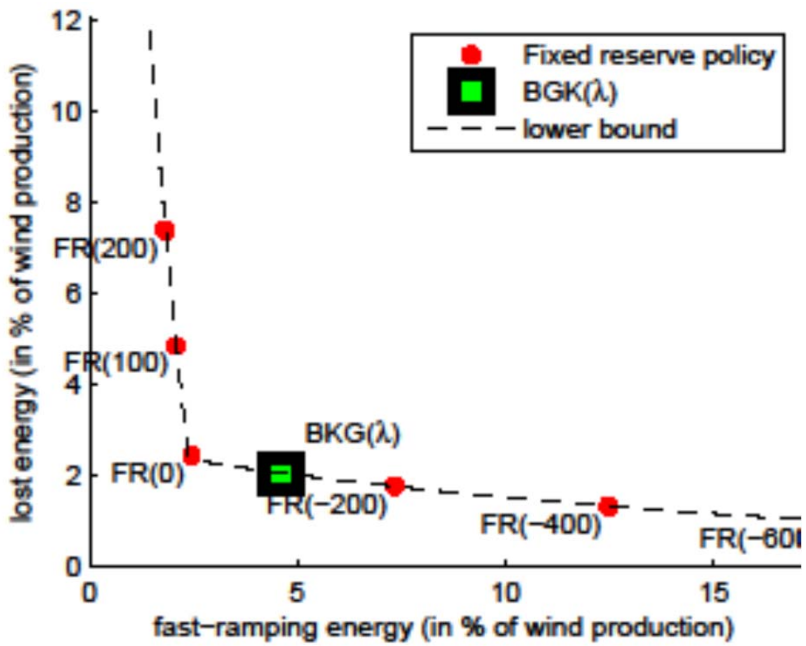
The BGK policy [Bejan, Gibbens, Kelly 2011]

- BGK [7] : try to maintain storage in a fixed level $\lambda B_{\max}$
  - Compute estimate of storage size $B_t^f(t+n)$

$$P_t^f(t+n) := D_t^f(t+n) - W_t^f(t+n) + u_t^f(t+n)$$

$$u_t^f(t+n) = \min(\frac{1}{\eta}(\lambda B_{\max} - B)^+, C_{\max}) - \min((\lambda B_{\max} - B)^-, D_{\max}).$$

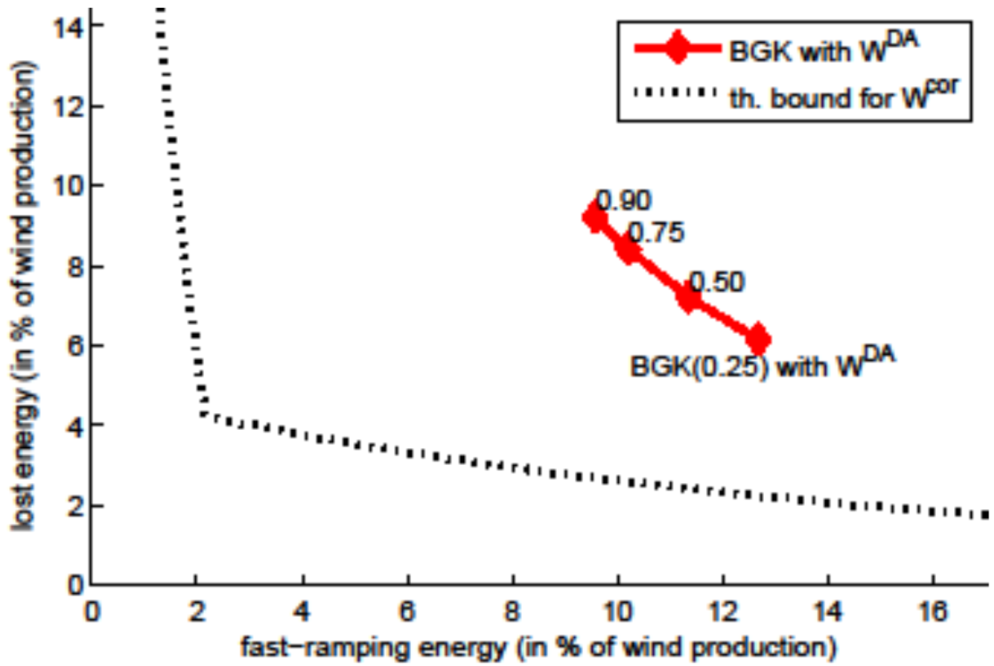




- Close to lower bound for large storage

Small storage capacity?

- BGK is far from lower bound:



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

Scheduling policies for small storage

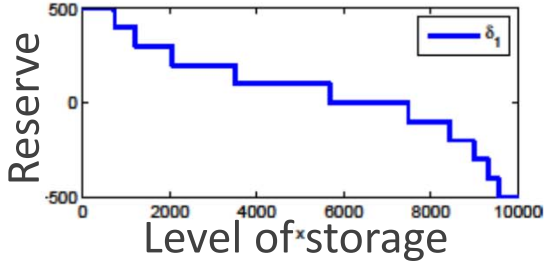
$$P_t^f(t+n) := D_t^f(t+n) - W_t^f(t+n) + u_t^f(t+n)$$

- Fixed reserve $u_t^f(t+n) = x$
- BGK [7] : try to maintain storage in a fixed level $\lambda B_{\max}$
  - Compute estimate of storage size $B_t^f(t+n)$
- Dynamic reserve
  - Based on a simplified Markov Decision Process (one time step evolution)

    $$B(t+1) = \phi(B(t), -\varepsilon(t+1) - u(t)).$$

    cost = energy loss + γ fast-ramping
  - Optimal policy $\delta_\gamma(x) := \arg\min_{u \in \mathbb{R}} \{\mathbb{E}\,(c(x,u) + v(\phi(x, -u-\varepsilon)))\}.$
  - Apply δ_γ to $B_t^f(t+n)$:

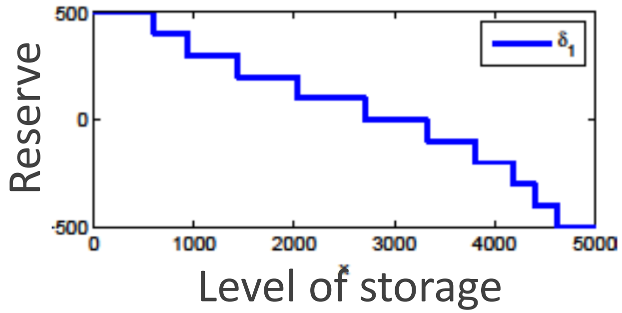
    $$u_t^f(t+n) = \delta_\gamma(B_t^f(t+n))$$

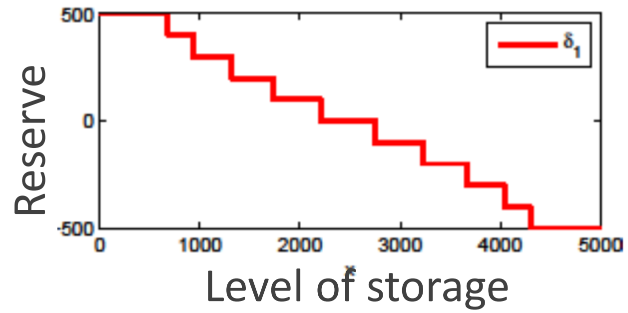


Control law for the Dynamic Reserve

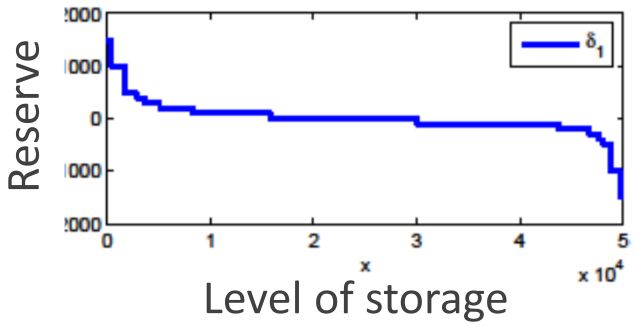
- Effective algorithm to the Dynamic Reserve policy

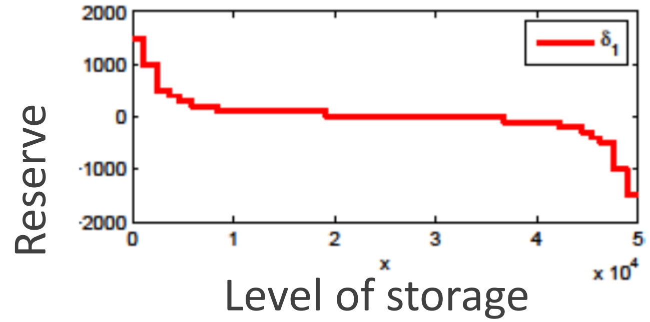
$B_{\max} = 5\text{GWh}, C_{\max} = D_{\max} = 2\text{GW}$





$B_{\max} = 50\text{GWh}, C_{\max} = D_{\max} = 6\text{GW}$



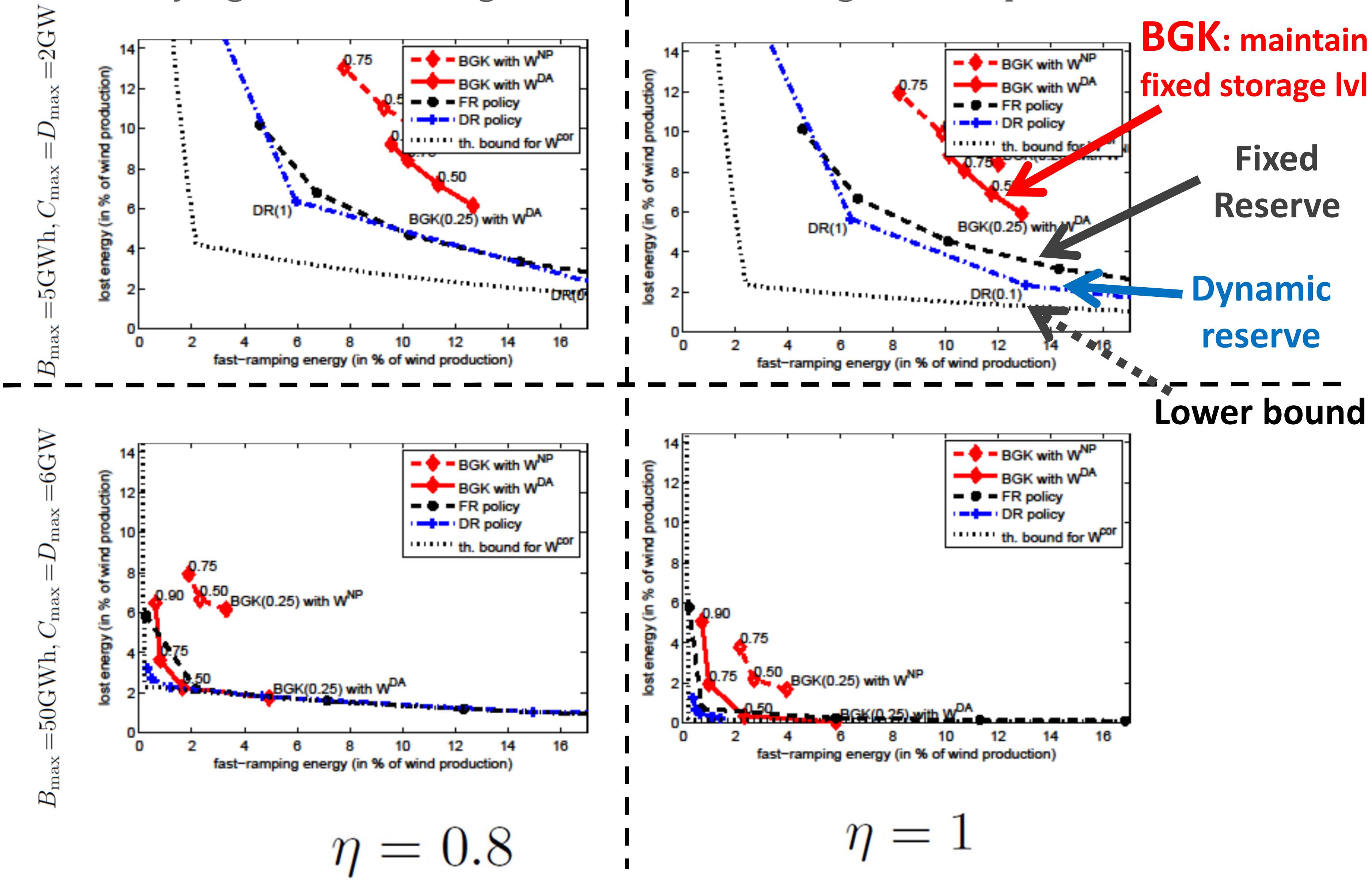


$\eta = 0.8$

$\eta = 1$

The Dynamic Reserve policies outperform BGK

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



Conclusion

- 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

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

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[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.