

Demand Response Management (DRM)

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Learning Objectives

Throughout this lecture, it is aimed for the students to be able to

Learn about the **basic concepts** in Demand Response Management (DRM)

Learn about different **pricing schemes** in smart grid

Understand the **energy scheduling** problem formulation for a **home energy management system**, solution, tool and applications related to demand response

Industry Invited Talk Today

Speaker

Kari Dalen, *Seniorrådgiver, System- og balansetjeneste, Statnett*

Title

**Demand Response Management:
An industrial perspective**

Statnett is Norway's main (national) grid owner and operator

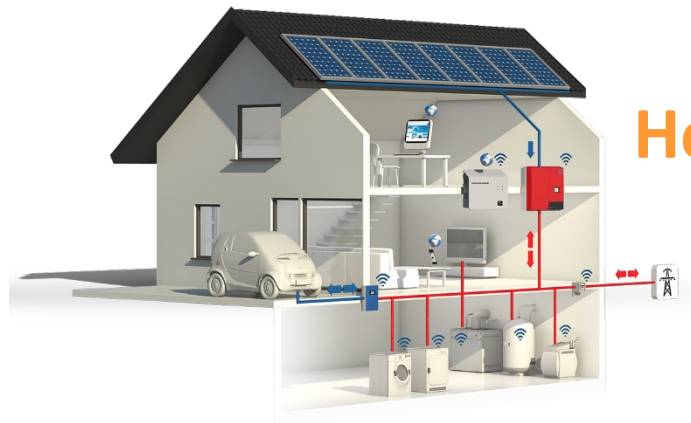


Statnett

Outline

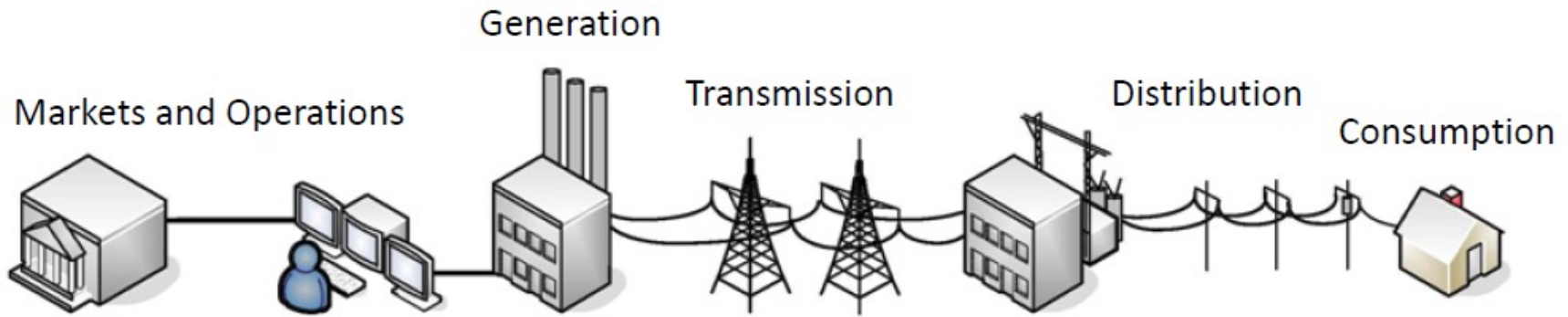


Definitions and Key Concepts

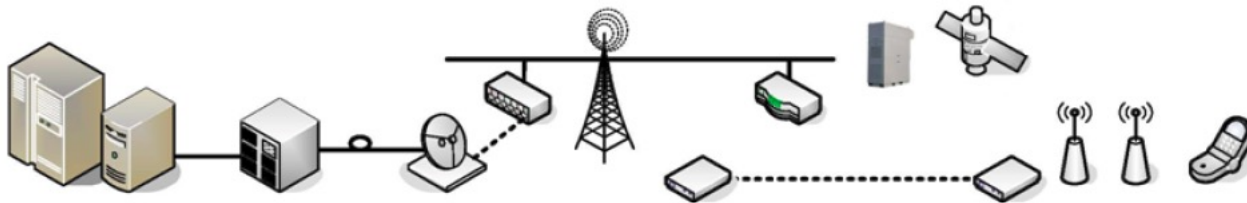
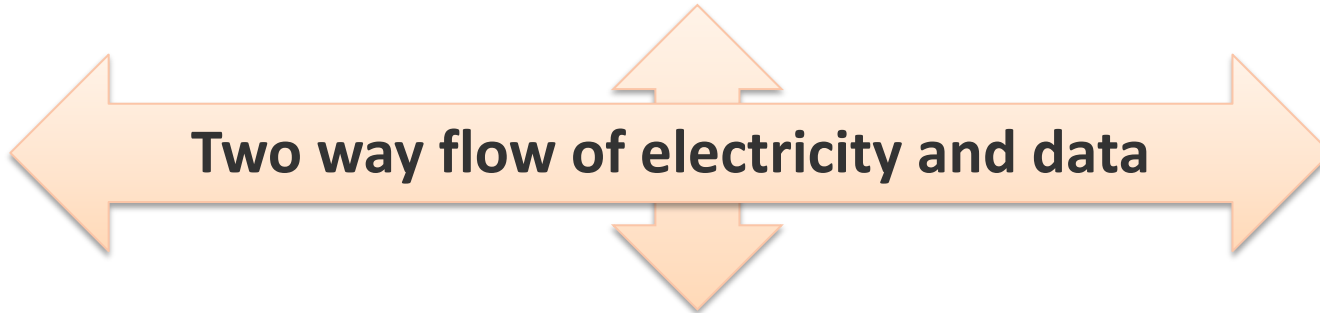


Home Energy Management

Smart Grid = Power Grid + ICT



Power infrastructure



Communications infrastructure

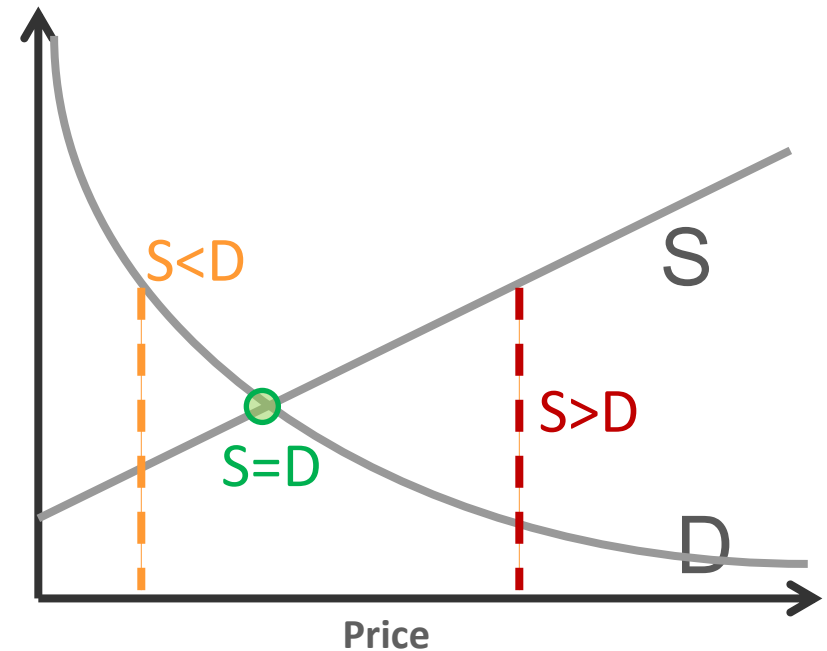
Energy balance: power generation is equal to power demand

Energy balance is very important for energy systems stability and economy.

Why?

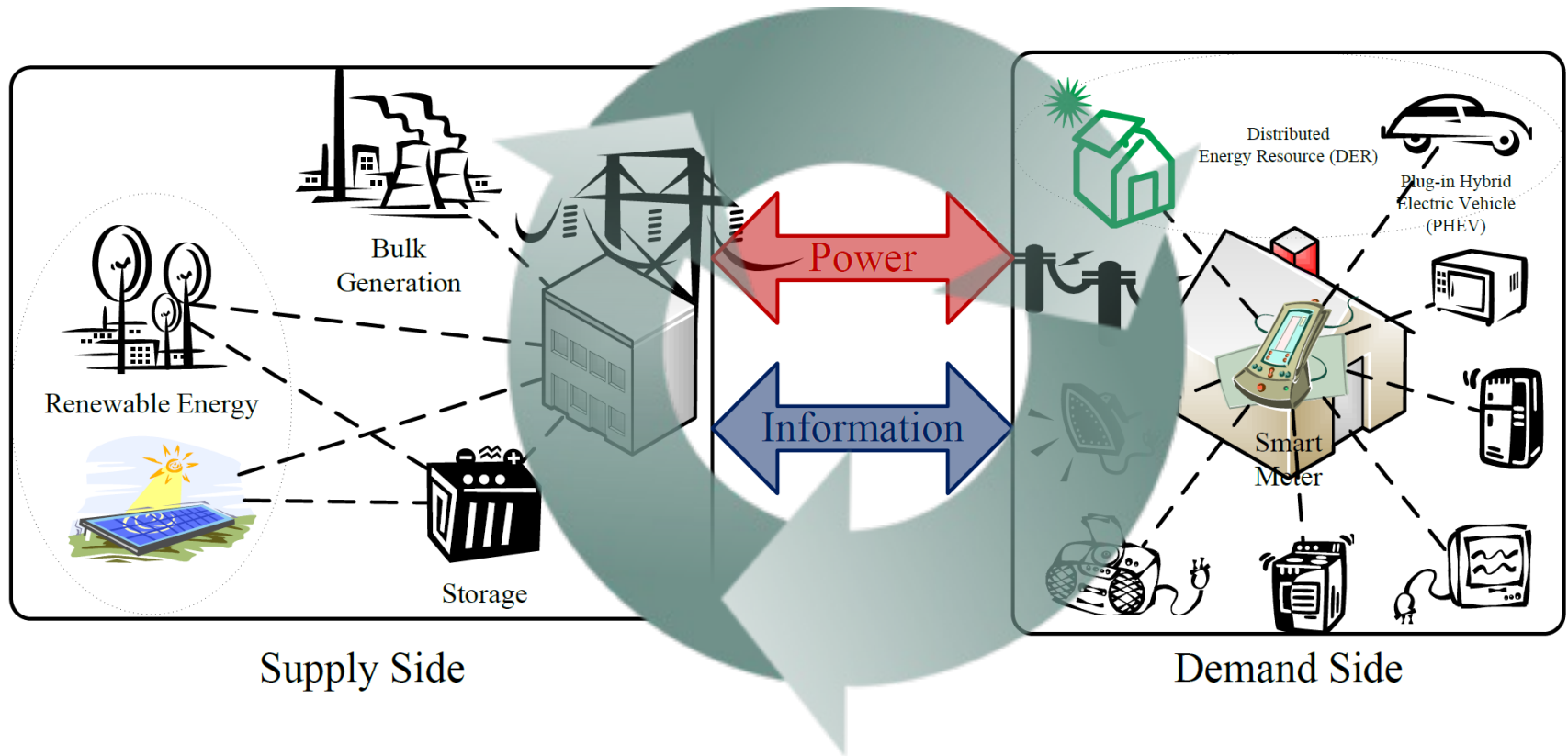
If $S > D$, power generation is higher, generators may suffer economic loss

If $S < D$, power generation is not sufficient, it may lead to power blackout



S: power supply from generators;
D: power demand from customers;
Energy balance point: $S=D$

Demand Response Management (DRM) is the main approach to achieve energy balance



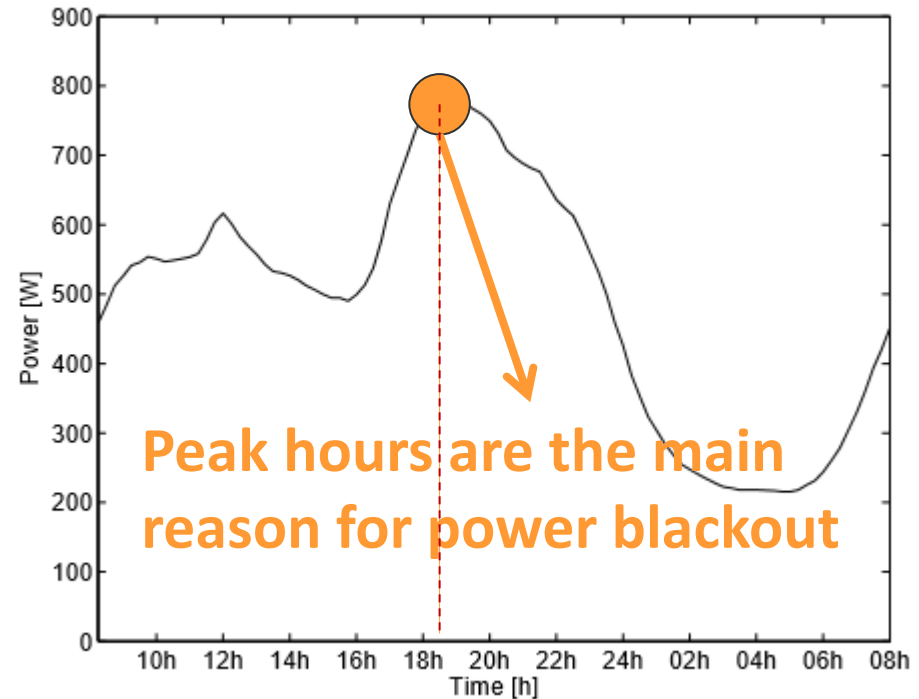
DRM studies the **interaction** between the supply and the demand sides through bidirectional flow of power and information.

A typical residential household load during winter

The power load may vary significantly over time and location

The practical load profile is rather unbalanced

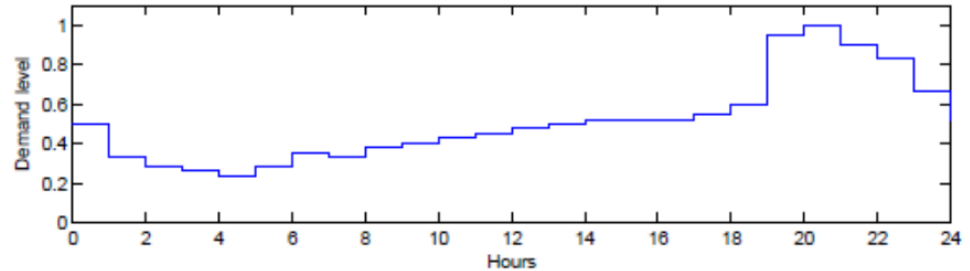
- Residential peak load (late afternoon)
- Industrial peak load (morning)



Household load in winter (source: www.vreg.be)

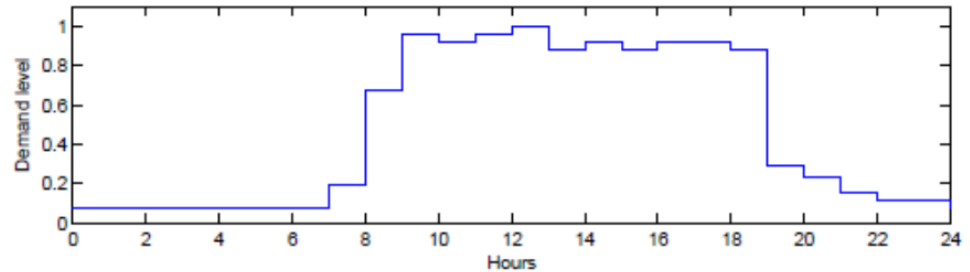
Different users have different power demand load

Residential users



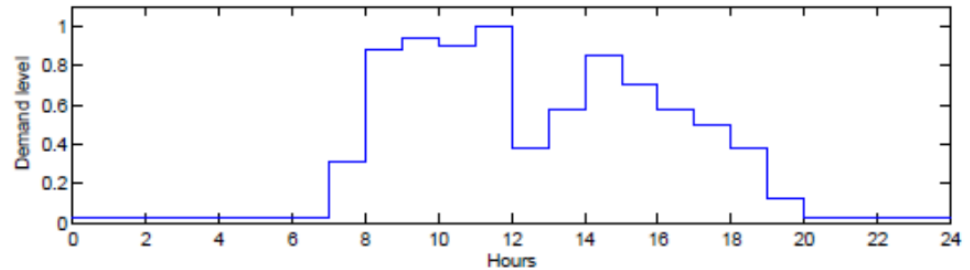
(a) Residential load.

Commercial users
(e.g., shopping malls)



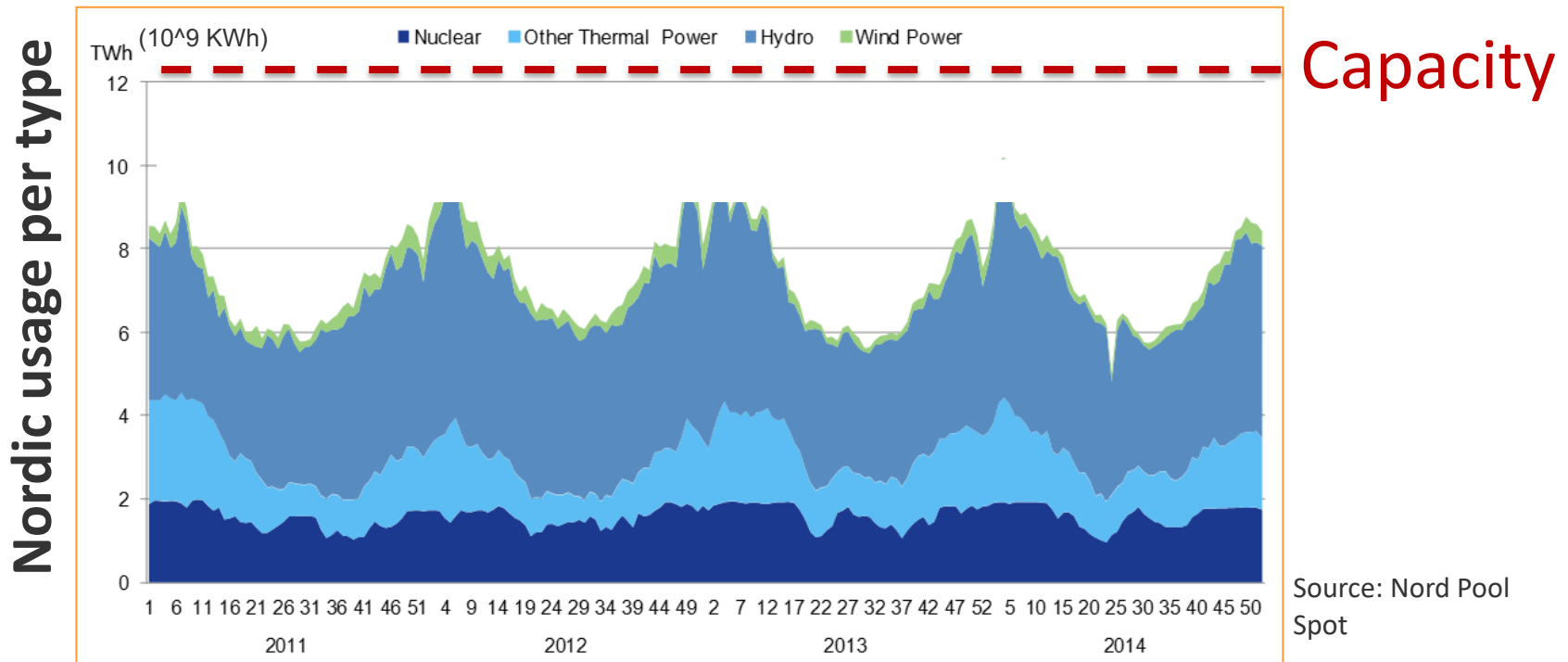
(b) Commercial load.

Industrial users
(e.g., factories)



(c) Industrial load.

The peak load issue



Power infrastructure is designed for peak loads.

Peaks have **less than 1%** of the time. Reducing peaks can then reduce power generation and **save considerable costs** and also **save investments** in the long run.

Demand Response Management (DRM) definition

According to the US. Department of Energy

Demand Response Management (DRM) is defined as **changes in electric usage by end-use customers** from their normal consumption patterns **in response to** changes in the **price** of electricity over time, or to **incentive payments** designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.

In plain language

Users will change energy usage behaviors according to different electricity prices, or incentive payments, or system reliability

Q: Can DRM help reduce peak load?

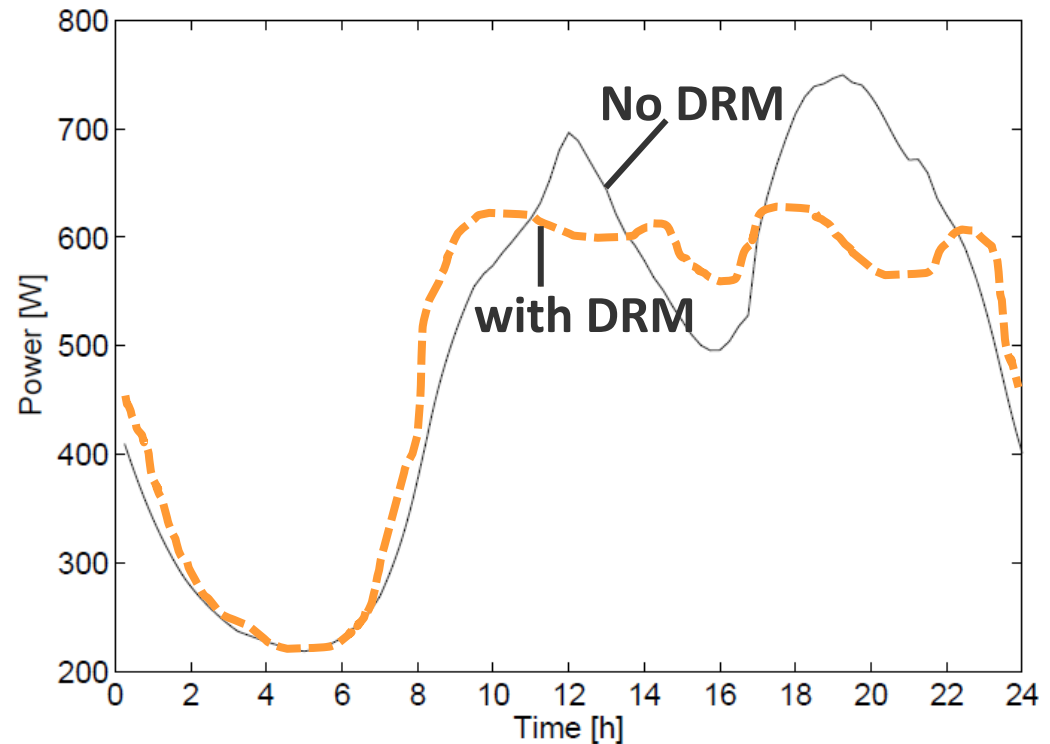
Objectives of DRM

Reduce energy consumption

- encourage energy-aware consumption patterns
- Reduce power generation

Shift the energy consumption

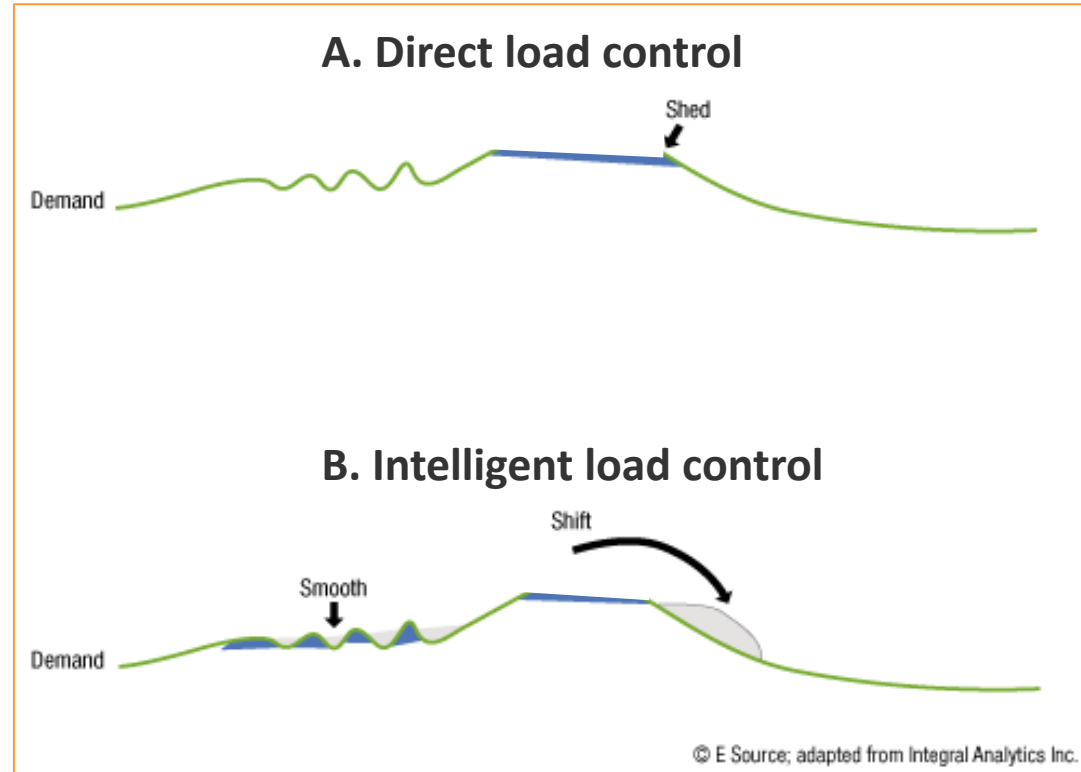
- Mitigate power load during the peak hours
- Improve grid reliability



Approaches to DRM

Direct Load Control (DLC)

Intelligent Load Control /
Pricing



Q: What is the difference between these two approaches?

Direct Load Control (DLC)

The utility has remote access to certain load of users

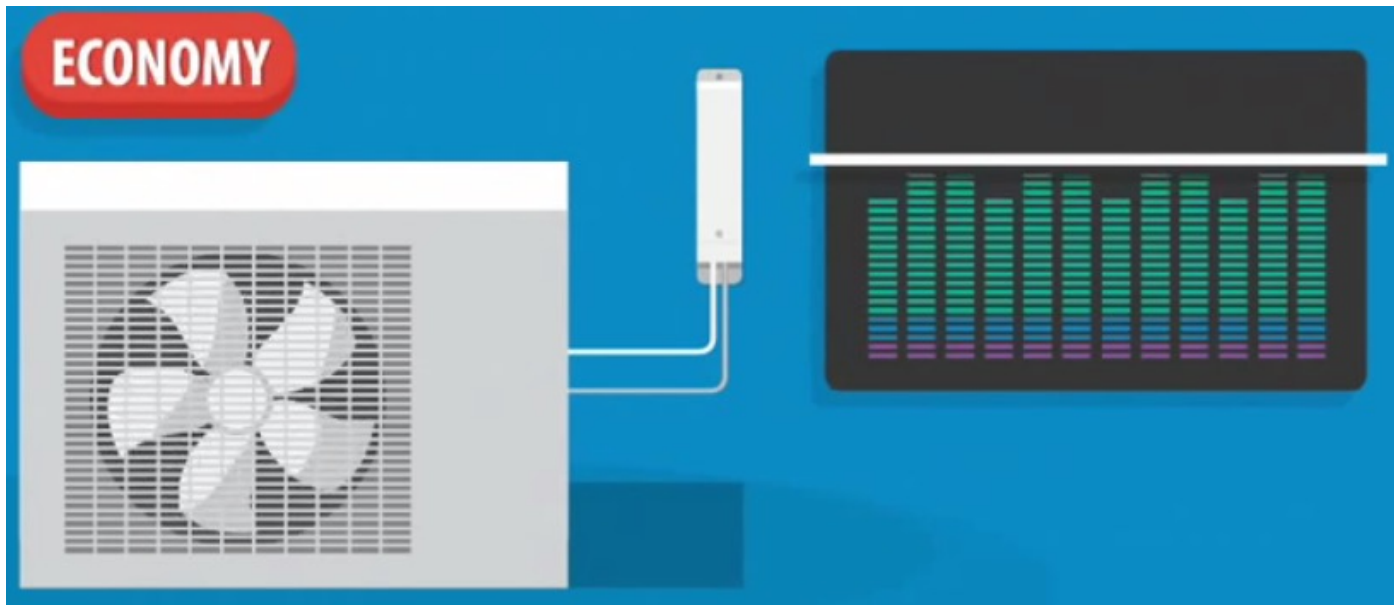
- Air conditioner
- Water heater

The utility can remotely turn on or off the load when needed

DLC should be transparent to users. **Why?**



Direct Load Control example – Energex in Queensland, Australia



New device: a signal receiver is installed in a air-conditioner. The utility can remotely turn on or off the load; or cap energy consumption when needed

Reward: participants are rewarded by up to \$400

Result: (1) be transparent to users (Q: Why?); (2) reduce peak

You may watch 2-minute video at: <https://youtu.be/fQQYNMofG5w>

Intelligent Load Control / Smart Pricing

Price-based program provides users **different prices at different times**

When users know about the price changes

- They will naturally use less electricity when electricity prices are high
- This will reduce the demand at peak hours

This program indirectly induces users to **dynamically change their energy usage patterns according to the variation in electricity prices**, instead of directly controlling their loads.

Three pricing models

- Time-of-Using (ToU) pricing
- Real-time Pricing (RTP)
- Inclining Block Rates (IBR)

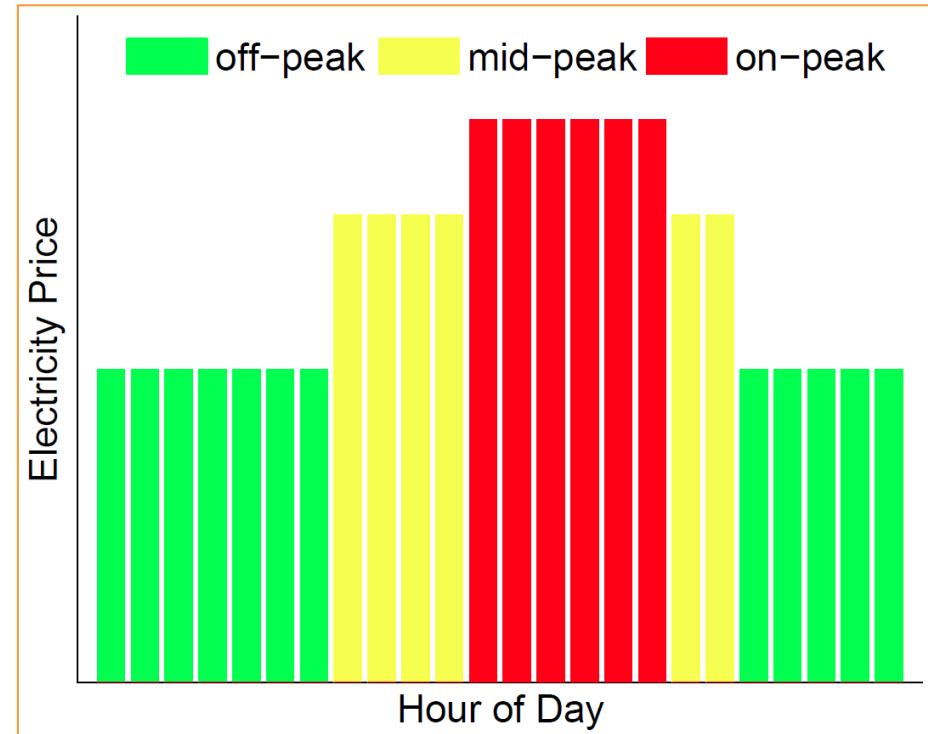
Time-of-Use (ToU) Pricing

When users consume energy at different time intervals of a day, they are charged at different electricity prices

ToU pricing is usually released far in advance, and keeps unchanged for a long time period.

Examples

- Ontario, Canada
- Ausgrid (Australia)



Three-level
(on-peak, mid-peak, off-peak) ToU pricing

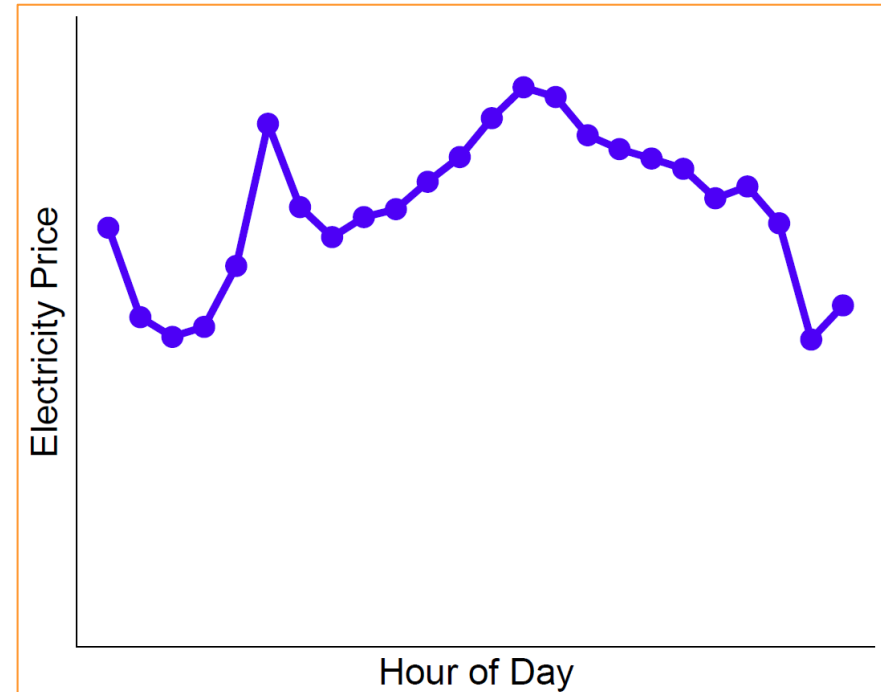
Real-Time Pricing (RTP)

The electricity price usually varies at different time intervals of a day (e.g., in each hour)

RTP is usually **released on an hour-ahead pricing or day-ahead pricing basis**

Examples

- Chicago uses hourly-based RTP
- In Oslo, you may have RTP from Sognekraft AS in the name of “Innkjøpspris” plan (source: <http://www.strompris.no>)



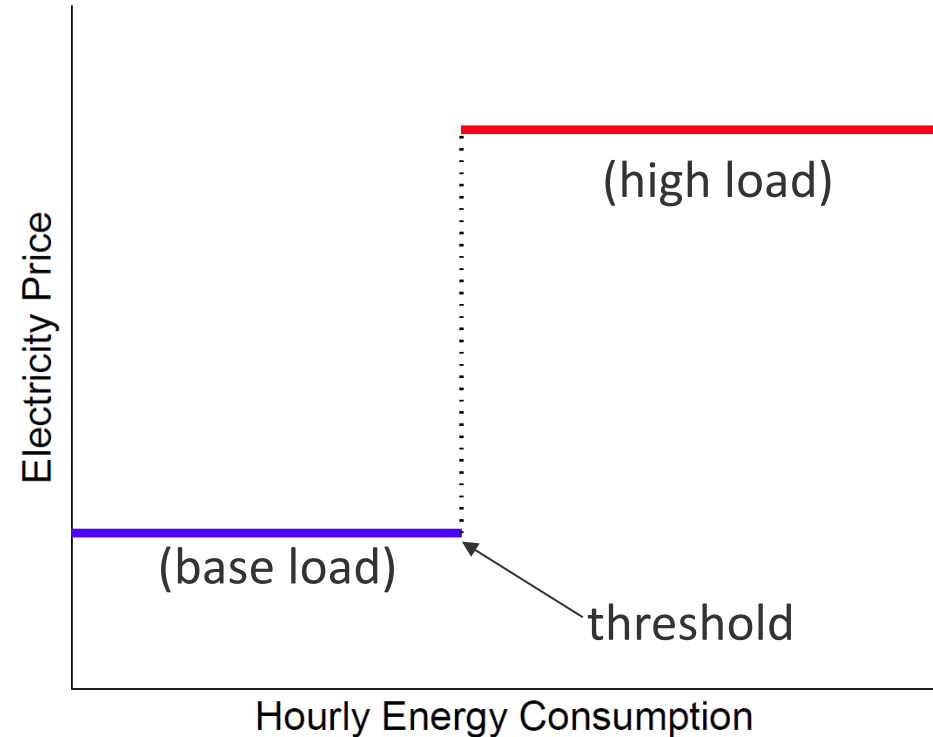
Inclining Block Rates (IBR)

Two-level rate structures

- base load and high load
- Price increases sharply if energy usage exceeds threshold

Motivations

- A user pays more when consuming more energy
- Users evenly distribute loads among different times of a day to avoid higher rates



Adopted by

- Pacific Gas and Electric, USA;
- British Columbia Hydro, Canada

Electricity Pricing in Oslo (source: <http://www.strompris.no>)

Fixed Price (e.g., Helgeland Kraft AS)

A fixed price for an agreed period of time, normally one year. In exchange you cannot change supplier within the period

Variable Price (e.g., FjordKraft AS)

Price will be as offered for the next 2-3 weeks. Maybe changed, normally with 2 weeks notice.

Purchase Price (e.g., Sognekraft AS)

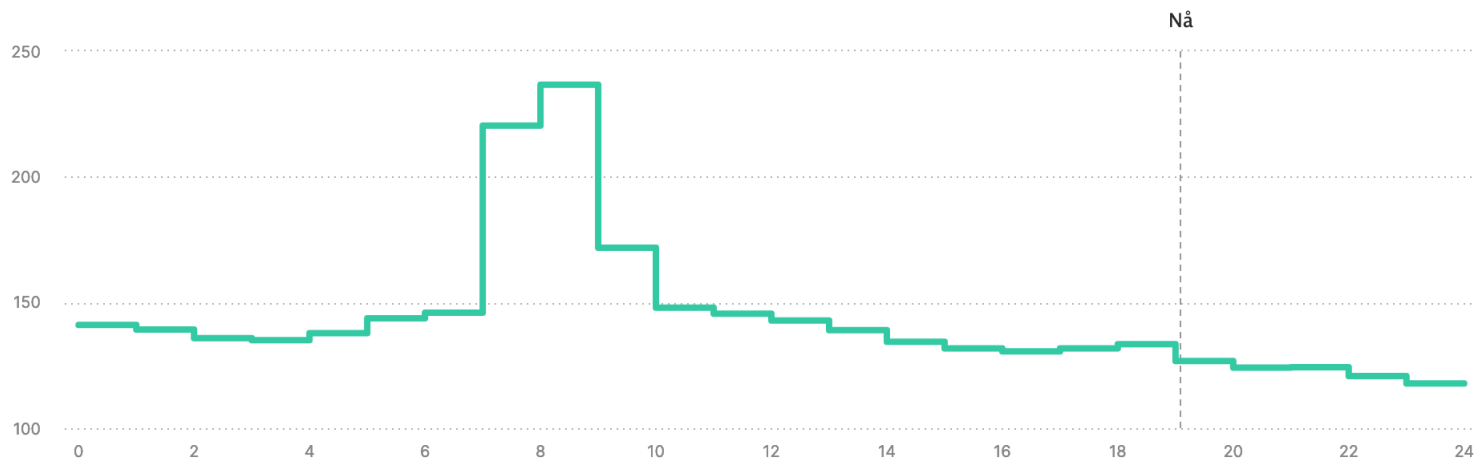
Price follows the hourly prices at the electricity exchange Nord Pool Spot

→ **Similar to real-time pricing**

Electricity Price in Norway

Så mye koster strømmen

Strømprisen i **Oslo** akkurat nå er **126,75 øre** per kWh (spotpris uten MVA, avgifter og nettleie). Gjennomsnittsprisen i dag er **144,1 øre**. Klokken 08-09 er strømmen dyrest. Da er prisen **236,68 øre**.



Velg tid

Strømprisene i dag er **390 %** høyere enn samme uke 2013-19 .

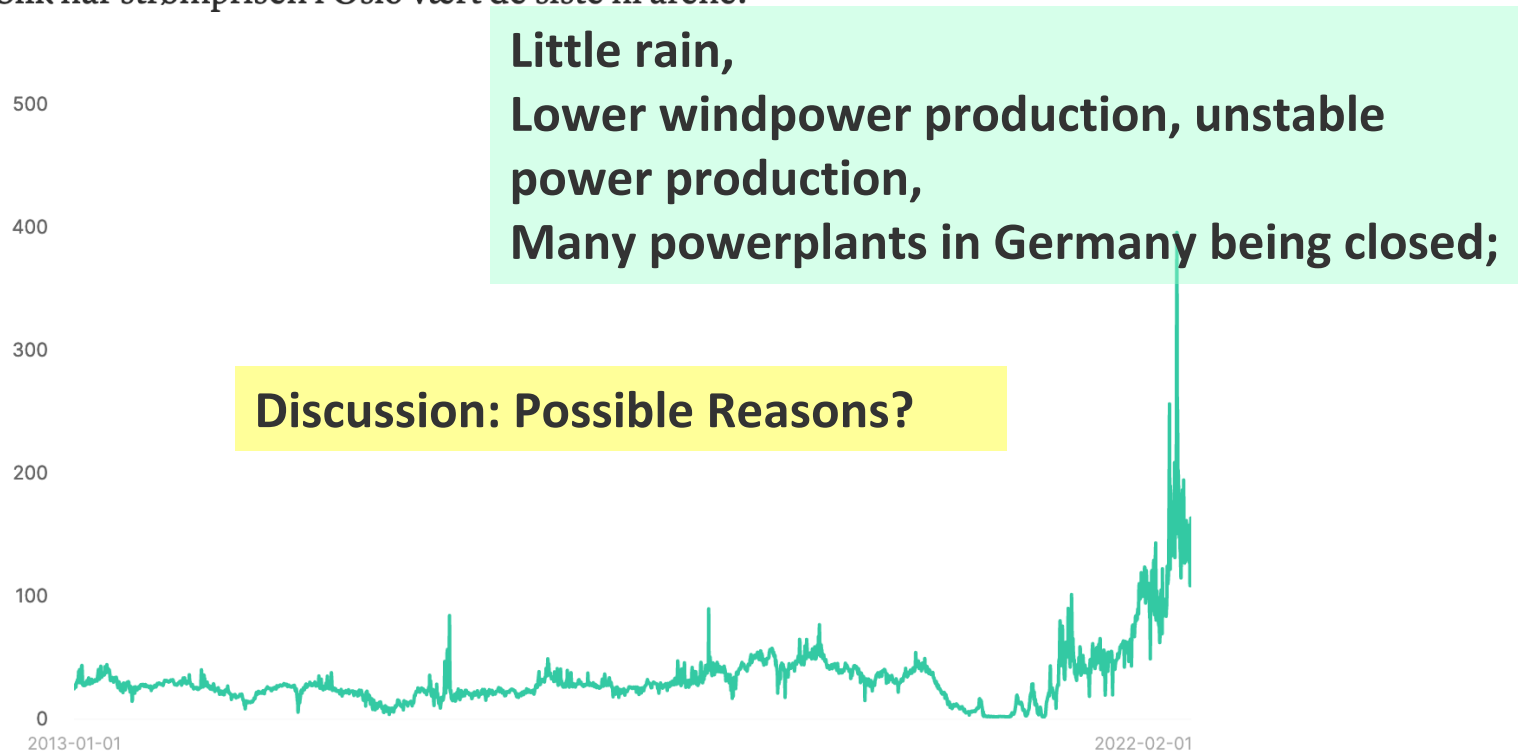
I morgen er gjennomsnittlig strømpris **134,77 øre** per kWh. Strømmen er dyrest i tiden 21-22. Da koster den **157,39 øre**.

Electricity Price in Norway

Historisk dyrt

Strømrekorden i Oslo var **tirsdag 21. desember 2021**. Da var gjennomsnittsprisen **395,41 øre** for én kWh.

Slik har strømprisen i Oslo vært de siste ni årene:

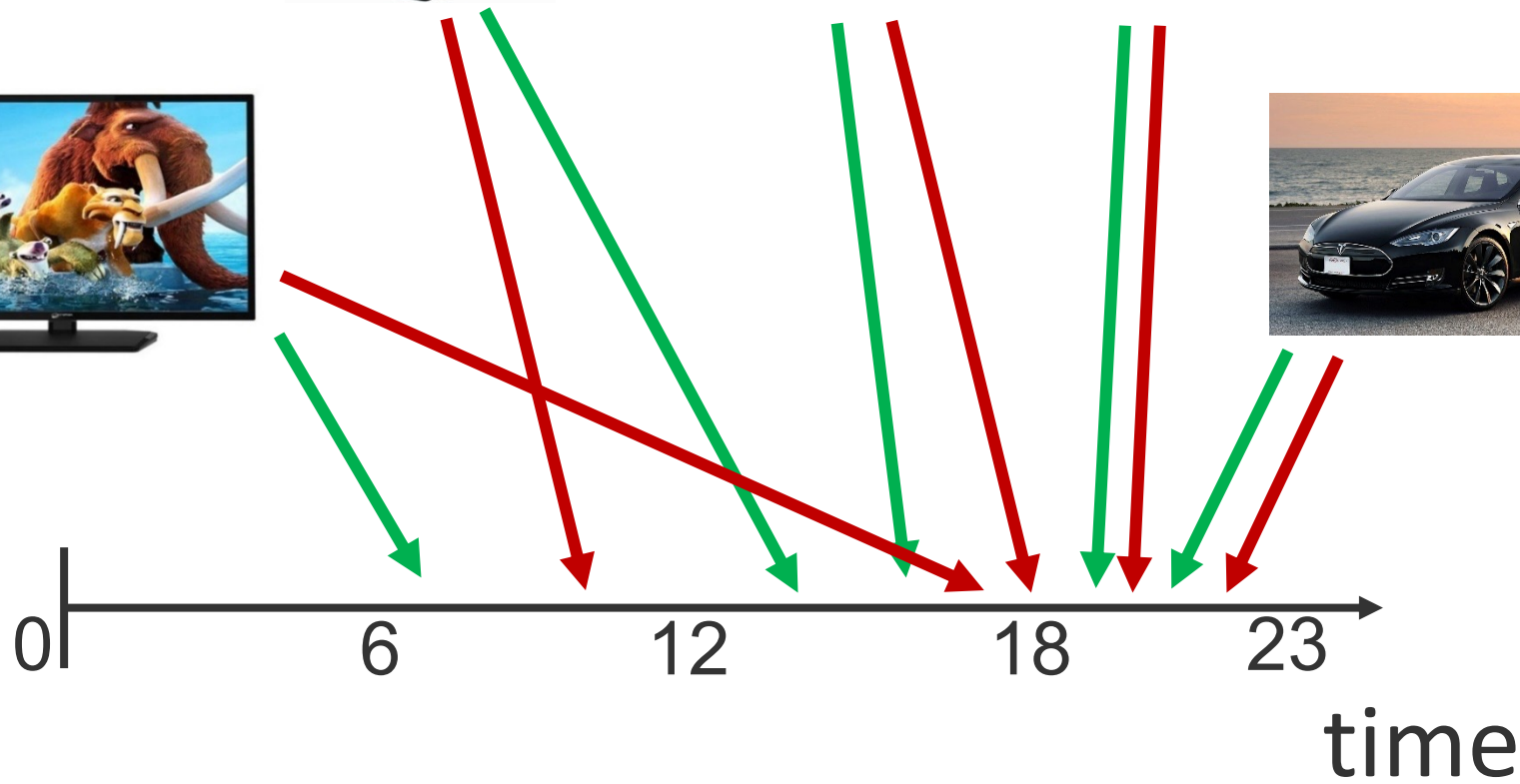


Fit for 55

<https://www.consilium.europa.eu/en/policies/green-deal/fit-for-55-the-eu-plan-for-a-green-transition/>

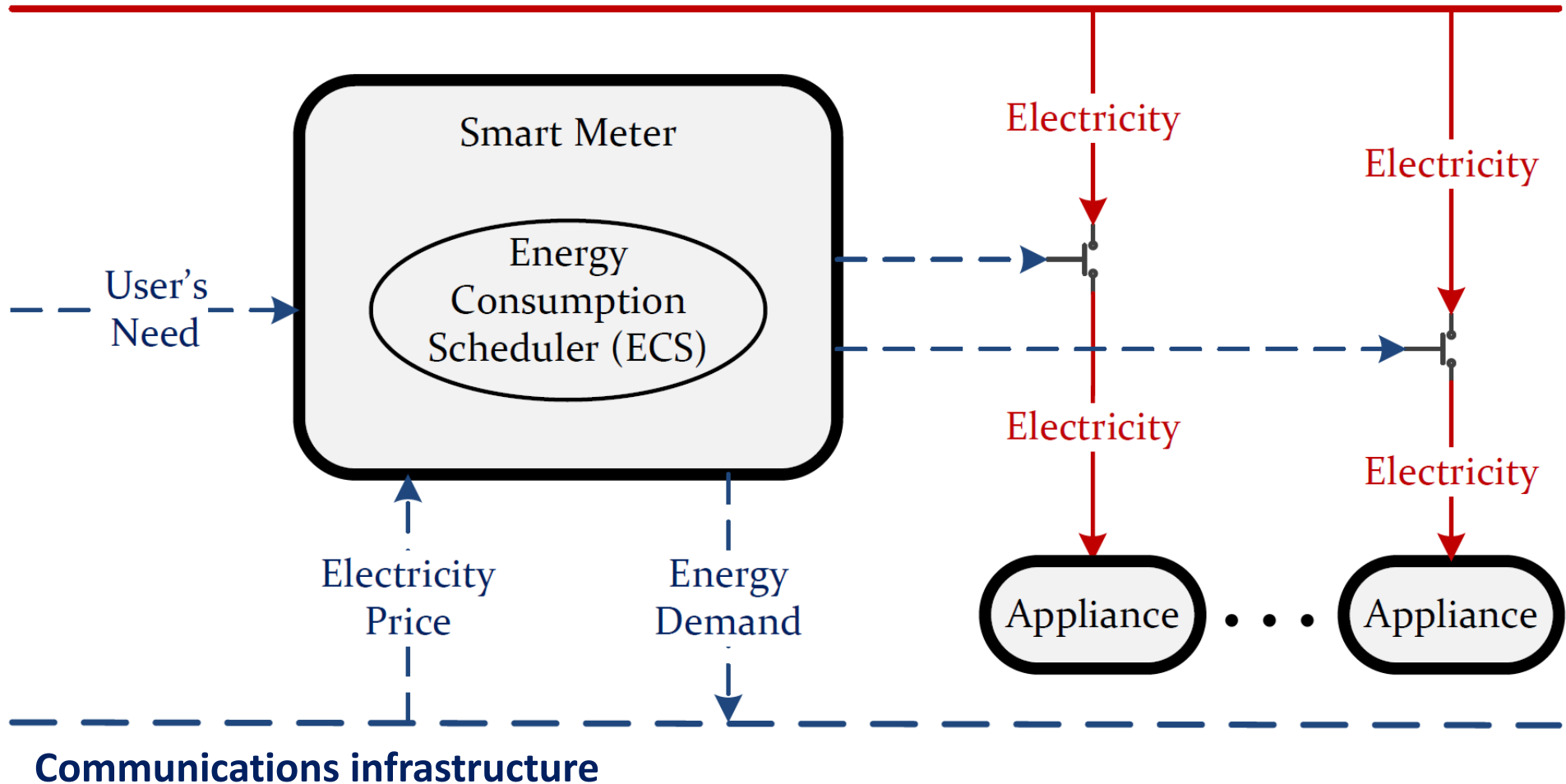
HOME ENERGY MANAGEMENT SYSTEM

When shall we use appliances/devices at home?



In a house, a smart meter can automatically coordinate appliances to satisfy the user's need via ON/OFF control

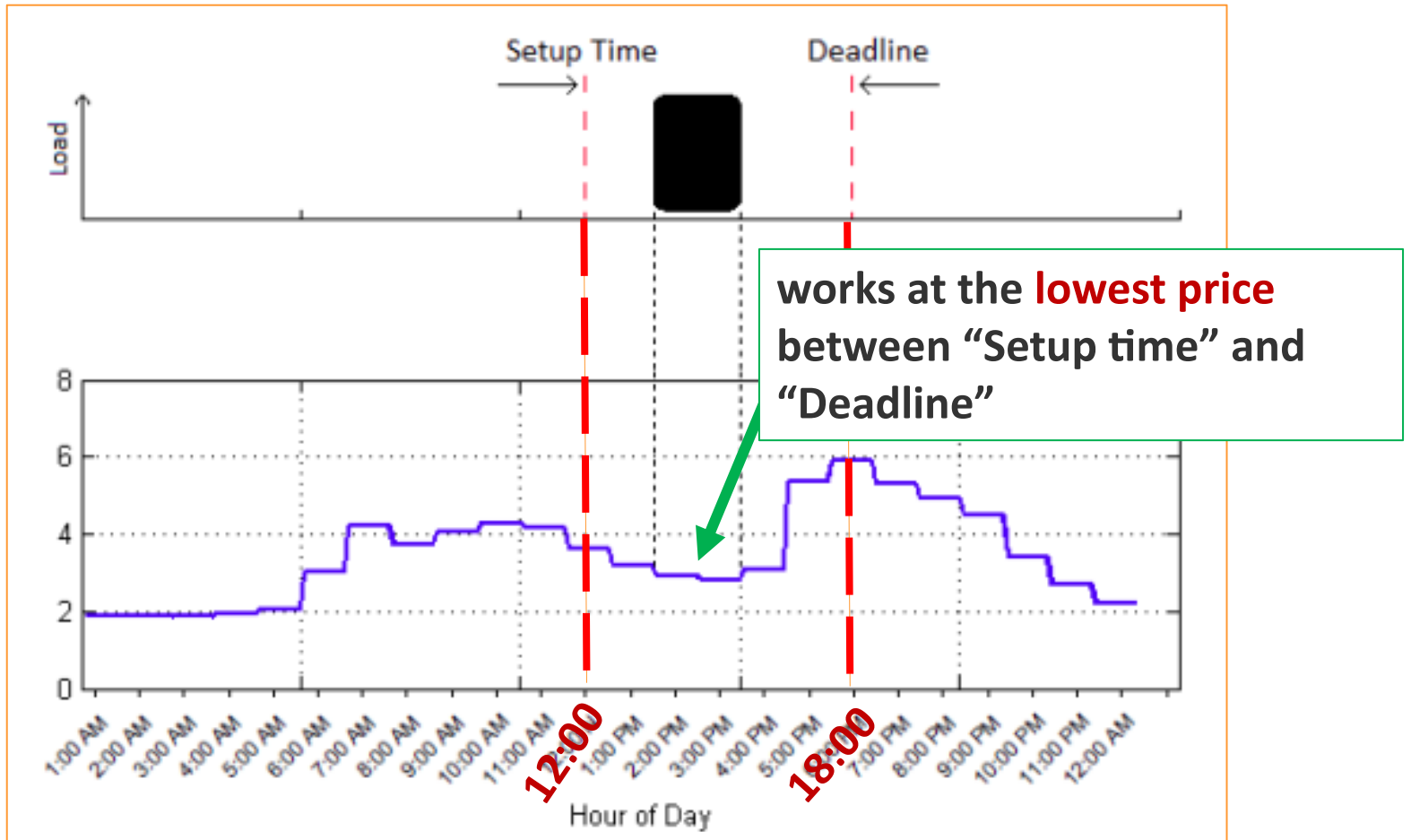
Power infrastructure



Energy Consumption Scheduling

A simple example: dishwasher after lunch

Q: why choose time period between 1:30-3:30pm?



Power consumption of appliances

Hvor mye strøm bruker jeg?

Spotprisen i Oslo akkurat nå er **206,75** øre per kWh.

Her ser du hva noen vanlige ting koster deg akkurat nå. Du kan endre tiden ved å skrive i feltene under.

Sekunder	Minutter	Timer
0 <input type="text"/>	10 <input type="text"/>	0 <input type="text"/>

What about scheduling the appliances that consume the most power?



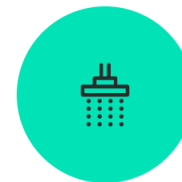
Lyspære (35 W)



Vaskemaskin



Varmeovn (1 kW)



Dusje

Energy Consumption Scheduling is actually not simple since we have many different appliances

Non-shiftable appliances

(e.g., TV, lights, cooking): must be kept ON for a certain period of time.



Shift able appliances

(e.g., washing machines, Electric Vehicles, and clothes dryers): the operation task can be shifted to a different time period



Q: which type of appliances?



refrigerator



dishwashers



fire alarm

Energy Consumption Scheduling problem

Q: Given the price values, how should we schedule the power load?

Scheduler should analyze

- User's energy consumption needs
- Price values

The schedule is normally an optimal solution with different preferences

- Minimize the cost of electricity
- Maximize user's comfort

} tradeoff

Energy Consumption Scheduling – parameters

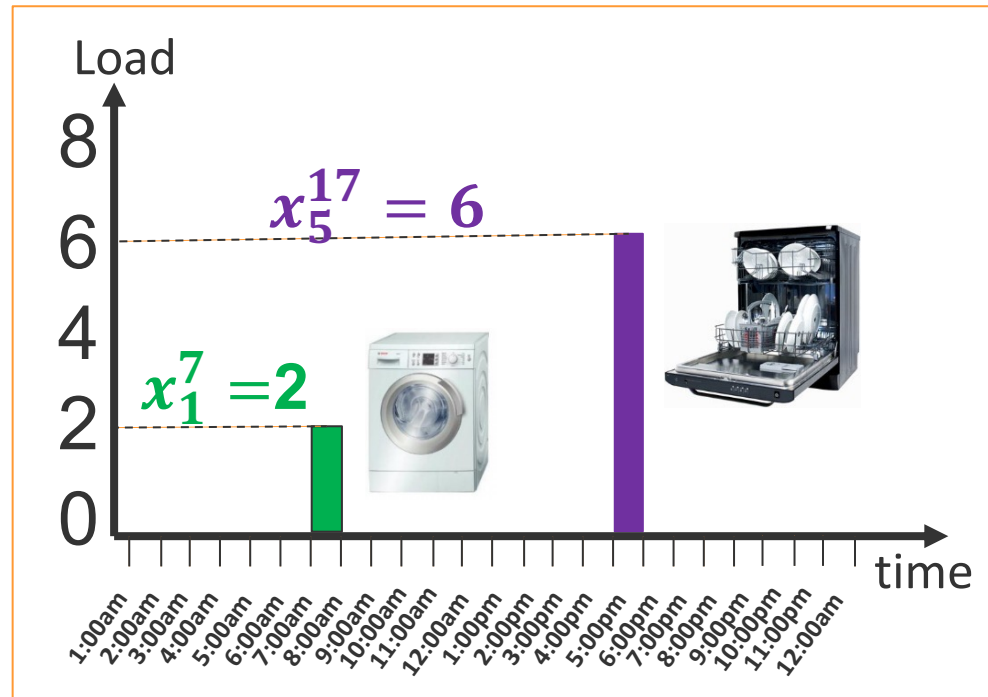
Let A denote the set of appliances

- Washing machines, TV, lights, Dryer, Dishwasher, EVs (Electric Vehicle)...

For each appliance $a \in A$, we define a daily **energy consumption scheduling vector** x_a :

$$x_a = [x_a^1, \dots, x_a^H]$$

where $H = 24$ hours



Energy Consumption Scheduling – operation time constraint

For each appliance $a \in A$, the user should indicate:

- α_a : beginning of the operation time (**setup time**)
- β_a : end of the operation time (**deadline**)

Operation should be scheduled within $[\alpha_a, \beta_a]$

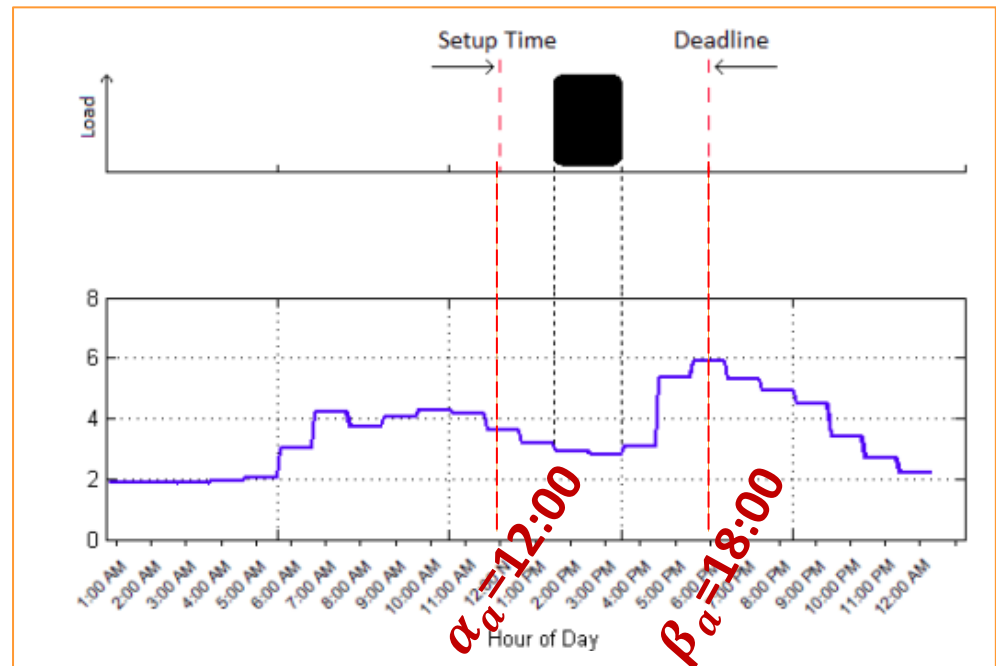
Example

Dish washer after lunch:

Setup time $\alpha_a = 12$ Noon and

deadline $\beta_a = 6$ PM

\bar{z} (make dishes ready for dinner)



Energy Consumption Scheduling – power level constraint

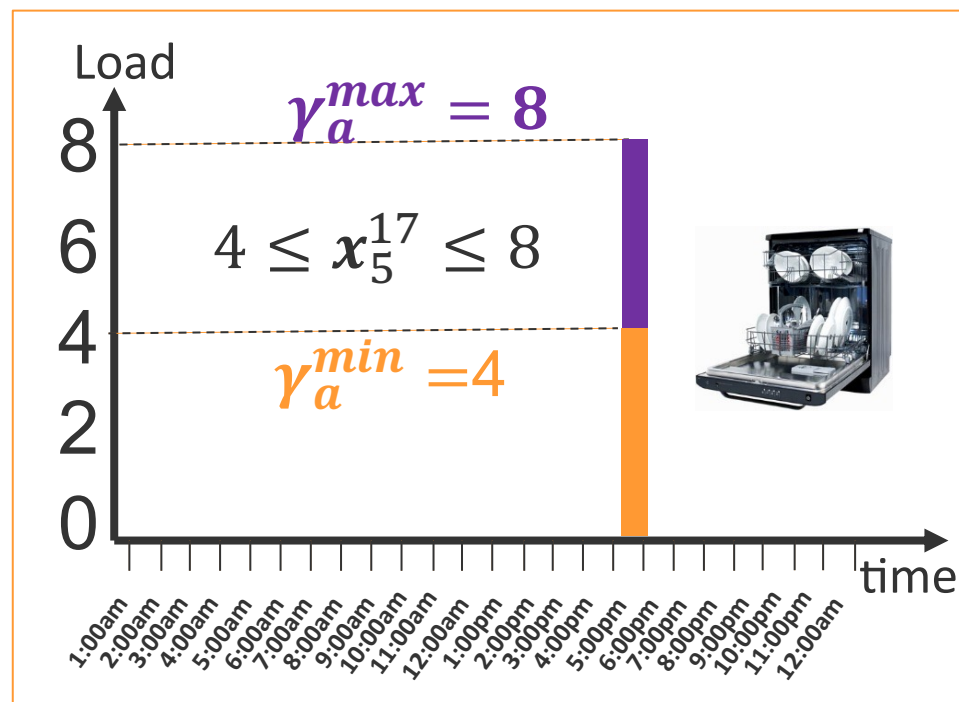
Each appliance $a \in A$ usually has a **maximum power** level γ_a^{max}

– NISSAN Leaf: charged up to 3.6 kW per hour

Each appliance $a \in A$ may also have a **minimum power** level γ_a^{min}

For each appliance $a \in A$, it is required that

$$\gamma_a^{min} \leq x_a^h \leq \gamma_a^{max}$$
$$\forall a \in A, h \in [\alpha_a, \beta_a]$$



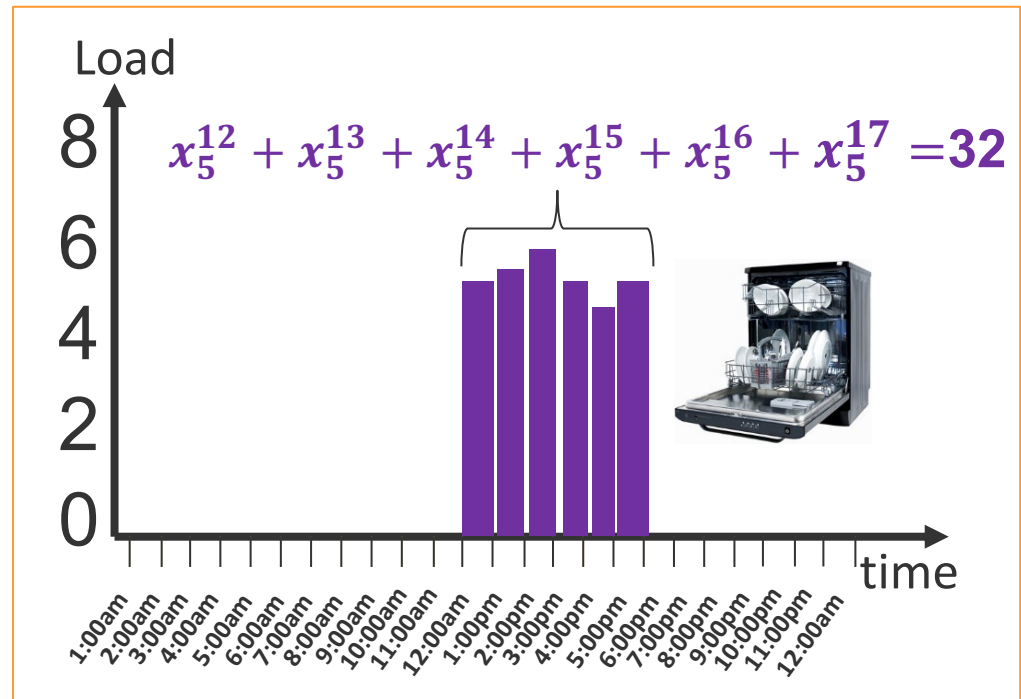
Energy Consumption Scheduling – total consumption constraint

Let E_a denote the **total energy needed** for the operation of appliance $a \in A$

- Bosch WAS20160UC washing machine: $E_a = 0.36$ kWh per operation

Given parameters E_a , α_a , and β_a , it is required that

$$\sum_{h=\alpha_a}^{\beta_a} x_a^h = E_a, \quad a \in A.$$



Cost Minimization

Energy Consumption Scheduling problem to minimize cost

$$\min_{\mathbf{x}} \sum_{h=1}^H p^h \times \left(\sum_{a \in A} x_a^h \right)$$

Load from all appliances
in hour h

Subject to

$$\sum_{h=\alpha_a}^{\beta_a} x_a^h = E_a, \quad \forall a \in A,$$

$$\gamma_n^{\min} \leq x_a^h \leq \gamma_n^{\max}, \quad \forall a \in A, h \in [\alpha_a, \beta_a]$$

$$x_a^h = 0, \quad \forall a \in A, h \notin [\alpha_a, \beta_a]$$

p^h : unit price of electricity in hour h .
Could be ToU or RTP model


Q: Is this a linear programming optimization problem?

Optimization Basics

Optimization in standard form

minimize $f_0(x)$  **objective function**

subject to $f_i(x) \leq b_i, \quad i = 1, \dots, m$

 **constraint functions**

$x = (x_1, x_2, \dots, x_n)$: optimization variables

Optimal solution

x^* has smallest value of f_0 among all vectors that satisfy the constraints

Linear Programming Basics

$$\begin{array}{ll} \text{minimize} & f^T x \\ \text{subject to} & Ax \leq b \end{array}$$

where $f = (f_1, f_2, \dots, f_n)$; $b = (b_1, b_2, \dots, b_n)$; $A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,n} \\ a_{2,1} & a_{2,2} & \dots & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \dots & a_{m,n} \end{pmatrix}$

Matlab **linprog** function solves linear programming optimization problem

$$\min_x f^T x \text{ such that } \begin{cases} A \cdot x \leq b, & \longrightarrow \text{inequality constraint} \\ A_{eq} \cdot x = b_{eq}, & \longrightarrow \text{equality constraint} \\ lb \leq x \leq ub. & \longrightarrow \text{bound constraint} \end{cases}$$

 $x = \text{linprog}(f, A, b, A_{eq}, b_{eq}, lb, ub)$

Other Programming Languages



- Free software environment for statistical computing.
<https://www.r-project.org/>
- Several solvers available for solving linear programming models. A list can be found in <http://bit.ly/1zkJpVw>.
- Of particular interest: `lp_solve` is implemented through the `lpSolve` and `lpSolveAPI` packages.
- More information: Google “linear programming with R”



- You can use package `scipy.optimize.linprog`
- An easy and good example:
<http://www.vision.ime.usp.br/~igor/articles/optimization-linprog.html>
- More information: Google “linear programming with Python”

Demand Response Example: two appliances at a home

Assumption:

Two appliances: EV and washing machine

We assume that we have 4 hours per day

Now, we need to decide:

For EVs, how much energy should be used in each timeslot

For washing machine, how much energy should be used in each timeslot

Demand Response Example: two appliances at household

We define

- x_i ($i=1,2,3,4$): amount of energy used for EV in hour i
- y_i ($i=1,2,3,4$): amount of energy used for washing machine in hour i
- p_i ($i=1,2,3,4$): price in each hour. Price is an input parameter

We need to decide optimal x_i and y_i to minimize the energy cost

- x_i^* ($i=1,2,3,4$)
- y_i^* ($i=1,2,3,4$)

Problem formulation

Cost minimization: $p1 * x1 + p2 * x2 + p3 * x3 + p4 * x4$
 $+ p1 * y1 + p2 * y2 + p3 * y3 + p4 * y4$

subject to

$x1 + x2 + x3 + x4 = 9.9$

total energy consumption per day for EV

$y1 + y2 + y3 + y4 = 5.0$

total energy consumption per day for washing machine

$x1 \leq 3.0$

$x2 \leq 3.0$

$x3 \leq 3.0$

$x4 \leq 3.0$

max power usage per hour for EV

$y1 \leq 1.5$

$y2 \leq 1.5$

$y3 \leq 1.5$

$y4 \leq 1.5$

max power usage per hour for washing machine

10 constraints

Programming in R (I)

```
p <- runif(4) #random function to generate price in each hour
```

```
f.obj <- c(p[1], p[2], p[3], p[4], p[1], p[2], p[3], p[4])
```

```
c1 <- c(1, 1, 1, 1, 0, 0, 0, 0)
```

```
c2 <- c(0, 0, 0, 0, 1, 1, 1, 1)
```

```
c3 <- c(1, 0, 0, 0, 0, 0, 0, 0)
```

```
c4 <- c(0, 1, 0, 0, 0, 0, 0, 0)
```

```
c5 <- c(0, 0, 1, 0, 0, 0, 0, 0)
```

```
c6 <- c(0, 0, 0, 1, 0, 0, 0, 0)
```

```
c7 <- c(0, 0, 0, 0, 1, 0, 0, 0)
```

```
c8 <- c(0, 0, 0, 0, 0, 1, 0, 0)
```

```
c9 <- c(0, 0, 0, 0, 0, 0, 1, 0)
```

```
c10 <- c(0, 0, 0, 0, 0, 0, 0, 1)
```


$$x_1 + x_2 + x_3 + x_4 = 9.9$$

$$y_1 + y_2 + y_3 + y_4 = 5.0$$


$$x_1 \leq 3.0; x_2 \leq 3.0;$$

$$x_3 \leq 3.0; x_4 \leq 3.0;$$


$$y_1 \leq 1.5; y_2 \leq 1.5;$$

$$y_3 \leq 1.5; y_4 \leq 1.5;$$

```
f.con <- matrix (c(c1, c2, c3, c4, c5, c6, c7, c8, c9, c10), nrow =  
10, byrow=TRUE)
```

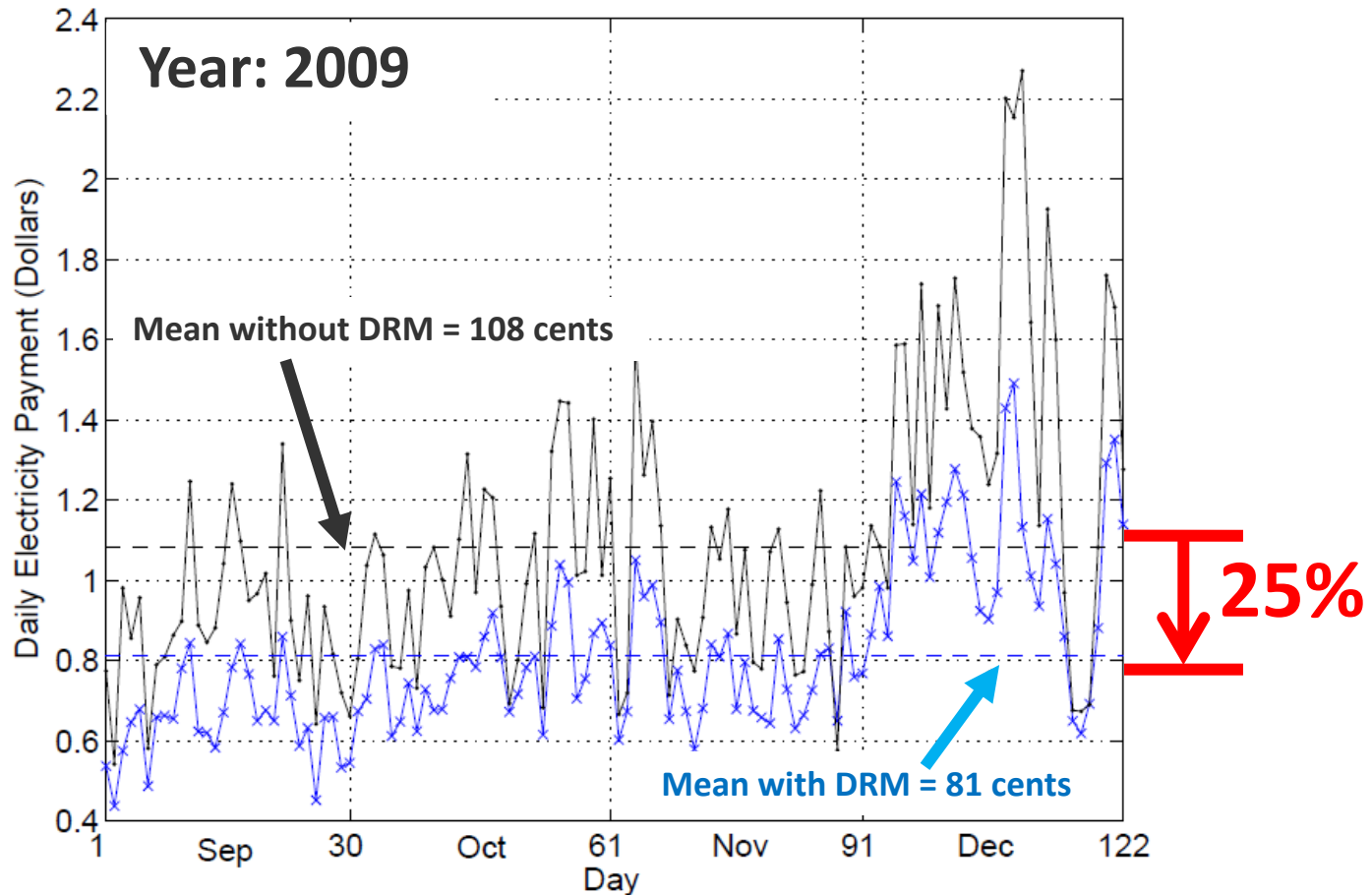
Programming in R (II)

```
f.dir <- c("=", "=", "<=", "<=", "<=", "<=", "<=",  
"<=", "<=", "<=")  
  
f.rhs <- c(9.9, 5.0, 3.0, 3.0, 3.0, 3.0, 1.5, 1.5, 1.5,  
1.5)  
  
# Now run.  
  
lp ("min", f.obj, f.con, f.dir, f.rhs)  
  
lp ("min", f.obj, f.con, f.dir, f.rhs)$solution
```

Output:

```
> lp ("min", f.obj, f.con, f.dir, f.rhs)  
Success: the objective function is 8.079396  
> lp ("min", f.obj, f.con, f.dir, f.rhs)$solution  
[1] 3.0 3.0 3.0 0.9 1.5 1.5 1.5 0.5  
> |
```

DRM reduces cost of electricity



A household with varying number of appliances (10-25) at each day and that has subscribed Real-Time Pricing (RTP)

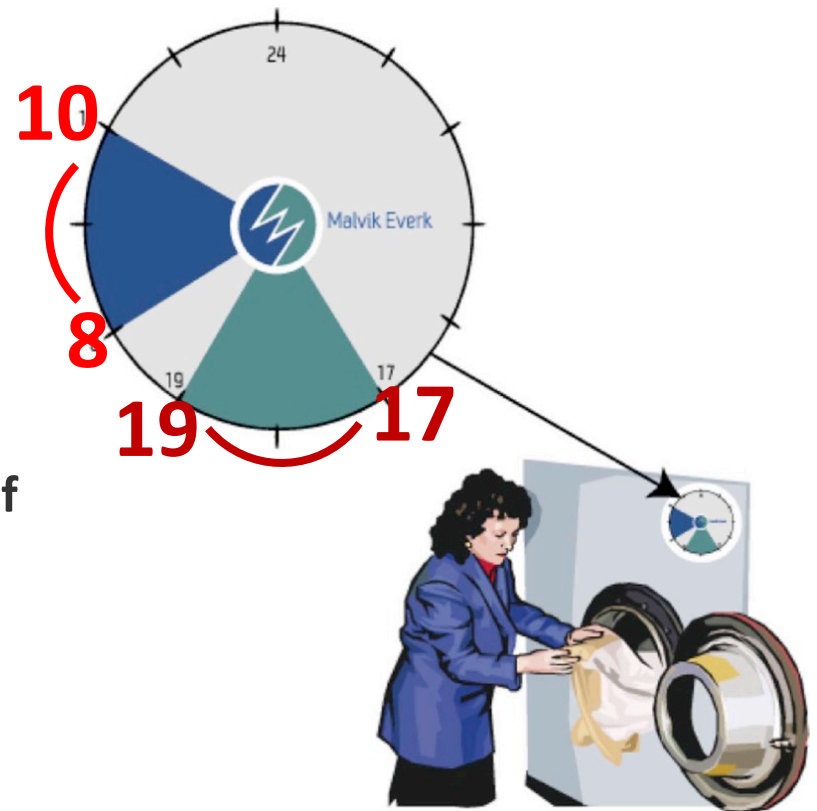
Demand Response Pilot Study – Norway (I)

Malvik Everk: Distribution Systems Operator (DSO) in Central-Norway



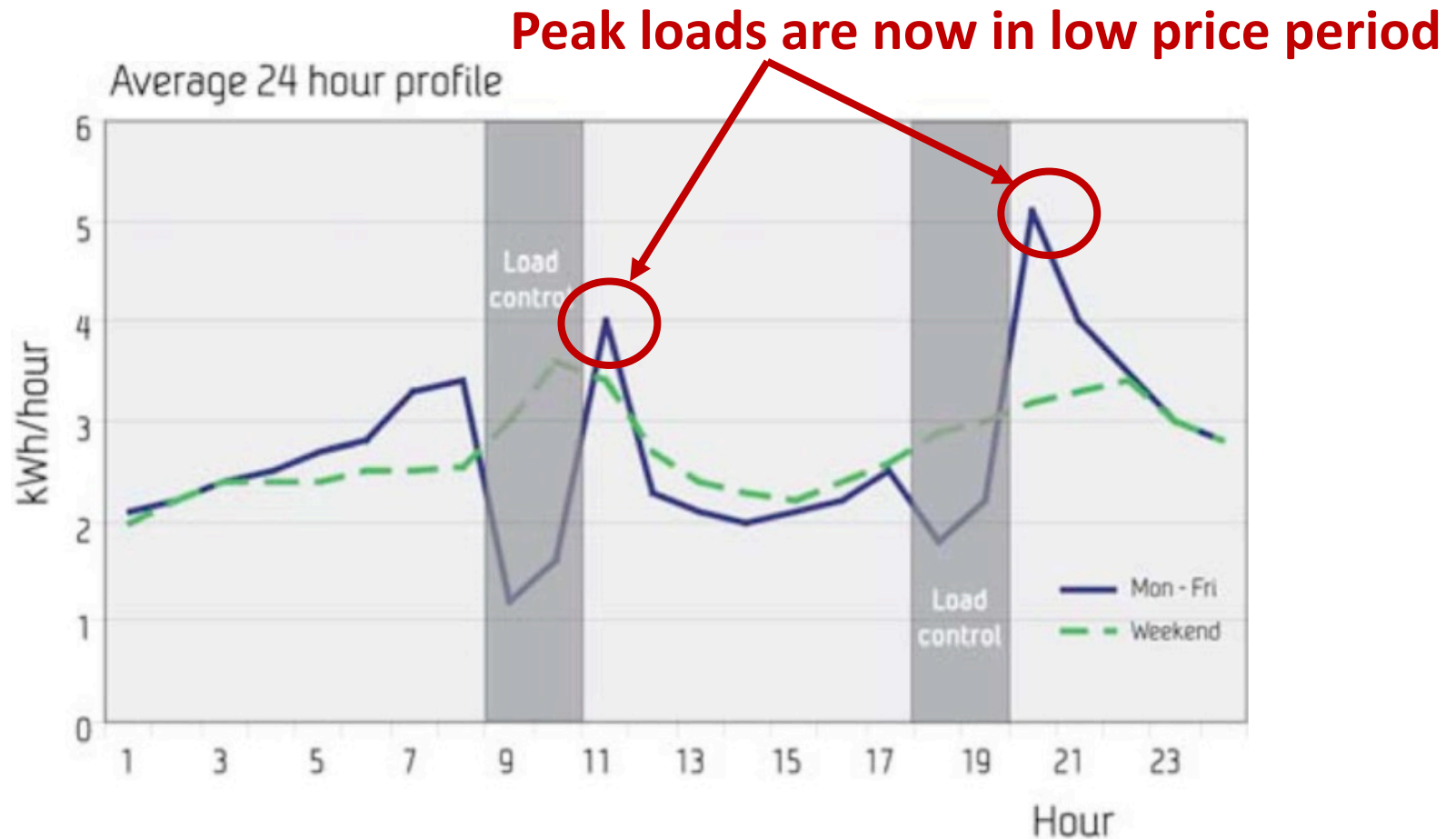
One year Pilot study:

- 40 household customers gave hourly metering of energy consumption
- Each household was equipped with the “EI-buttons,” to be placed on dishwashers, washing machines, etc., to remind the households to avoid usage of these energy consuming appliances in the predefined peak load periods.



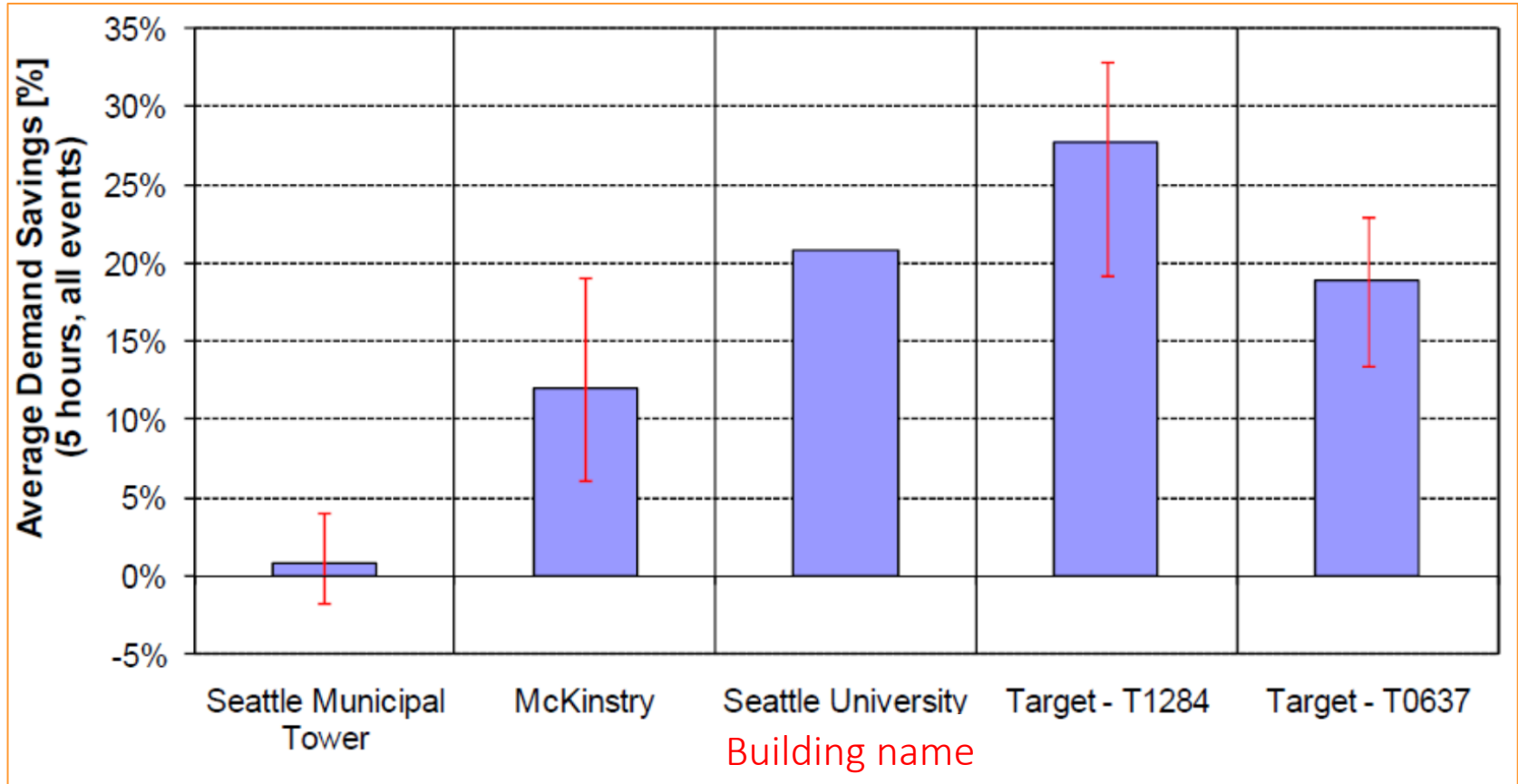
H. Sæle and O.S. Grande, *Demand response from household customers: experiences from a pilot study in Norway*, IEEE T. Smart Grids 2(1):90–97 (March 2011)

Demand Response Pilot Study – Norway (II)



Main observation: load shifting from peak periods to off-peak periods. This resulted in an economic benefit for the customers due to moving loads from hours with high prices to hours with lower prices.

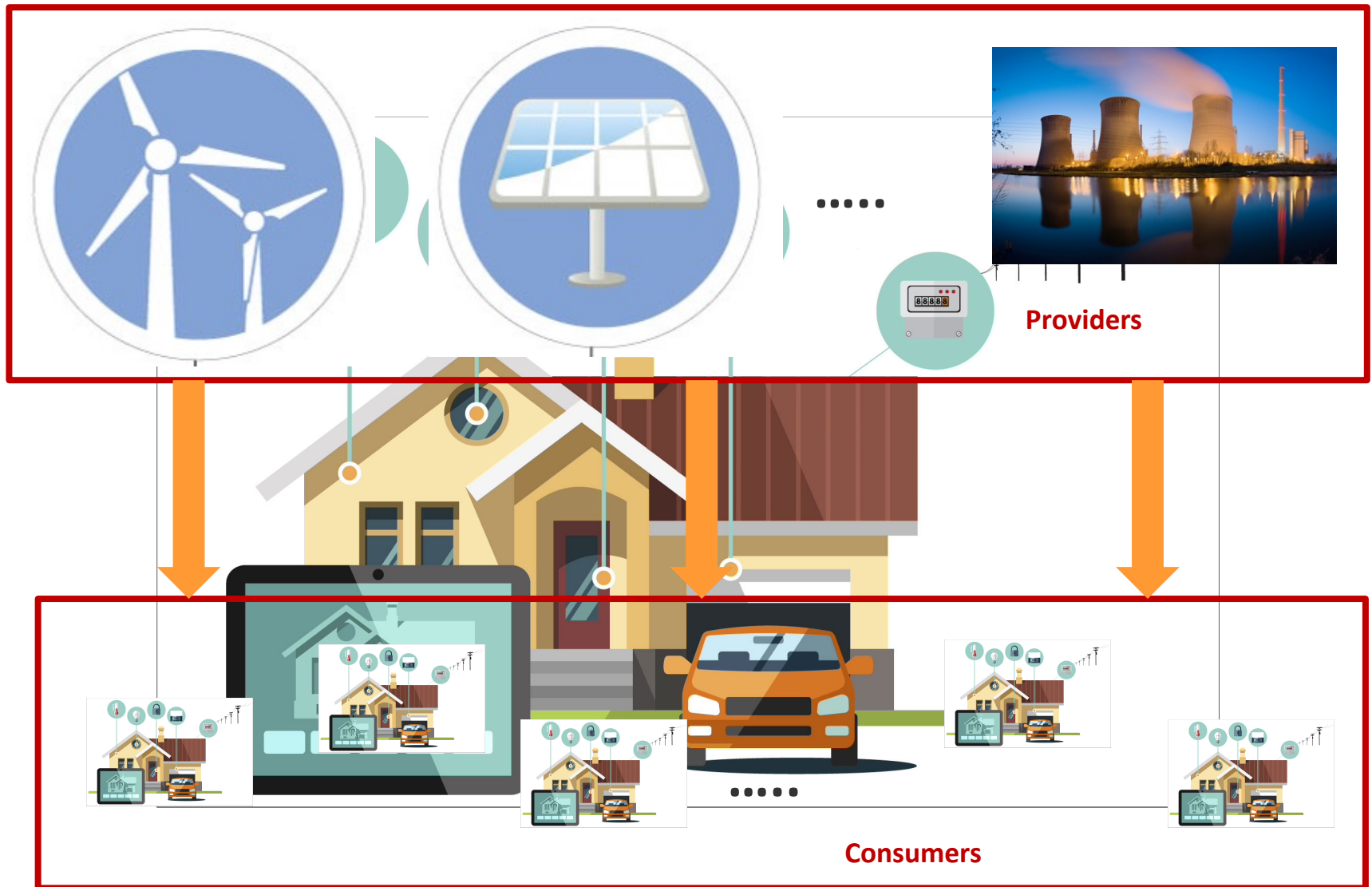
Demand Response Pilot Study - Seattle



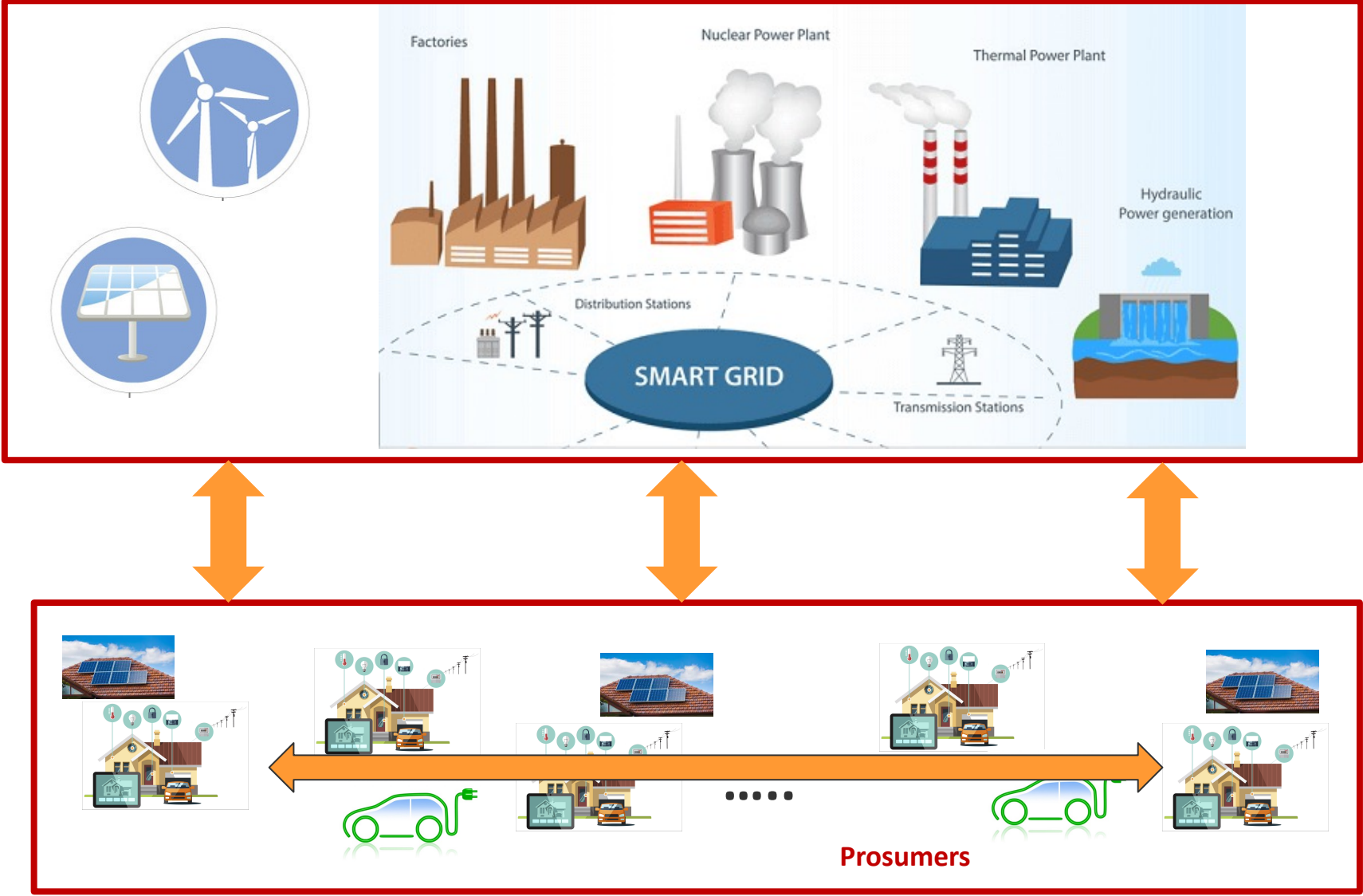
Power demand reduction at each building during summer after using demand response

MORE CONSIDERATIONS...

Demand Response Management involving multiple providers: Selection of providers or amount?



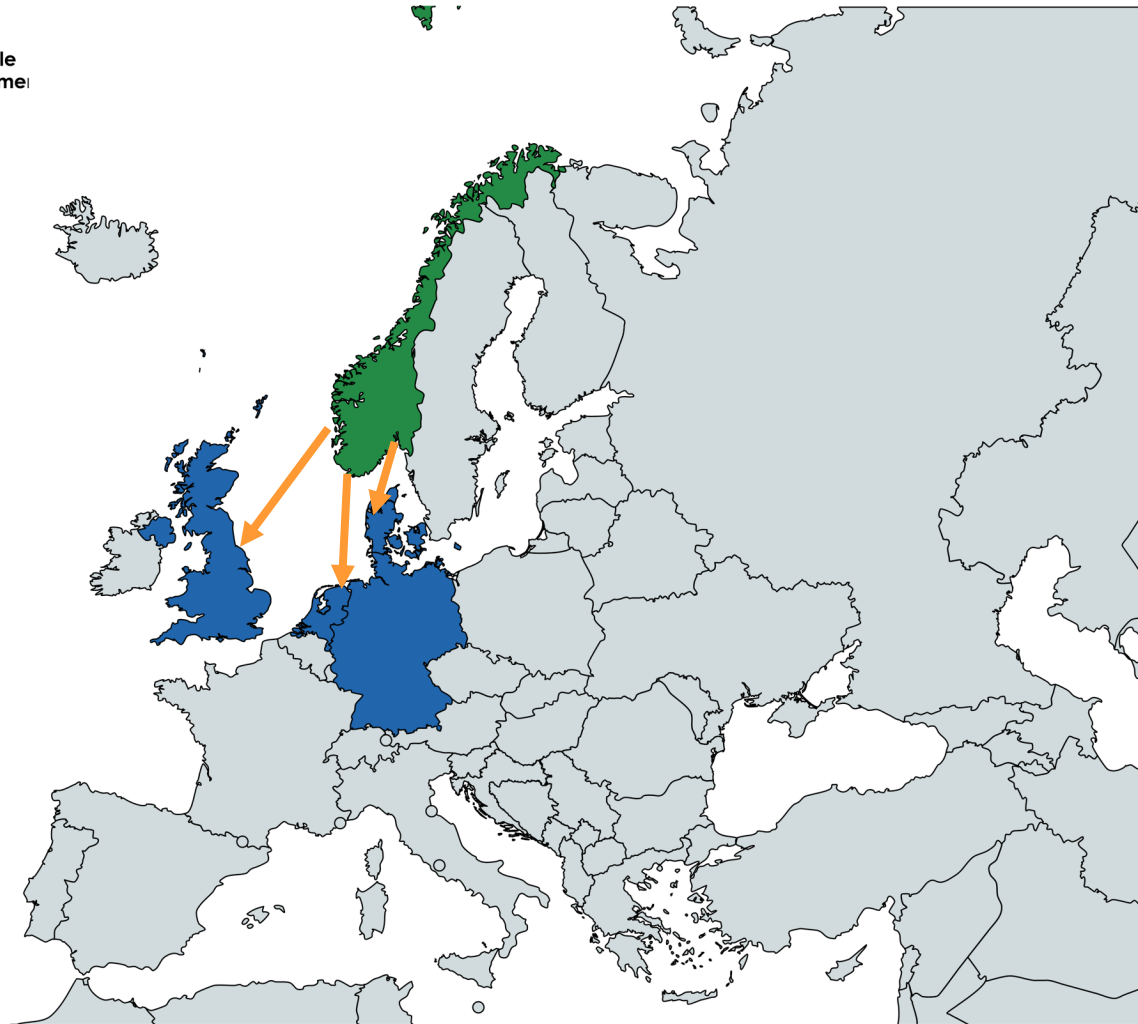
Demand Response Management involving multiple prosumers



Cross border electricity trade: An example of demand response management

Cross border trade: An example of demand response management

- Seller
- Buyers



Demand response applications: Data Centers

Daily services supported by data centers

- Gmail
- Facebook
- Dropbox
- DNB (supported by Green Mountain data center in Stavanger)
- **Q:** more?



Google Data Centre at Mayes County, Oklahoma

Demand response applications: Data Centers

Q: Why place data centers in Finland or undersea?

Data centers are huge energy consumers, in particular cooling systems, and

- pay a lot for electricity bill
- make power grid instable during peak hours

Cooling system uses sea water from the Bay of Finland and reduces energy use

Google data center in Finland



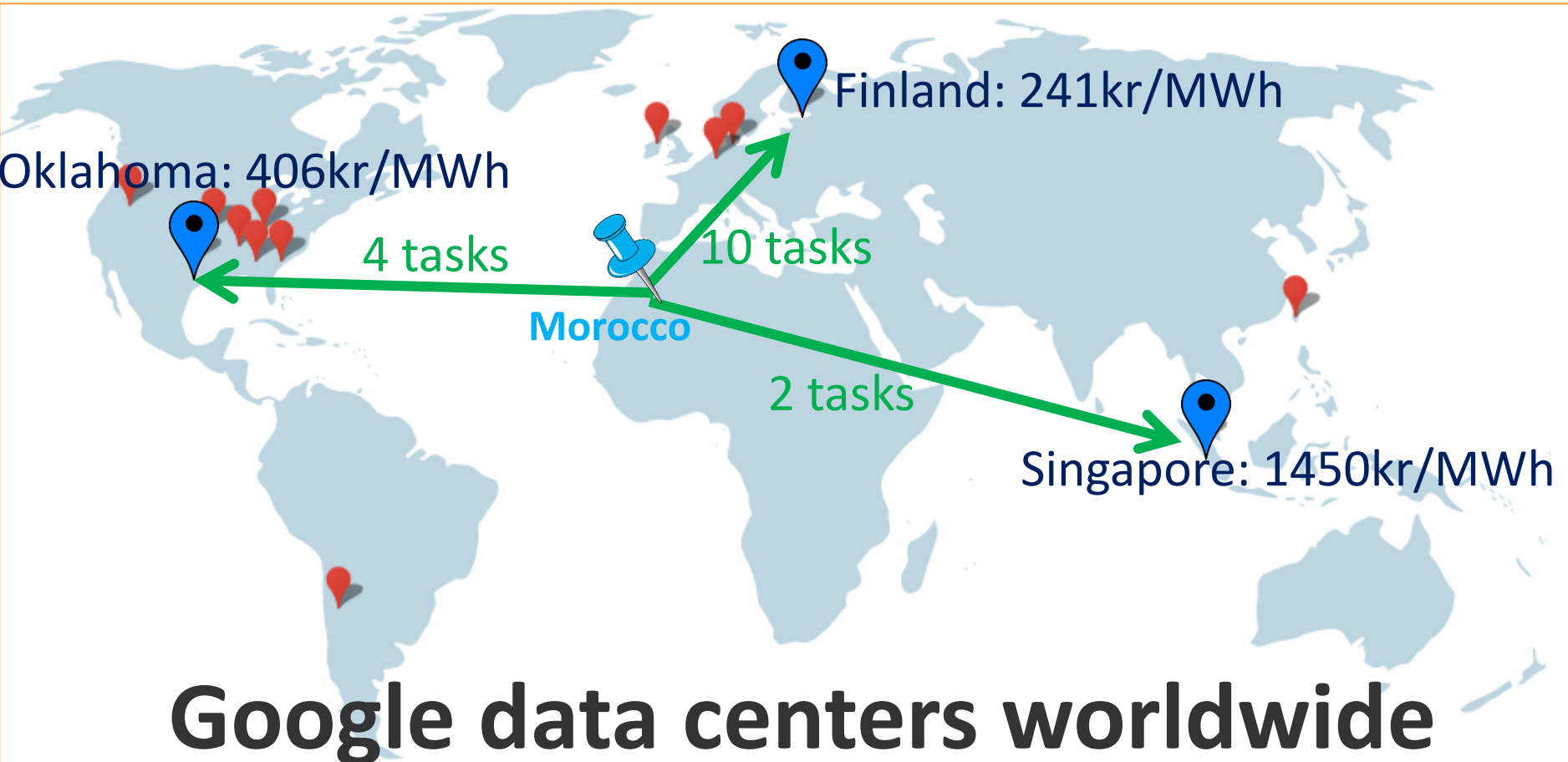
Microsoft undersea data center



Demand response applications: Data Centers

Q: can DRM help data centers to reduce energy cost?

Allocate computation tasks to locations with cheaper prices



References

R. Deng, Z. Yang, M. Chow and J. Chen, “A Survey on Demand Response in Smart Grid: Mathematical Models and Approaches,” *IEEE Trans. Industrial Informatics*, vol. 11, no. 3, June, 2015

A. Mohsenian-Rad, V. W. Wong, J. Jatskevich, R. Schober, and A. Leon- Garcia, “Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid,” *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320–331, Dec. 2010.

Roy H. Kwon, *Introduction to Linear Optimization and Extensions with MATLAB*, **chapter 1**, CRC Press, 2013

Thank you!