ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

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Introduction to Demand Response

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What is demand response ?
An illustration with seven examples
A taxonomy

2.
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WHAT IS DEMAND RESPONSE ?

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Terminology
Demand Response (DR)
≈ Demand Side Management (DSM)

A clothes dryer connected to a load control "smart" switch (Wikimedia Commons)

- *Demand Side Management*
  = electric utility manipulates user appliance
- *Demand Response*
  = Demand Side Management as a response to price
- in practice both phrases often used interchangeably
- ≥ 100 years old ("Load Management", inband tones "ripple control", AM signal)

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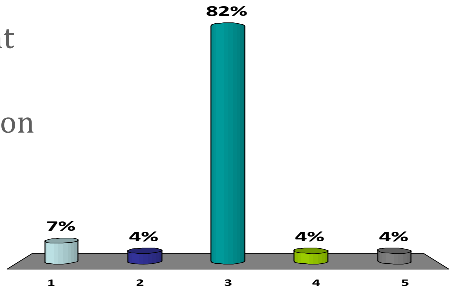
Demand Response (DR) = Demand Side Management (DSM) Why invented ?

1. To reduce costs for consumers
2. To save energy
3. To optimize management of the electrical grid
4. To prevent night operation of noisy equipment
5. Je ne sais pas



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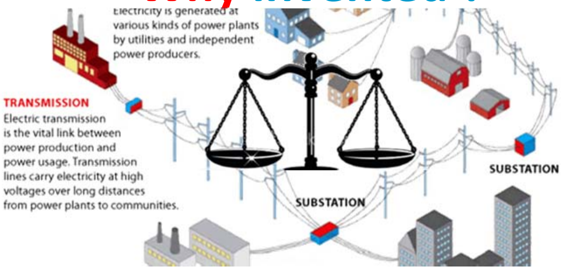
Why invented ?



- electrical systems must balance energy instantly
- energy balance in electrical grid is mainly done by adjusting supply to demand :
  - scheduling and forecasting + large scale interconnection ; frequency response; reserves
- demand response = adjust *demand* to supply is one of the tools used to manage the power grid
- energy *efficiency* is obtained by managing demand efficiently but is outside the scope of this tutorial

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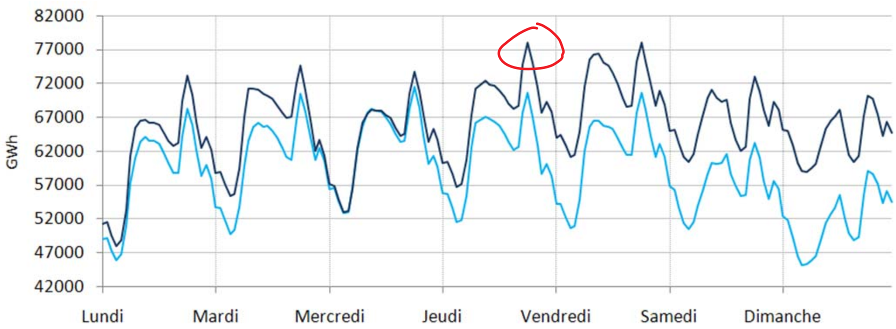
Examples of Use of Demand Response

- peak shaving



France's comsumption on cold and average november week; Xavier Brossat (EDF), Energy Systems Week, 2013

- response to failures (avoid blackout)
- mitigate volatility of wind and solar energy
- mitigate network problems (congestion, voltage)

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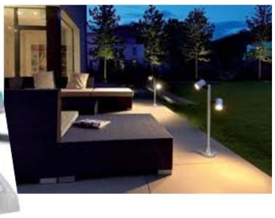
What can be subject to Demand Response ?

- Demand response applies to *elastic* loads (load = consumer of electricity)
- Non elastic loads
  - lighting, watching TV, hair drying



- Elastic loads
  - boiler, car or bicycle battery, data center, fridges and freezers, air conditioner, washing machine

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Demand Response Example 1
Norway's pilot study [Saele and Grande 2011]

- tariff is increased at pre-defined times (8-10, 17-19)
- users made aware of high tariffs and times
- In some homes heating is also directly controlled
- study concludes that it works

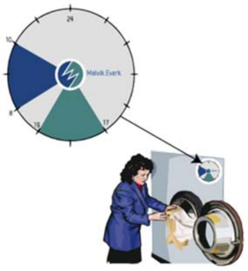


Fig. 7. Customer information token, the "El-button" [13].

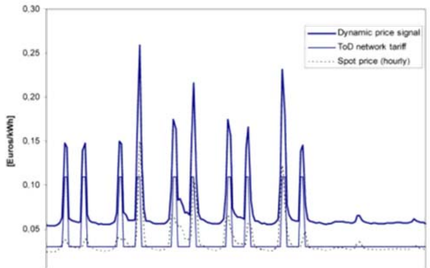


Fig. 8. Load profile for a household customer with hot water space heating system and RLC [13].

Norway's pilot study [Saele and Grande 2011]
Demand Response may reduce prices

- 120 EUR/MWh difference between 2 areas inside Norway
- [Saele and Grande 2011] claims that the price peak would be suppressed with demand response

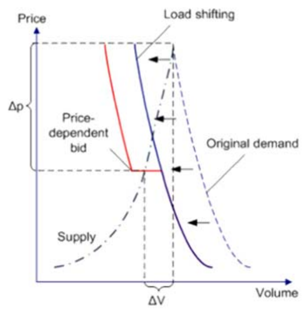


Fig. 2. Different bid curves for demand response.

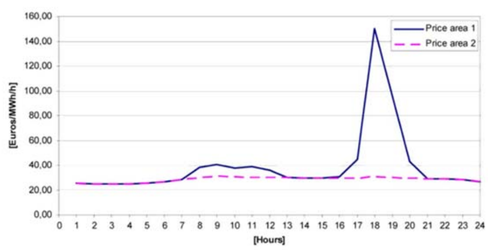


Fig. 3. Hourly spot prices in two price areas in Norway, 6 February 2007 (data source: NordPool).

A similar example (GulfPower, USA)

[Borenstein et al 2002]

7/17/02 1-Hour Critical
(139 Homes)

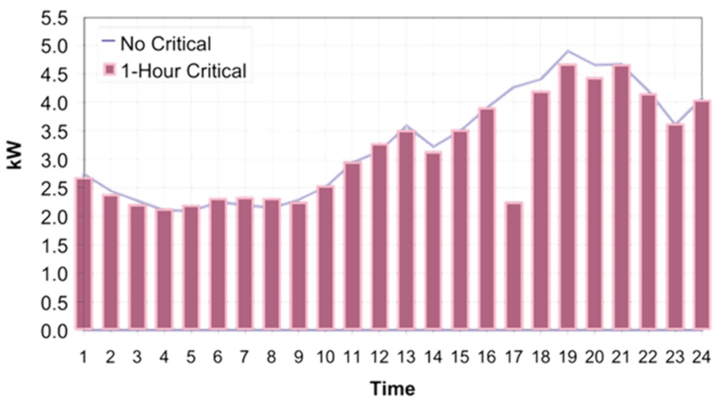
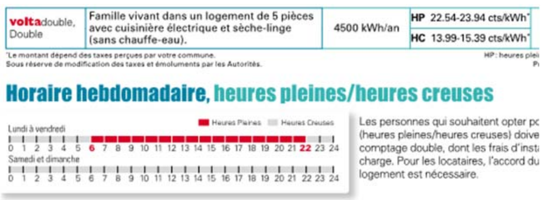


Figure 3-h. Average Load and Load Reduction in Gulf Power CPP program. The TOU rate (11 a.m. to 8 p.m.) was 9.3 ¢/kWh. The 1- and 2-hour CPP was 29 ¢/kWh, an extra 20 ¢/kWh. The 1-hour CPP dispatch was at hour 17.

Source: Brian White, Gulf Power

Example 2 : Romande Energie

- *Time of Use* tariff
  Night tariff is lower



- *Interruptible Supply*:
  interruptible supply (service is available e.g. 20 hours per day)
  [Le Boudec and Tomozei 2011]

Interruptible Court, Interruptible Court

Ce tarif est destiné particulièrement au chauffe-eau électrique (boiler). Il dispose d'une fourniture journalière de 8 heures sur 24.
Cette application nécessite un compteur additionnel qui engendre des frais supplémentaires de branchement, mais pas de frais de location de compteur.

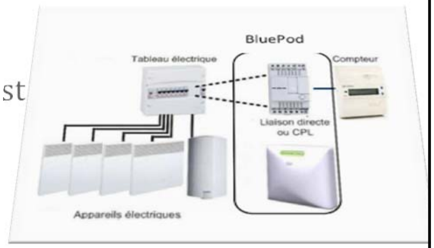
Interruptible Long, Interruptible Long

Ce tarif peut être utilisé pour des applications pompe à chaleur et chauffe-eau électrique. Il dispose d'une fourniture journalière de 20 heures sur 24 (4 x 1 heure de délestage réparties sur la journée).
Cette application nécessite un compteur additionnel qui engendre des frais supplémentaires de branchement, mais pas de frais de location de compteur. Nous déconseillons ce tarif pour les pompes à chaleur situées en altitude.

http://www.romande-energie.ch/images/File/Tarifs/2013_tarifs_RE.pdf

Example 3 :Voltalis

- Widely deployed in France
- *Interruptible Load*
  Voltalis device stops electrical resistive heating / boiler for at most 60 mn per day
- Device («Bluepod») receives GSM signal and stops thermal loads
- No charge / no payment
- Acceptance based on
  - Voltalis claims energy usage reduction
  - Good citizens
- Similar schemes with incentive payment to users: PeakSaver (Canada), www.pge.com (USA), New Zealand, NGT frequency service (UK)



VOLTALIS
The e-power company
www.voltalis.com

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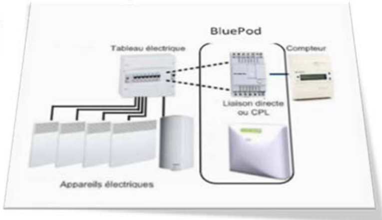
Voltalis does not pay nor charge anything to consumers but claims that consumers benefit by seeing a reduced electricity bill. Do you think this is true ?

1. Yes, there must be a reduction in total energy consumed
2. No, there cannot be any reduction in total energy consumed
3. Total energy consumed is increased
4. Ich weiss nicht



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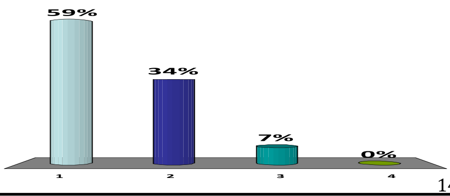

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Example 4: Dynamic Demand

- also called frequency service
- smart fridges, smart boilers, smart heaters / HVACs
- recall that frequency is the first signal of power imbalance

- primary frequency control traditionally done with *dynamic generators* -- fossil fuel generators, using droop control

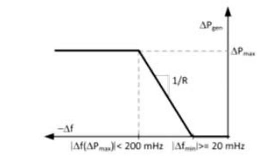
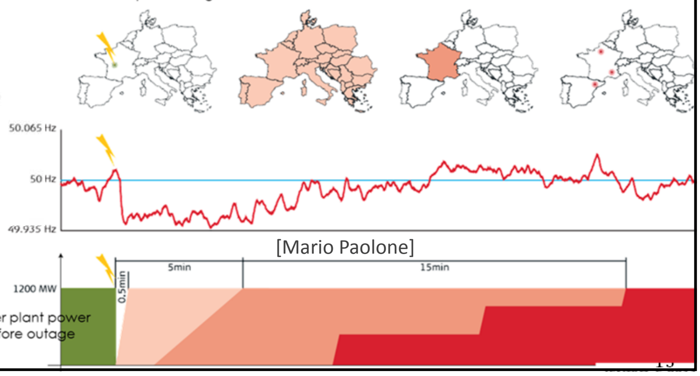


Fig. 1. UCTE specification for primary frequency reserve.

[Molina-Garcia et al 2011]



[Mario Paolone]

Example 4: Dynamic Demand

- *dynamic demand* is an alternative to dynamic generators
- How it works:("*grid friendly controller*")
  (underfrequency): fridge delays compressor when frequency drops and anticipates when freq. increases [Molina-Garcia et al 2011]

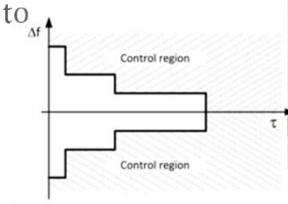
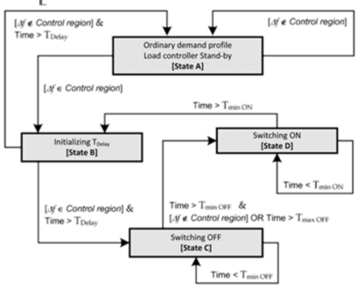


Fig. 2. Individual load controller Δf-time characteristic.



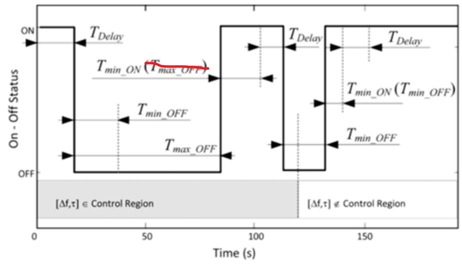
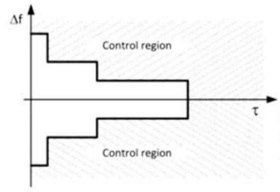


Fig. 5. Example of energy recovery time periods. Underfrequency.

Is something missing with this algorithm ?

1. Nothing
2. Timers need to be randomized
3. Internal temperature needs to be taken into account
4. Outside temperature needs to be taken into account
5. Non lo so



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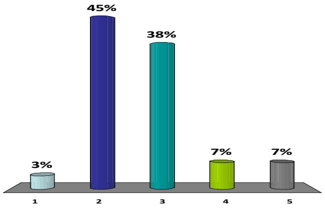

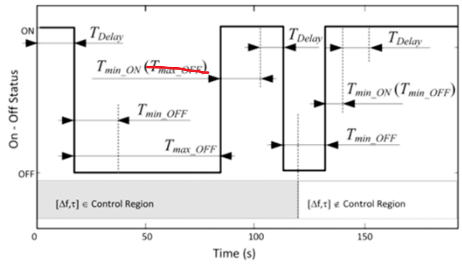

Fig. 5. Example of energy recovery time periods. Underfrequency.

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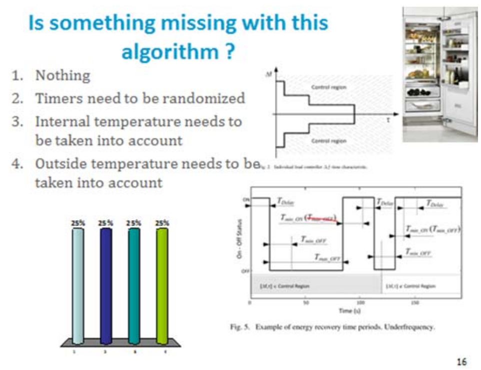
- Avoid synchronized response ⇒ [Molina-Garcia et al 2011] uses randomized Tdelay
- Internal temperature should be accounted for -- See [Christakou et al 2012] for a variant that accounts for internal temperature



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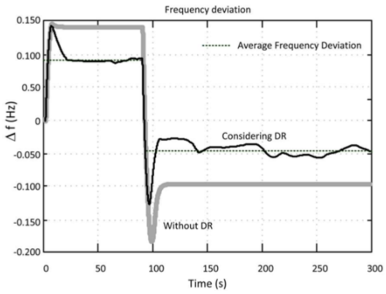
Dynamic Demand

- Simulation results for [Molina-Garcia et al 2011] with 10% of loads implementing dynamic demand in a hypothetical country grid



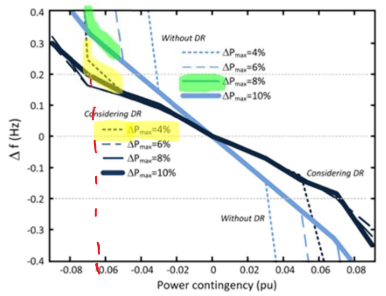


Fig. 10. Δf average simulated values with different amounts of primary frequency response available from the generation.

dynamic demand ≈ doubles the reserve

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Dynamic Demand

- Simulation results for [Molina-Garcia et al 2011] with 10% of loads implementing dynamic demand in a hypothetical country grid – dynamic demand ≈ doubles the reserve
- Fridges as primary/secondary response could provide ca 1 GW of reserve to UK grid [Milborrow 2009]
- 70% of secondary regulation power (8 sec to 3 mn) in the US can be provided by building air conditioning and heating *fans* alone [Hao et al 2012]

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Example 5: Boilers as Tertiary Reserve [Sundstrom et al 2012]

- Primary reserve = real time
  Secondary reserve = within minutes
  Tertiary reserve = starts after 15 mn
- Thermal loads can be anticipated or delayed
- Upper and lower energy curves for one boiler give bounds on feasible energy provision *schedules*

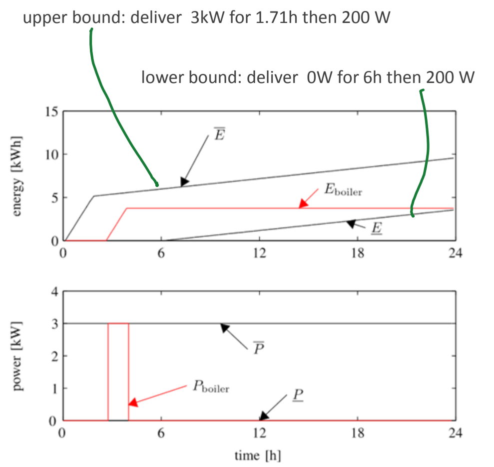

Figure 8. Flexibility of a sample boiler with 6 kWh equivalent energy storage, an initial energy level of 1.2 kWh, and an average consumption of 200W.

[Sundstrom et al 2012]

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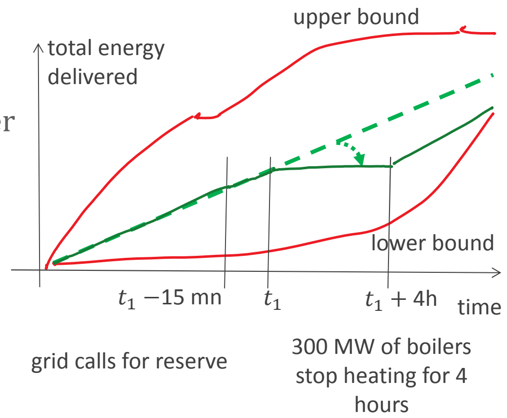
Boilers as Tertiary Reserve

- Assume operator (“Service aggregator”) controls a large set of boilers and can predict the upper and lower bounds for the aggregate energy curves.

  Service aggregator can select a middle trajectory and therefore obtain some reserve that can be sold to grid.

  Can be implemented with pricing and /or smart meters



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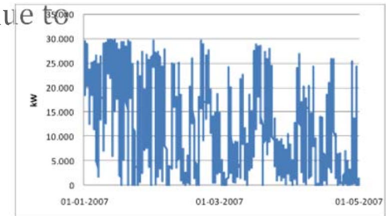
Example 6: Island with Large Penetration of Renewables

- [James-Smith and Togeby 2007]
- Bornholm (DK) object of EcoGrid EU project
- Electricity : Peak demand 55 MW, Supply 30MW wind turbines, 60MW AC cable to mainland, one Combined Heat and Power plant (coal, 35 MW total)

- Issue: operation in islanded mode due to frequent cable cuts
  - *Wind volatility*
  - Generation may become large
  - Coal plant is not fast enough
  - $\pm$3 MW of additional fast response (within 15 mn) is required



[James-Smith and Togeby 2007]

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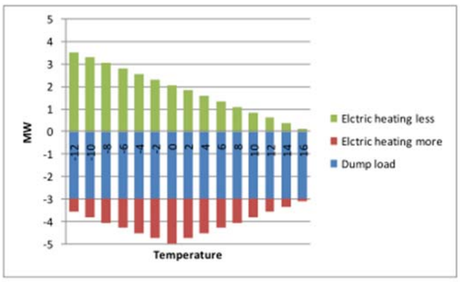
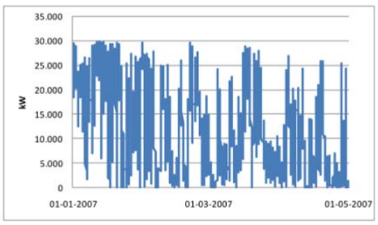
Example 6: Findings in [James-Smith and Togeby 2007]

- Demand response in homes (heating, hot water, refrigerators) can provide 3MW of capacity in winter
- Positive demand response (homes, district heating system) can avoid spilling wind energy





[James-Smith and Togeby 2007]

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Example 7: Impact of e-car charging on distribution network [Clement-Nyns et al 2010]

- E-car charges are high power (4kW), stress electrical distribution network – peak demand at nights

TABLE I
RATIO OF POWER LOSSES TO TOTAL POWER [%] FOR THE 4 kW CHARGER IN CASE OF UNCOORDINATED CHARGING

Charging period	Penetration level	0%	10%	20%	30%
21h00-06h00	Summer	1.1	1.4	1.9	2.2
	Winter	1.4	1.6	2.1	2.4
18h00-21h00	Summer	1.5	2.4	3.8	5.0
	Winter	2.4	3.4	4.8	6.0
10h00-16h00	Summer	1.3	1.8	2.6	3.2
	Winter	1.7	2.2	3.0	3.6

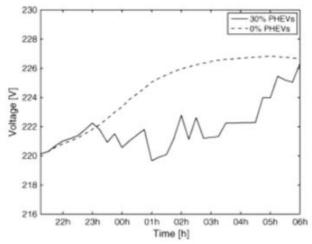

Fig. 4. Voltage profile in a node with 30% PHEVs compared to the voltage profile with 0% PHEV.

TABLE II
MAXIMUM VOLTAGE DEVIATIONS [%] FOR THE 4 kW CHARGER IN CASE OF UNCOORDINATED CHARGING

Charging period	Penetration level	0%	10%	20%	30%
21h00-06h00	Summer	3.1	3.5	4.4	5.0
	Winter	4.2	4.4	4.9	5.5
18h00-21h00	Summer	3.0	4.4	6.5	8.1
	Winter	4.8	6.3	8.5	10.3
10h00-16h00	Summer	3.0	4.1	5.6	6.9
	Winter	3.7	4.9	6.4	7.7

Simulation of 34-bus residential grid [Clement-Nyns et al 2010]

Scheduled Charging

- problem can be solved by *scheduling* the loads (e-cars), i.e. coordinate them
- e-cars communicate with a scheduler, through smart meter or other communication means
- coordinator solves optimization problem and sends schedule to e-car chargers

$$\min \sum_{t=1}^{t_{max}} \sum_{l=1}^{lines} R_l \, I_{l,t}^2$$

≈ power loss

$$s.t. \begin{cases} \forall t, \forall n \epsilon \{nodes\} : 0 \leq P_{n,t} \leq P_{\max} \\ \forall n \epsilon \{nodes\} : \sum_{t=1}^{t_{max}} P_{n,t} \cdot \Delta t \cdot x_n = C_{max} \\ x_n \epsilon \{0,1\}. \end{cases}$$

power scheduled to car n at time t

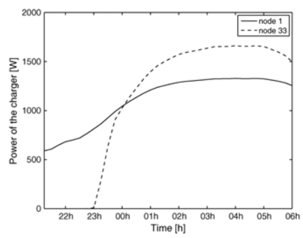

Fig. 7. Load profile of the 4 kW charger for the charging period from 21h00 until 06h00 during winter.

- requires : model of grid; of state and availability of e-cars; is frequently recomputed to address stochastic changes

Scheduled charging can eliminate need to upgrade distribution network

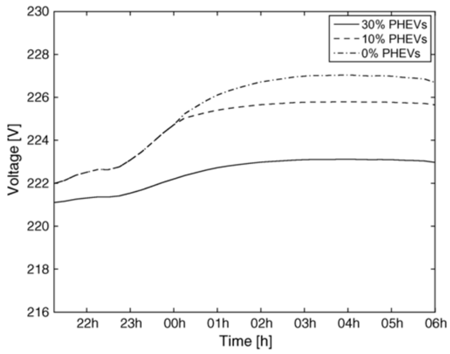

Fig. 6. Voltage profile in a node with 30% and 10% PHEVs compared to the voltage profile with 0% PHEV for coordinated charging.

TABLE III
RATIO OF POWER LOSSES TO TOTAL POWER [%] FOR THE 4 kW CHARGER IN CASE OF COORDINATED CHARGING

Charging period	Penetration level	0%	10%	20%	30%
21h00-06h00	Summer	1.1	1.3	1.7	1.9
	Winter	1.4	1.5	1.8	2.1
18h00-21h00	Summer	1.5	2.3	3.7	4.7
	Winter	2.4	3.3	4.7	5.8
10h00-16h00	Summer	1.3	1.7	2.3	2.8
	Winter	1.7	2.1	2.7	3.2

TABLE IV
MAXIMUM VOLTAGE DEVIATIONS [%] FOR THE 4 kW CHARGER IN CASE OF COORDINATED CHARGING

Charging period	Penetration level	0%	10%	20%	30%
21h00-06h00	Summer	3.1	3.1	3.3	3.7
	Winter	4.2	4.2	4.2	4.3
18h00-21h00	Summer	3.0	4.1	5.8	7.2
	Winter	4.8	6.0	7.8	9.1
10h00-16h00	Summer	3.0	3.3	4.1	4.7
	Winter	3.7	4.0	4.9	5.5

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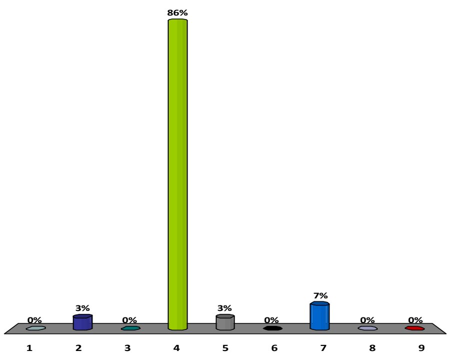
Say what is true

Demand Response can be used…
1. … to mitigate the impact of a weak grid
2. … to compensate for energy imbalance
3. … as an alternative to nuclear energy

1. 1
2. 2
3. 3
4. 1 and 2
5. 1 and 3
6. 2 and 3
7. All
8. none
9. N’ouzhon ket



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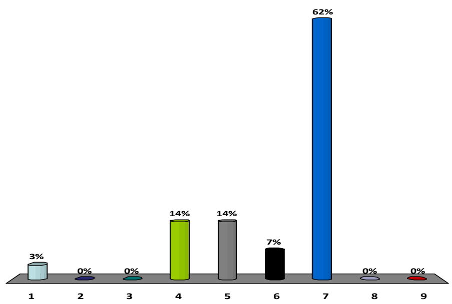
Say what is true

1. Demand response can decrease the cost of electricity by reducing the required peak capacity
2. Voltalis makes money by selling Negawatts
3. Demand response may increase the cost of electricity in some time slots.

1. 1
2. 2
3. 3
4. 1 and 2
5. 1 and 3
6. 2 and 3
7. All
8. None
9. I don't know



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Taxonomy of Demand Response

- **Type of user contract**
1. Time of use (e.g day versus night)
2. Control by tariff (dynamic prices)
3. Control by quantity (interruptible supply, schedules)
- **Mode of communicat**ion
1. inband tones (Ripples)
2. powerline communication and smart meters
3. radio communication

- **Time scale of operation**
1. Static
2. Dynamic
   5mn-24 hours (smart meters)
3. Real time
   (frequency response)

- **Global Effect**
4. Shift the load (delay or anticipate)
5. Reduce demand (emergency, shave the peak on exceptional days)

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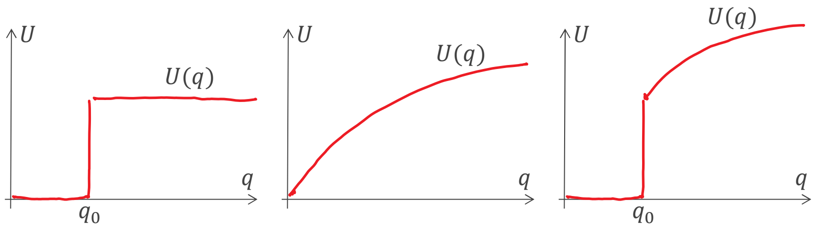
QUESTIONS ?

ELEMENTS OF THEORY

1. Demand and Supply Curves
2. Elasticity
3. Evaporation
4. Earliest and latest schedules

1. The Economic Theory of Demand Response Consumer Side

- The economic theory of Demand Response is based on the following model.
- Assume consumers are willing to consume some amount of energy q at a price p ; in a given time slot, the *utility* of q is assumed to be measurable and equal to $U(q)$; the consumer chooses the value of q that maximizes $U(q) - pq$



non elastic load | elastic load | elastic load with minimum requir’t

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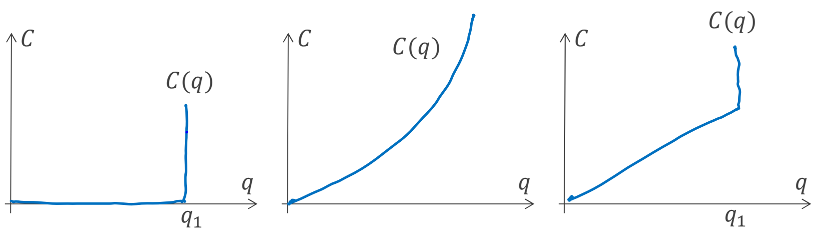
The Economic Theory of Demand Response Supplier Side

- Assume suppliers users are willing to sell some amount of energy q at a price p ; in a given time slot, the *running cost* of generating q is assumed to be measurable and equal to $C(q)$; the supplier chooses the value of q that maximizes $pq - C(q)$



wind supplier | flexible supplier | flexible supplier with maximum capacit

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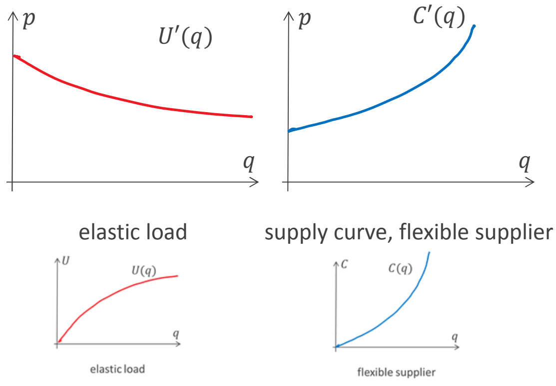
Demand and Supply Curves

- *Demand Curve* = how much consumer is willing to buy at a given price
  Supply curve = how much supplier is willing to sell at a given price
- Consumer maximizes $U(q) - pq$ therefore $U'(q) = p$
  Supplier maximizes $pq - C(q)$ therefore $C'(q) = p$

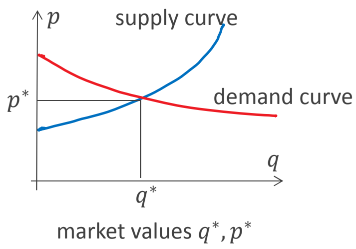
  demand curve is $q \mapsto U'(q)$
  supply curve is $q \mapsto C'(q)$
- U concave $\Rightarrow$
  $U'$is decreasing
- C convex $\Rightarrow$
  $C'$is increasing



35

Market Equilibrium

- Assume there is a perfect market to fix prices; the supplier and consumer prices are equal
  Price and quantity are given by intersection of supply and demand curves



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Supply and Demand Curves Without Demand Response [Kirschen 2003]

- No demand response means loads are inelastic ;generation or grid outages cause prices to surge
- Elastic loads may avoid price peaks

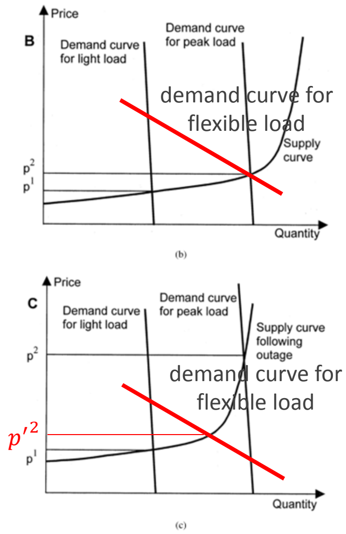

Fig. 1. (a) Market equilibria for a "normal" commodity. (b) Typical supply and demand curves for electrical energy. (c) Supply and demand curve following a major generation outage.

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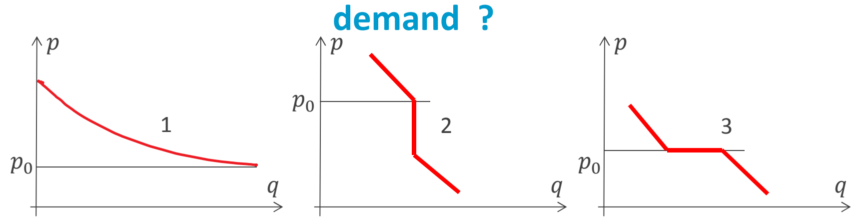
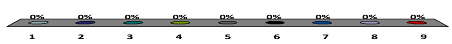
Assume some loads disconnect when price becomes $> p_0$ Which curve could be a demand curve for the aggregate demand ?



1. Curve 1
2. Curve 2
3. Curve 3
4. Either 1 or 2
5. Either 1 or 3
6. Either 2 or 3
7. All
8. None
9. Ne znam



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Norway's pilot study [Saele and Grande 2011] Demand Response may reduce prices

- 120 EUR/MWh difference between 2 areas inside Norway
- [Saele and Grande 2011] claims that the price peak would be suppressed with demand response

Fig. 2. Different bid curves for demand response.

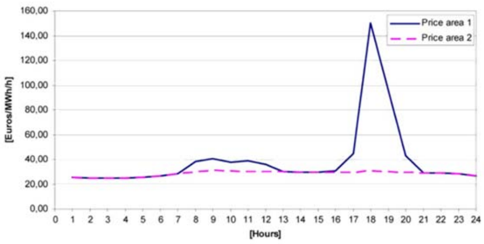

Fig. 3. Hourly spot prices in two price areas in Norway, 6 February 2007 (data source: NordPool).

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Supply Curve for Industrial Customers

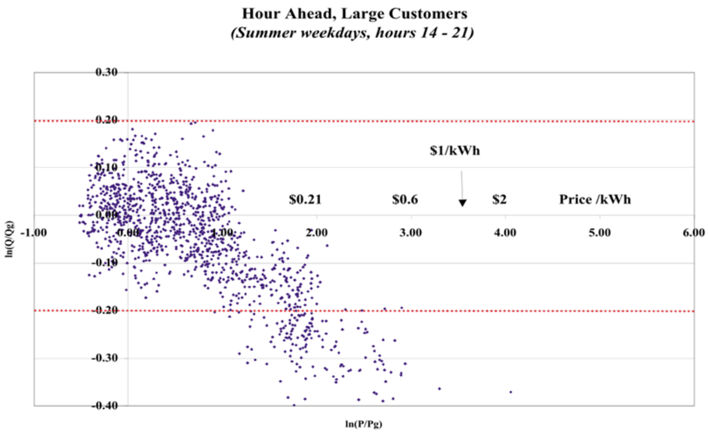

Figure 3-k. Demand response of large industrial Hour-Ahead customers in Georgia Power's RTP program. Scales are logarithmic. We have added on the x-axis a few price levels in $ per kWh.

Source: Braithwait, Christensen and Associates

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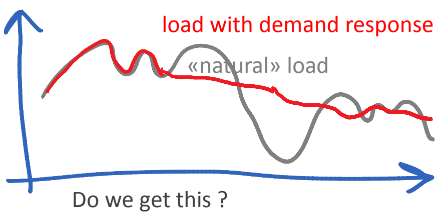
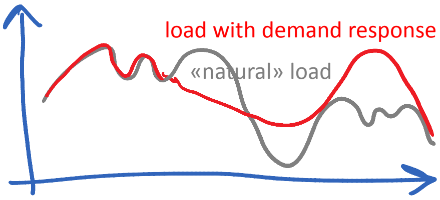
2. Elasticity



Do we get this ?



... or that ?

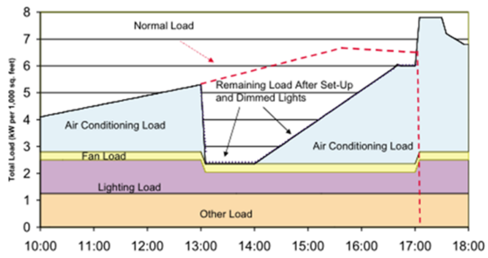


Figure 3-d is a conceptual illustration of the response of a building to CPP on a hot afternoon. The example assumes CPP is invoked from 13:00 to 17:00. The figure shows two different usage patterns in a single sketch. Pattern 1 (Normal Load) is a typical office, where loads drop at about 5 p.m. For Pattern 2, the air conditioning demand actually increases after 5 p.m. because the thermostat has been set back down to 72° F.

Source: Pat McAuliffe, CEC

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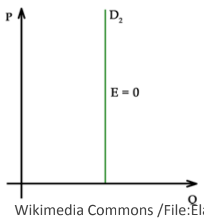
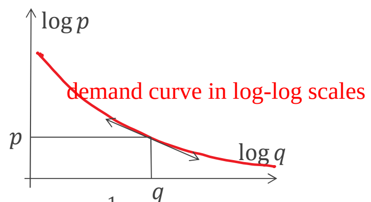
Elasticity and Cross-Elasticity

- Demand response causes demand reduction and time shifting
- The quantitative effect is captured by

$$\text{(self)-elasticity} := \frac{dq}{dp}\frac{p}{q} = \frac{d(\log p)}{d(\log q)}$$



Wikimedia Commons /File:Elasticity-inelastic.png



$\frac{1}{\text{slope}}$ is the elasticity at p

and

$$\text{cross-elasticity } E_{t+h,t} := \frac{\partial q_{t+h}}{\partial p_t}\frac{p_t}{q_{t+h}}$$

defined for example for $h \in [-24\text{hours}, +24 \text{ hours}]$

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Example of Cross-Elasticity [Kirschen et al 2000]

- Users expect some prices p_t based on historical data
  Resulting demand is q_t
  assumes two demand response models with cross-elasticity
- Market decides for different prices, Δp_t = difference between expected price and actual price. Demand response cause users to change their loads. [Kirschen et al 2000] assumes that

$$\Delta q_t = \sum_{h=-24}^{+24} \frac{\Delta p_{t+h}}{p_{t+h}} \, \varepsilon_{t,t+h} \, q_{t+h}$$

where $\varepsilon_{t,t+h}$ is called the *Cross-Elasticity Coefficient*

(it slightly differs from $E_{t,t+h}$)

$\varepsilon_{t,t+h} \times \frac{\Delta p_{t+h}}{p_{t+h}}$ is the fraction of the load at time $t+h$ that is moved to time t due to a change in price at time $t+h$

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Example of Cross-Elasticity Coefficients

- $\Delta q_t = \sum_{h=-24}^{+24} \frac{\Delta p_{t+h}}{p_{t+h}} \, \varepsilon_{t,t+h} \, q_{t+h}$
- [Kirschen et al 2000] considers two possible scenarios
  Scenario 1: (Time Shifting, "Inflexible"):

  $$\varepsilon_{t-3,t} = \varepsilon_{t-2,t} = \varepsilon_{t-1,t} = +0.0033$$
  $$\varepsilon_{t+3,t} = \varepsilon_{t+2,t} = \varepsilon_{t+1,t} = +0.0033$$
  $$\varepsilon_{t,t} = -0.20$$

  i.e. change in price at t changes load by $-0.2 \times \%$ price increase
  load is transferred to 3 hours before and 3 hours after t
- **Scenario 2:** ("Optimizer"):

  $$\varepsilon_{0,t} = \cdots = \varepsilon_{2,t} = \varepsilon_{16,t} = \cdots = \varepsilon_{23,t} = +0.01$$
  $$\varepsilon_{4,t} = \cdots = \varepsilon_{7,t} = +0.025$$
  $$\varepsilon_{t,t} = -0.20$$

  i.e. change in price at t changes load by $-0.2 \times \%$ price increase
  most load is transferred to early and late hours of the day

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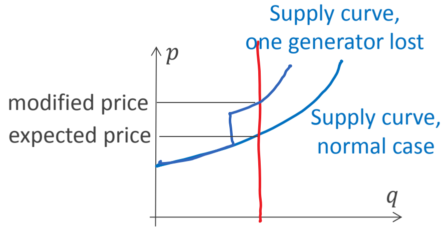
Impact on Price

- Assuming no elasticity, prices are formed by matching demand
  let $\vec{q} \mapsto \vec{p} = \vec{F}(\vec{q})$ the process of price formation where $\vec{p} = (p_0, p_1, \dots, p_{23})$
- [Kirschen et al 2000] studies a case with normal operation and with planned loss of generator



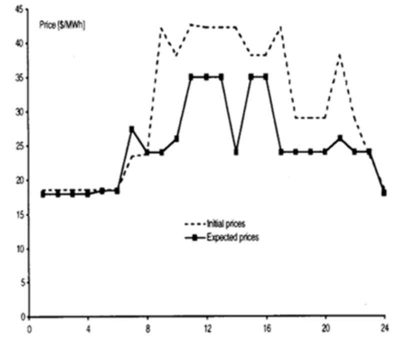


Fig. 5. Expected prices and initial prices.

Impact on Price (continued)

- Assume now elastic loads with known cross-elasticity. The actual load depends on the market price: let $\vec{p} \mapsto \vec{q} = \vec{G}(\vec{p})$ be the process of load adaptation
- Assume market aggregator knows elasticity; she can compute market prices by solving a fixed point problem

$$\begin{cases} \vec{p} = \vec{F}(\vec{q}) \\ \vec{q} = \vec{G}(\vec{p}) \end{cases}$$

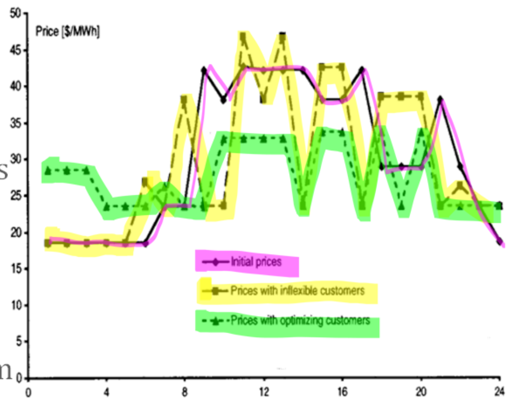
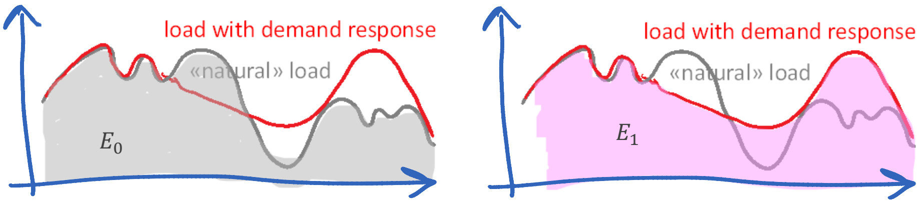


Fig. 7. Initial prices and prices as modified by elasticities.

[Kirschen et al 2000]

3. Evaporation

- Evaporation = fraction of energy that is saved due to demand response [Le Boudec and Tomozei 2013]



$$\text{evaporation} = \frac{E_0 - E_1}{E_0}$$

What can we say about the evaporation for this scenario ?

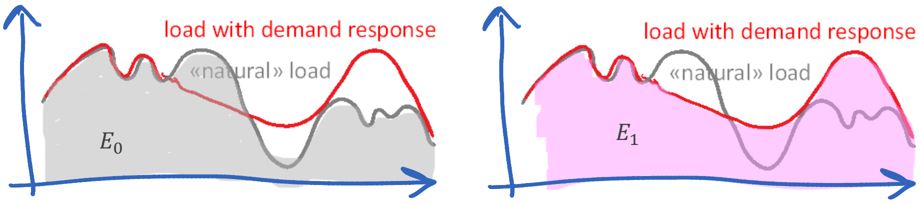
1. > 0
2. < 0
3. $= 0$
4. Nothing, it depends on other factors.
5. Não sei

Example of Cross-Elasticity Coefficients

- $\Delta q_t = \sum_{h=-24}^{+24} \frac{\Delta p_{t+h}}{p_{t+h}} \varepsilon_{t,t+h} q_{t+h}$
- [Kirschen et al 2000] considers two possible scenarios
  Scenario 1: (Time Shifting, "Inflexible"):
  $\varepsilon_{t-3,t} = \varepsilon_{t-2,t} = \varepsilon_{t-1,t} = +0.0033$
  $\varepsilon_{t+3,t} = \varepsilon_{t+2,t} = \varepsilon_{t+1,t} = +0.0033$
  $\varepsilon_{t,t} = -0.20$
  i.e. change in price at t changes load by $-0.2 \times$ % price increase
  load is transferred to 3 hours before and 3 hours after t

Evaporation

- Evaporation = fraction of energy that is saved due to demand response [Le Boudec and Tomozei 2013]

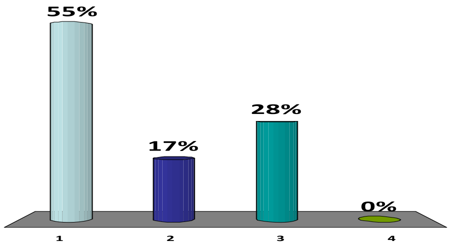


$$\text{evaporation} = \frac{E_0 - E_1}{E_0}$$

- with pure demand shifting, evaporation = 0
- If it is true that demand response saves energy, we should see evaporation > 0
- What do we expect in general ?

(Should I keep my chalet warm ?) When I am away I interrupt heating. Does this save energy ?

1. Yes, there must be a reduction in total energy consumed
2. No, there cannot be any reduction in total energy consumed
3. Total energy consumed is increased
4. I weiss nid



We have seen this question already…

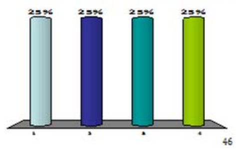
Voltalis does not pay nor charge anything to consumers but claims that consumers benefit by seeing a reduced electricity bill. Do you think this is true ?

1. Yes, there must be a reduction in total energy consumed
2. No, there cannot be any reduction in total energy consumed
3. Total energy consumed is increased
4. I don't know

VOLTALIS
The e-power company

(Should I keep my chalet warm ?) When I am away I interrupt heating. Does this save energy ?

1. Yes, there must be a reduction in total energy consumed
2. No, there cannot be any reduction in total energy consumed
3. Total energy consumed is increased
4. I don't know



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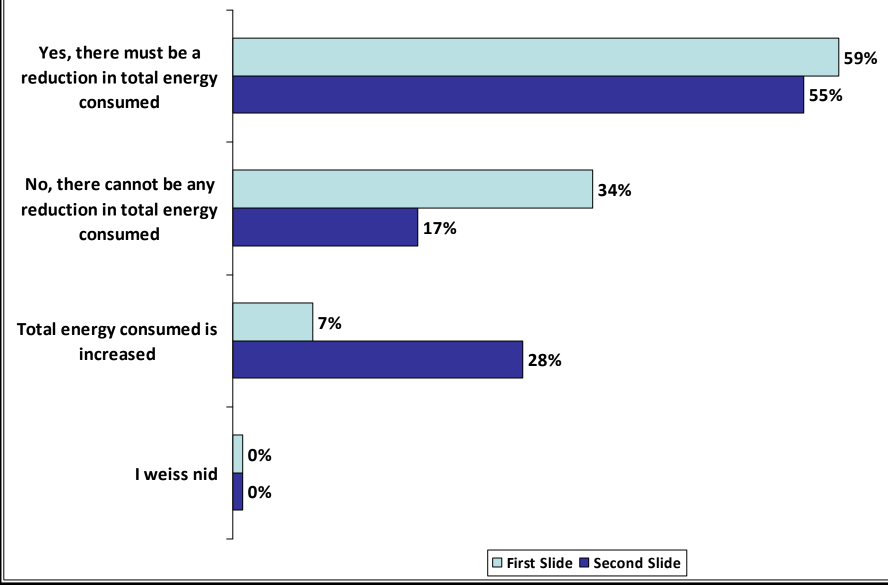
(Should I keep my chalet warm ?) When I am away I interrupt heating. Does this save energy ?



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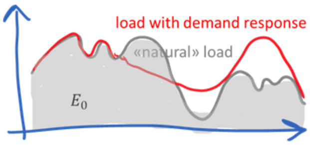
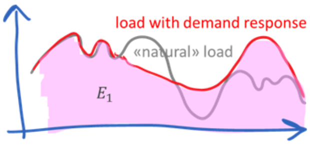
Evaporation is not the same as “Rebound Effect”

Q1. Does shutting down the heating today imply reducing total energy consumption compared to keeping temperature constant ?
= is evaporation positive ?
A. we will see later.

Q2. Does shutting down the heating today (and swithing it off tomorrow) imply increasing tomorrow’s energy consumption?
A. Yes (this is the rebound effect).





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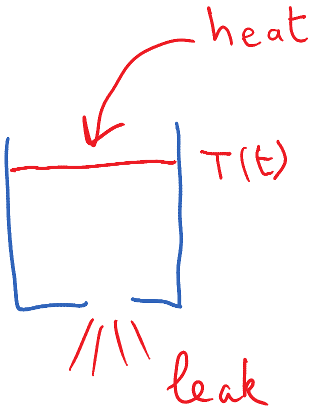
- Assume the house model of [McKay 2008]

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

leakiness outside inertia



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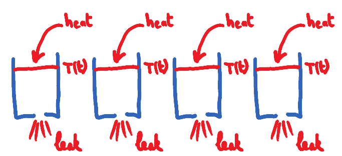
heat provided to building $\boxed{d(t)\epsilon} = \underbrace{\boxed{K}}_{\text{leakiness}}(T(t) - \underbrace{\theta(t)}_{\text{outside}}) + \underbrace{\boxed{C}}_{\text{inertia}}(T(t) - T(t-1))$

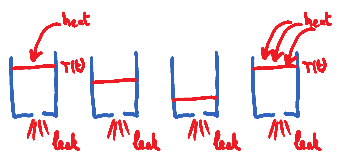
sum over t from 1 to τ :

$$\underbrace{\epsilon}_{\text{efficiency}} \underbrace{\boxed{\sum_{t=1}^{\tau} d(t)}}_{\text{E, total energy provided}} = K \sum_{t=1}^{\tau} \left(\underbrace{\boxed{T(t}}_{\text{achieved t}^{\text{o}}}) - \theta(t)\right) + C(T(\tau) - T(0)$$

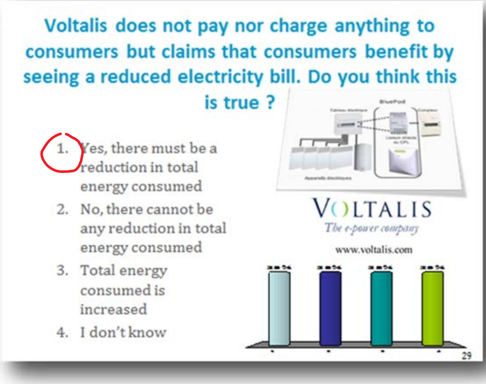
$$\underbrace{\epsilon}_{\text{efficiency}} \underbrace{\boxed{\sum_{t=1}^{\tau} d(t)}}_{\text{E, total energy provided}} = K \sum_{t=1}^{\tau} \left(\underbrace{\boxed{T(t}}_{\text{achieved t}^{\text{o}}}) - \theta(t)\right) + C(T(\tau) - T(0)$$

Scenario	***No interruption***	***With interruption***
Building temperature	$T^*(t), t = 0 \dots \tau$	$T(t), t = 0 \dots \tau$, $T(t) \leq T^*(t)$
Heat provided	$E^* = \frac{1}{\epsilon}\left(K \sum_{t=1}^{\tau} (T^*(t) - \theta(t)) + C(T^*(\tau) - T^*(0)\ )\right)$	$E < E^*$





Q1. Does shutting down the heating today imply
reducing total energy consumption compared to
keeping temperature constant ?
= is evaporation positive ?
A. yes, it reduces energy consumption, due to less leakage



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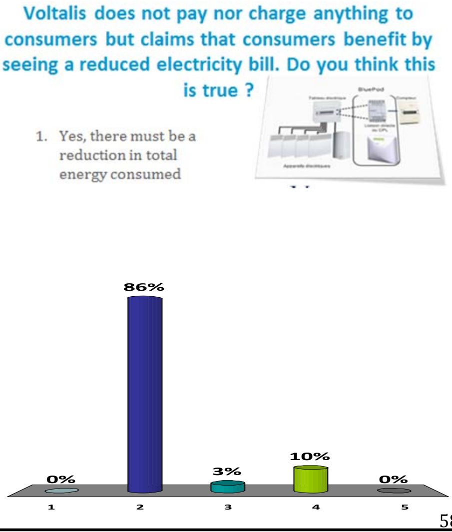
The French ADEME agency finds that consumers with Voltalis's load switching devices save ≈ 10% on heating but there is no significant saving on hot water boilers [ADEME 2012]. How do you interpret this ?

1. The model we saw is too simple and its finding do not apply.
2. Boiler leakage is small, house leakage is not.
3. House leakage is small, boiler leakage is not.
4. Hot water boiling is negligible consumption compared to house heating
5. I don't know.



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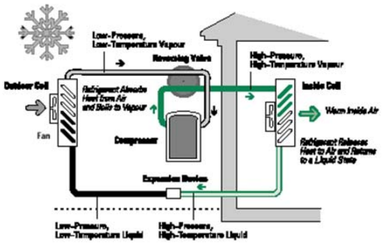
Evaporation

- Resistive heating system with poorly insulated building:
  evaporation is positive.

- If heat = heat pump, coefficient of performance ϵ may be variable.
  Evaporation may be positive or negative; negative evaporation is possible (heat pump operating at night in cold air).

- Electric vehicle: we expect evaporation = 0 (pure time shifting). However charge intensity impacts losses; fast charging may consume more energy, negative evaporation is possible.



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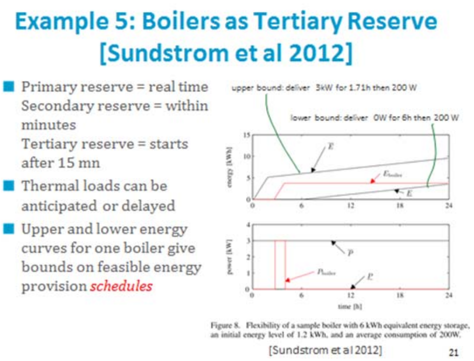
4. Earliest and Latest Schedules

- Assume market aggregator schedules energy consumption
- Assume evaporation = 0

(e.g. boilers, e-cars with not too high charge intensity)

- Then there are always earliest and latest schedules, and these can be computed, as we see next



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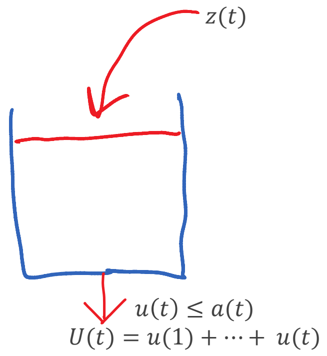
A Simple Storage Problem

- Assume an infinite buffer into which we store some goods (e.g. energy); $z(t)$ units of good are stored during slot; $z(t)$ is known.
- We have to decide $u(t)$, how many units of good we output at time t. We have to satisfy the constraint $u(t) \le a(t)$, where $a(t)$ is known.
- Let $U(t)$ be the total amount output from time *0* to time t.



- What is the $U()$ that corresponds to the most aggressive output ?

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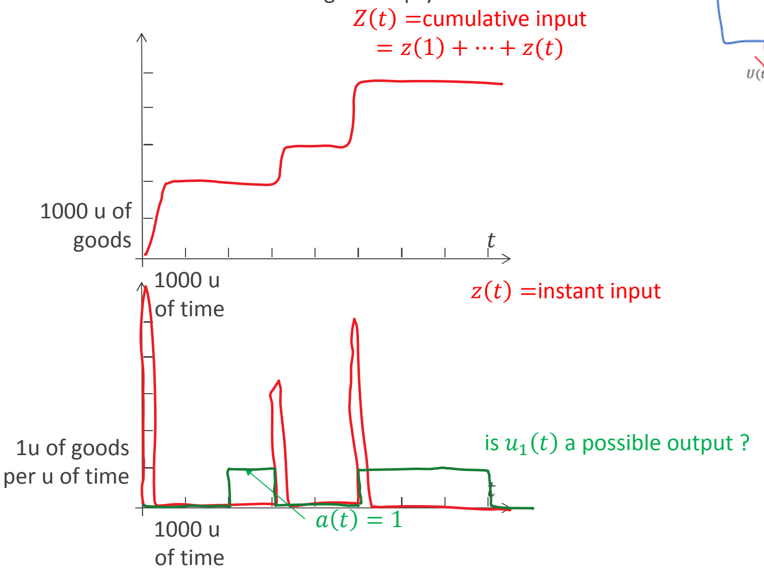
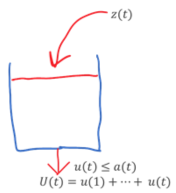
Example

$a(t) = 1$ unit of good / unit of time
storage is empty at time 0





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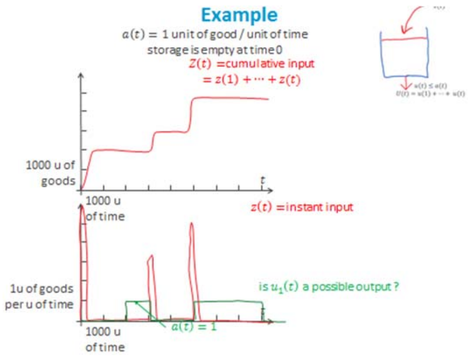
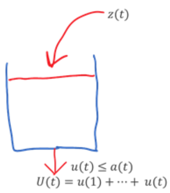
Is $u_1()$ a feasible output for my storage problem ?

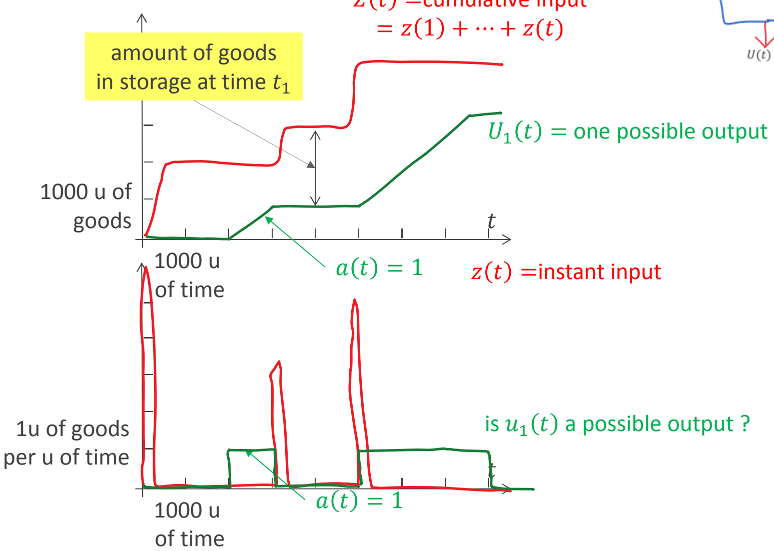
1. Yes
2. No
3. It depends on other elements not shown on picture
4. I don't know



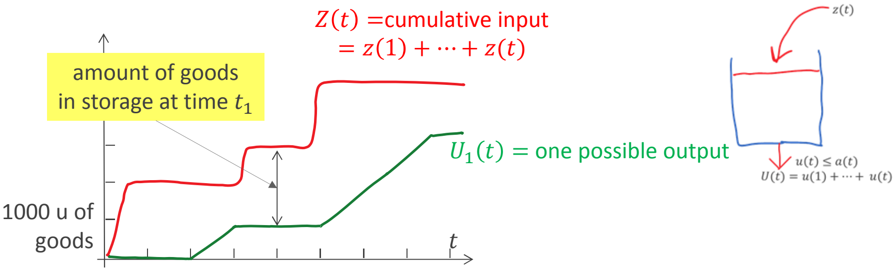
Solution

$a(t) = 1$ unit of good / unit of time
storage is empty at time 0
$Z(t)$ =cumulative input
$= z(1) + \cdots + z(t)$





Storage system are best studied using cumulative input and output curves



- $u()$ is a feasible output iff

$$0 \leq u(t) \leq a(t)$$
$$U(t) \leq Z(t)$$

where $U(t) = u(1) + \cdots + u(t)$

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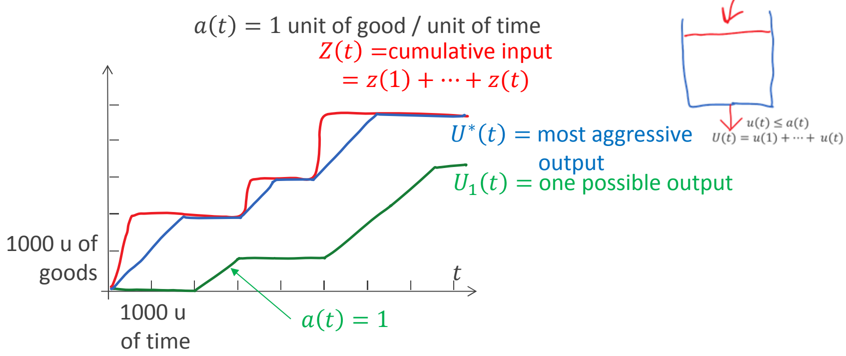
The Most Aggressive Output $U^*()$...



- is the one that minimizes storage content at any time, given the constraints on output rate $a(t)$
- satisfies $U_1(t) \leq U^*(t)$ for any other feasible output U_1
- can be computed online (i.e. is causal) by

  $u^*(0) = 0,$

  $u^*(t) = \min\{a(t), \ \ Z(t) - U^*(t-1)\}, t = 1,2, \ldots$

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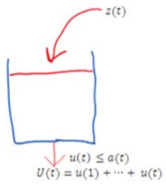
The Maximum Solution Theorem



- Consider the problem

$$\begin{cases} 0 \le u(t) \le a(t), t = 1, 2, \dots \\ U(t) \le Z(t), t = 0, 1, \dots \end{cases}$$

  with $U(0) \le Z(0) = 0$ and $u(t) \coloneqq U(t) - U(t-1)$. Here $U()$ is the unknown function and the functions $Z(), a()$ are known.

i.e. we have constraints on the function $U()$ and its discrete time derivative $u()$

- This problem has one unique *maximum* solution U^*, i.e. U^* is a solution and for any other solution U, we have $U(t) \le U^*(t), \forall t$
- $U^*()$ can be defined by causal iteration on time:

$$u^*(0) = 0$$
$$u^*(t) = \min\{a(t),\ Z(t) - U^*(t-1)\}$$

- The proof is based on the formula [Le Boudec and Thiran 2001]

$$U^*(t) = \min_{s=0,\dots,t} \left(Z(s) + a(s+1) + \cdots + a(t)\right)$$

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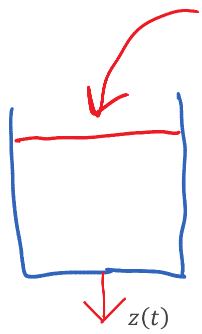
Another Simple Storage Problem

- Assume an infinite buffer into which we store some goods (e.g. energy); $v(t)$ units of good are stored during slot; $v(t)$ is to be decided. The initial storage content $V(0)$ is also to be decided.
- We have to satisfy the constraint $v(t) \le a(t)$, where $a(t)$ is known.
- We have to output $z(t)$ at any time slot $t = 1, \dots T$, where $z(t)$ is known
- Let $V(t)$ be the total amount input from time *0* to time t.
- What is the $V()$ that corresponds to the *laziest* input (i.e. as late as possible) ?

$V(t) = V(0) + v(1) + \cdots + v(t)$

$v(t) \le a(t)$



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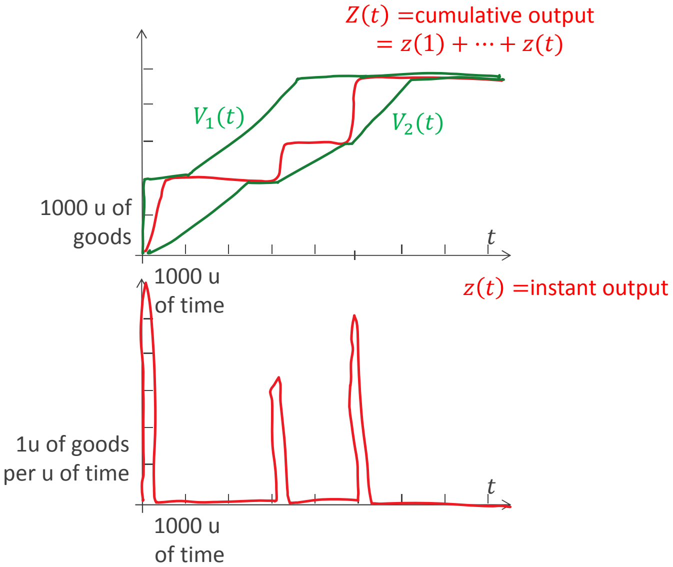
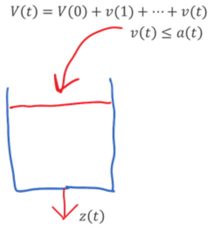
The Laziest Input $V_*()$...

$a(t)$ = 1 unit of good / unit of time





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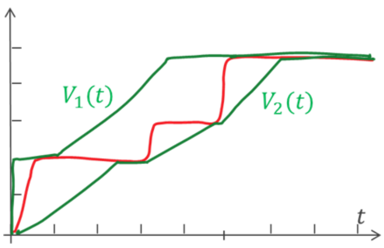
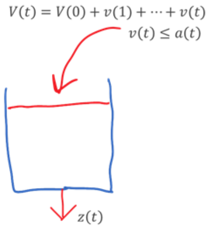
Say what is true...





1. $V_1()$ is the laziest input
2. $V_2()$ is the laziest input
3. None of them is the laziest input
4. I don't know

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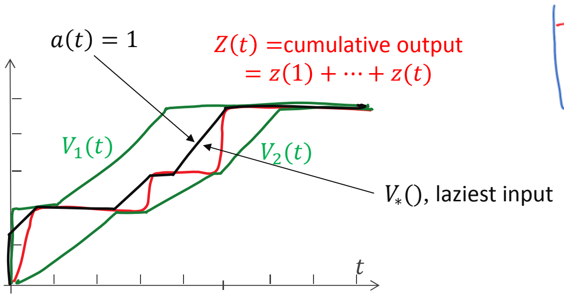
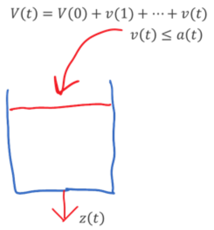
Solution

$a(t)$ = 1 unit of good / unit of time





- $V_1()$ is a feasible input but is not the laziest (can be delayed)
- $V_2()$ is not a feasible input
- The laziest input is drawn backwards in time

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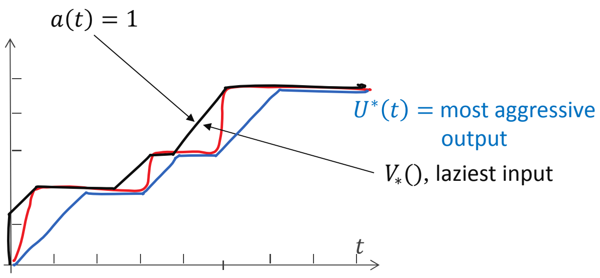
The Laziest Input $V^*()$...



- is the one that minimizes storage content at any time, given the constraints on output rate $a(t)$
- satisfies $V_1(t) \ge V^*(t)$ for any other feasible input V_1
- can be computed *backwards in time*:

$$V^*(T) = Z(T),$$
$$v^*(t) = \min\{a(t),\ V^*(t) - Z(t-1)\}, t = T, T-1, \ldots 1$$
$$V^*(t-1) = V^*(t) - v^*(t)$$

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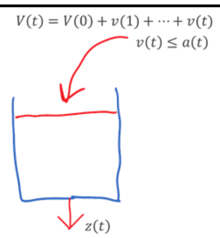
The Minimum Solution Theorem



- Consider the problem

$$\begin{cases} 0 \le v(t) \le a(t), t = 1, 2, \dots, T \\ V(t) \ge Z(t), t = 0, 1, \dots, T \end{cases}$$

with $V(T) \ge Z(T) \ge Z(0) = 0$ and $v(t) := V(t) - V(t-1)$. Here $V()$ is the unknown function and the functions $Z(), a()$ are known.

- This problem has one unique *minimum* solution V_*, i.e. V_* is a solution and for any other solution V, we have $V(t) \ge V_*(t), \forall t = 0, \dots T$

- $V_*()$ can be defined by backwards iteration on time:

$$V_*(T) = Z(T)$$
$$v_*(t) = \min\{a(t),\ V_*(t) - Z(t-1)\}, t = T, T-1, \dots 1$$
$$V_*(t-1) = V_*(t) - v_*(t)$$

- The proof is based on the formula [Le Boudec and Thiran 2001]

$$V_*(t) = \max_{s=t,\dots,T} \left(Z(s) - a(t+1) - \cdots - a(s) \right)$$

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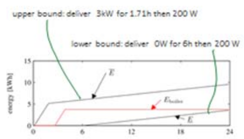
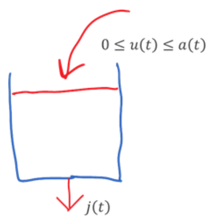
The Energy Scheduling Problem

- Assume you want to schedule energy delivery to a storage (e.g. boiler) over a period $[0, T]$
The problem is to schedule $u(t)$, energy in slot t
- The anticipated consumption $j(t)$ (hot water) is assumed to be known.
- The constraints on the system are:

Example 5: Boilers as Tertiary Reserve [Sundstrom et al 2012]

- Primary reserve = real time
Secondary reserve = within minutes
Tertiary reserve = starts after 15 mn
- Thermal loads can be anticipated or delayed





(1) $0 \le u(t) \le a(t)$
power limit

(2) $J(t) \le U(t) + B_0$
consumption constraint

(3) $U(t) - J(t) + B_0 \le B_{\max}$
no overflow

B_0 = storage level at $t = 0$
$B_{\max}$ = storage capacity

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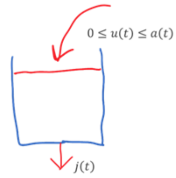
The earliest and latest schedules

- A feasible schedule is constrained by (1) and (3) maximum solution theorem $\Rightarrow U(t) \leq U^*(t)$ where $U^*(t)$ is the most aggressive, i.e. earliest schedule (trying to keep the storage full)



(1) $0 \leq u(t) \leq a(t)$
power limit
(2) $J(t) \leq U(t) + B_0$
consumption constraint
(3) $U(t) - J(t) + B_0 \leq B_{\max}$
no overflow

B_0 = storage level at $t = 0$
$B_{\max}$ = storage capacity

$U^*(t)$ can be computed iteratively:
$u^*(t) =$
$\min\{a(t),\ B_{\max} - B_0 + J(t-1) - U^*(t)\}$

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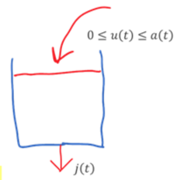
The earliest and latest schedules

- A feasible schedule is constrained by (1) and (2) minimum solution theorem $\Rightarrow U(t) \geq U_*(t)$ where $U_*(t)$ is the laziest (i.e. latest) schedule (trying to deliver energy as late as possible)



(1) $0 \leq u(t) \leq a(t)$
power limit
(2) $J(t) \leq U(t) + B_0$
consumption constraint
(3) $U(t) - J(t) + B_0 \leq B_{\max}$
no overflow

B_0 = storage level at $t = 0$
$B_{\max}$ = storage capacity

$U_*(t)$ can be computed iteratively backwards in time, starting from $U_*(T) = J(T) - B_0$:
$u_*(t) =$
$\min\{a(t), -B_0 + J(t-1) - U_*(t)\}$
$U_*(t-1) = U_*(t) - u_*(t)$

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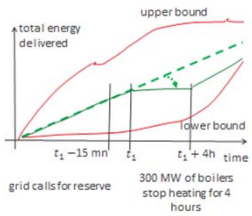
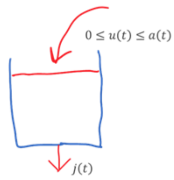
The earliest and latest schedules

- **Theorem**: A tentative schedule $u(t)$ is feasible if and only if it satisfies (1) and
  $U_*(t) \leq U(t) \leq U^*(t)$





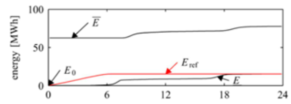
(1) $0 \leq u(t) \leq a(t)$
power limit

(2) $J(t) \leq U(t) + B_0$
consumption constraint

(3) $U(t) - J(t) + B_0 \leq B_{\max}$
no overflow

B_0 = storage level at $t = 0$
$B_{\max}$ = storage capacity

- i.e. any schedule that satisfies the power constraints and is between the earliest and latest schedules is feasible



e-car charging
[Sundstrom and Binding 2012]

Conclusion

- Demand Response adapts loads to cope with variability
- Is required as long as storage of electricity is expensive
- Can use pricing or control by quantity

- Network problem involves economic theory and scheduling

- User problem involves model predictive control (MPC) -- see next lecture

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BONUS

ISSUES WITH DEMAND RESPONSE

[Le Boudec and Tomozei 2013]

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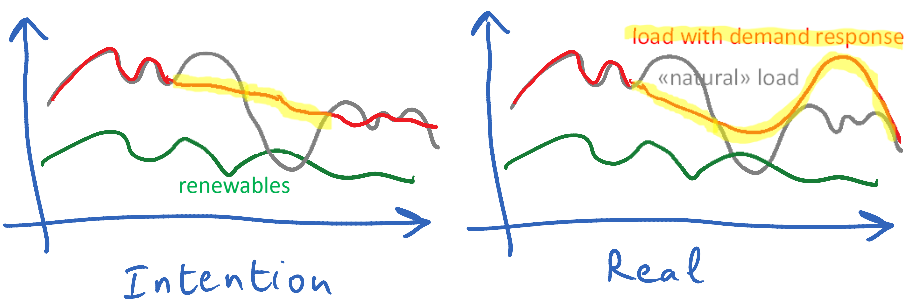
Issue with Demand Response: Grid Changes Load

- Widespread demand response may make load hard to predict



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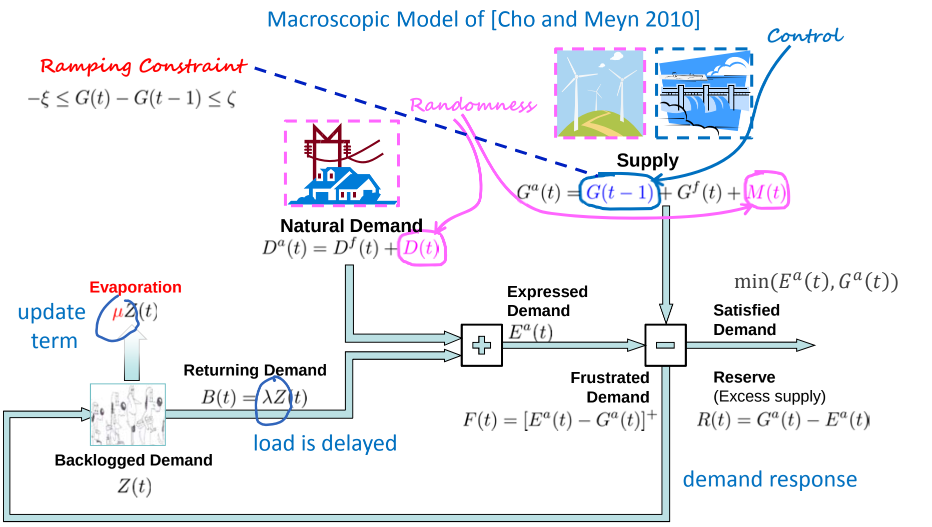
A Macroscopic Model of Demand Response



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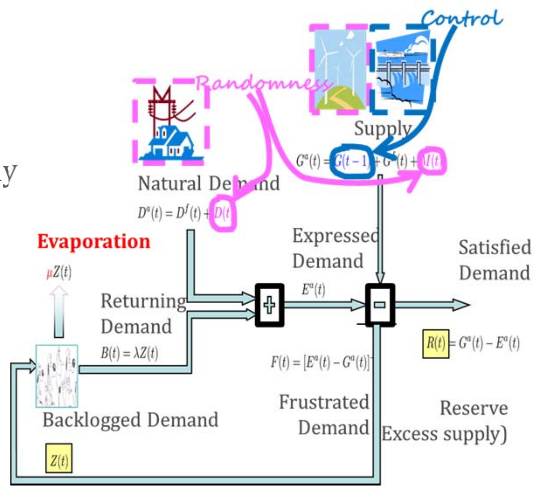
The Control Problem

- **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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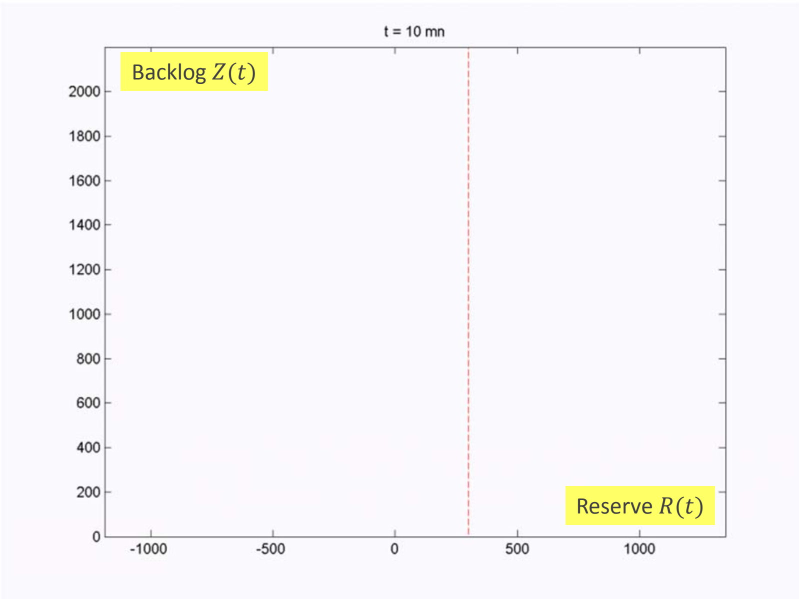
Simulations (evaporation $\mu > 0$)



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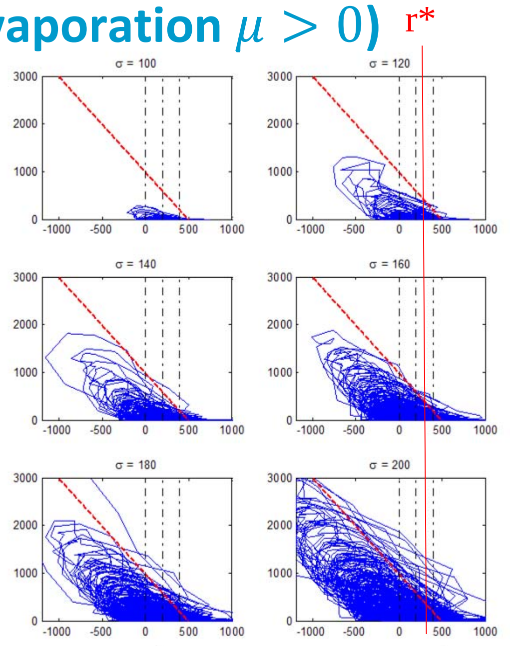
Simulations (evaporation $\mu > 0$)

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



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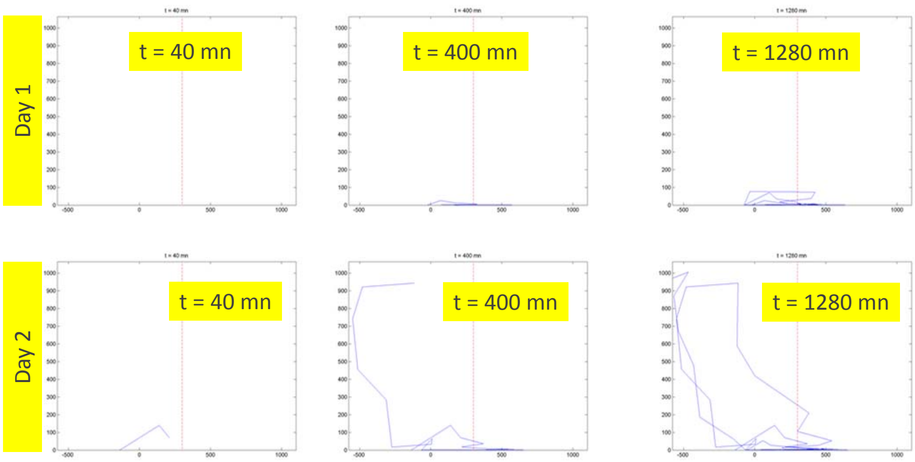
Large backlogs may occur within a day, at any time (when evaporation $\mu > 0$)



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

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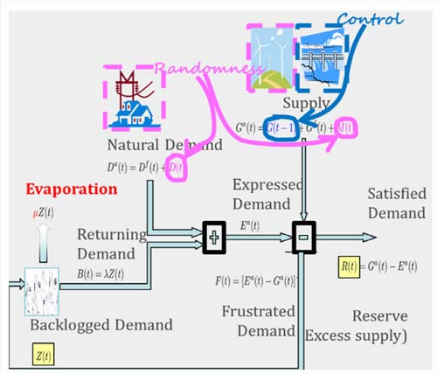
Findings : Stability Results

- 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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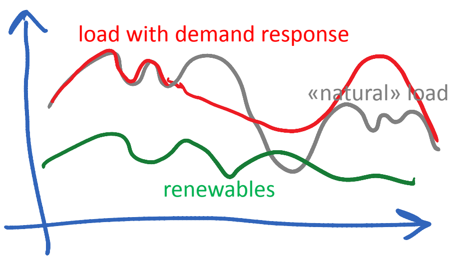
What this suggests about Demand Response:

- 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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