June 15th, 2017
Technical University of Denmark, Lyngby, Denmark

Modern Challenges in Power System Operation and Electricity Market: An Optimization Perspective

Distributed Optimization and Dual Decomposition: Application to the Coordination of Flexible Loads

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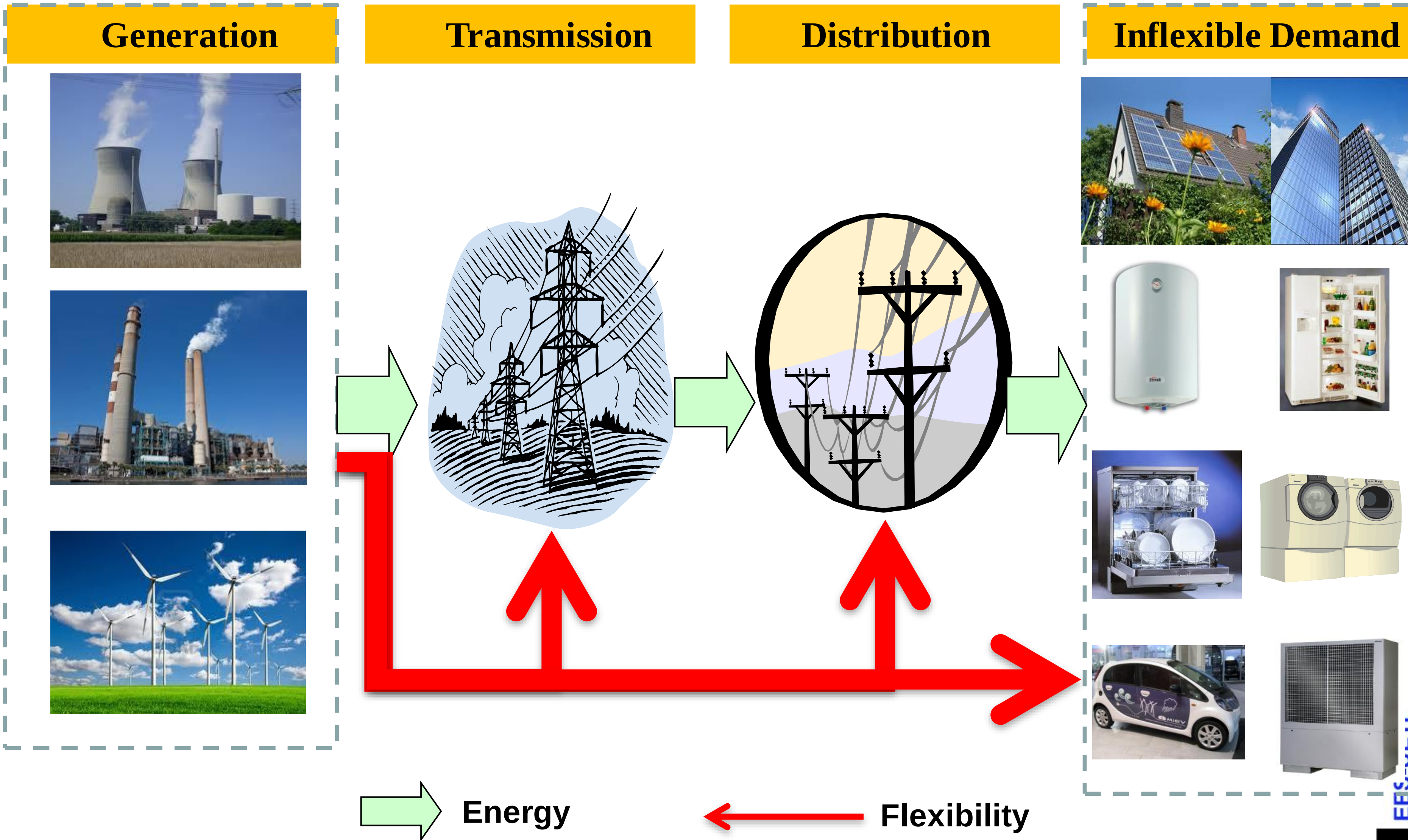
Structure of the Lecture

- Emerging challenges for power systems
- Role of flexible loads in addressing emerging challenges
- Challenges of centralized coordination of flexible loads
- Developing a mechanism for distributed coordination of flexible loads
  - Application of dual decomposition
  - Solution infeasibility and sub-optimality challenges
  - Strategies to deal with demand response concentration
  - Recent results and challenges

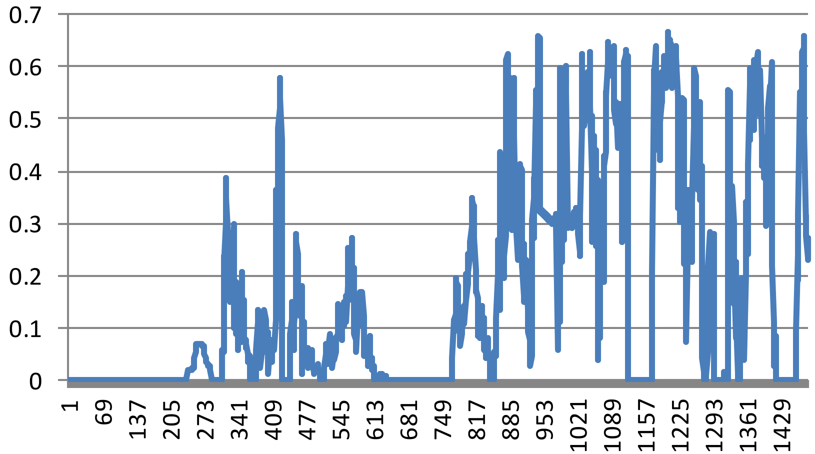
Emerging power systems

Challenges brought by decarbonization of generation and demand

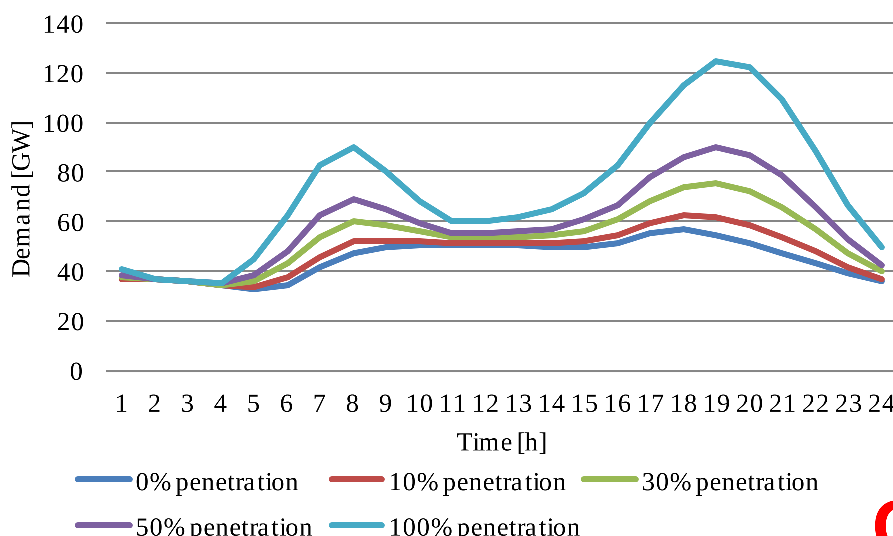


Emerging power systems

Challenges brought by decarbonization of generation and demand



- Under-utilized conventional generation needs to remain in the system as a “back-up” energy source and flexibility provider



- Under-utilized generation and network capacity needs to be built in order to cover new demand peaks

COST EFFICIENCY?

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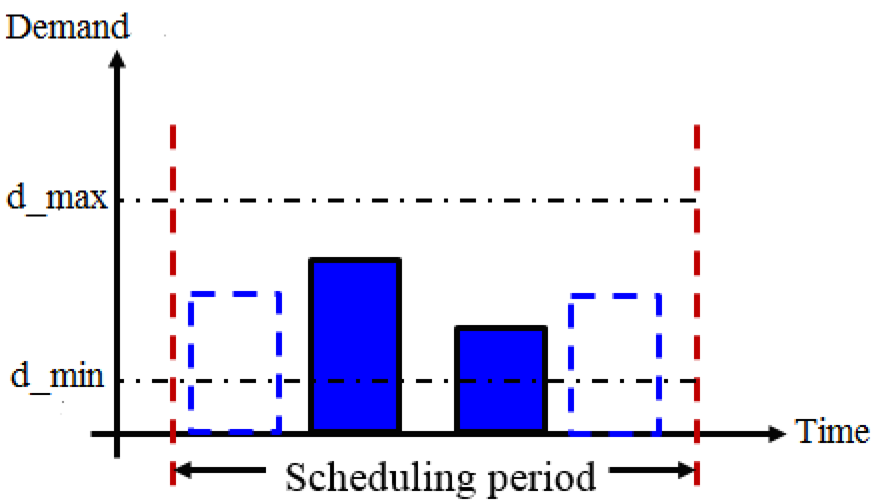
Flexible loads

Potential to support system balancing and reduce demand peaks

Flexible loads

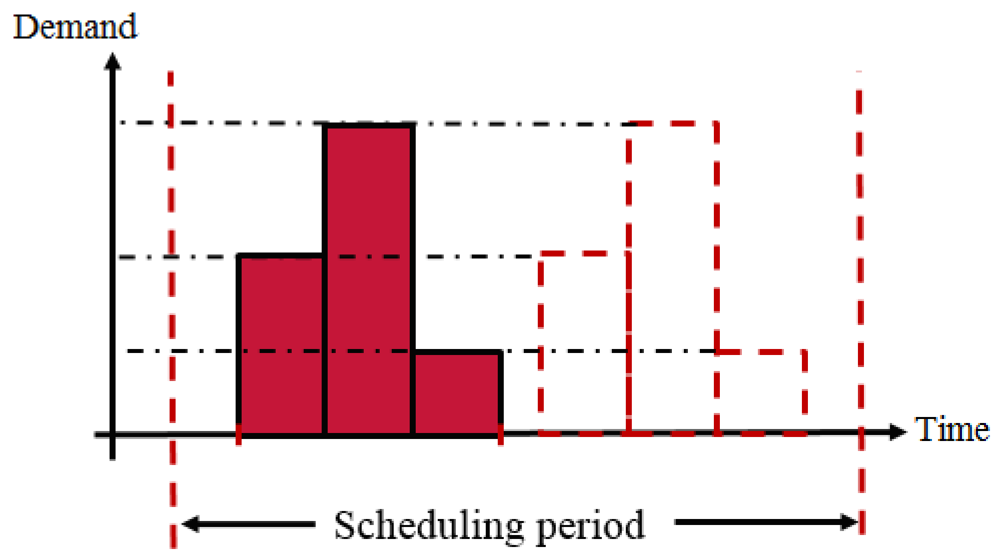
Modeling different types of demand flexibility

Continuously adjustable power



- Flexibility is associated with the maximum instantaneous power limit
- Example: smart-charging electric vehicles

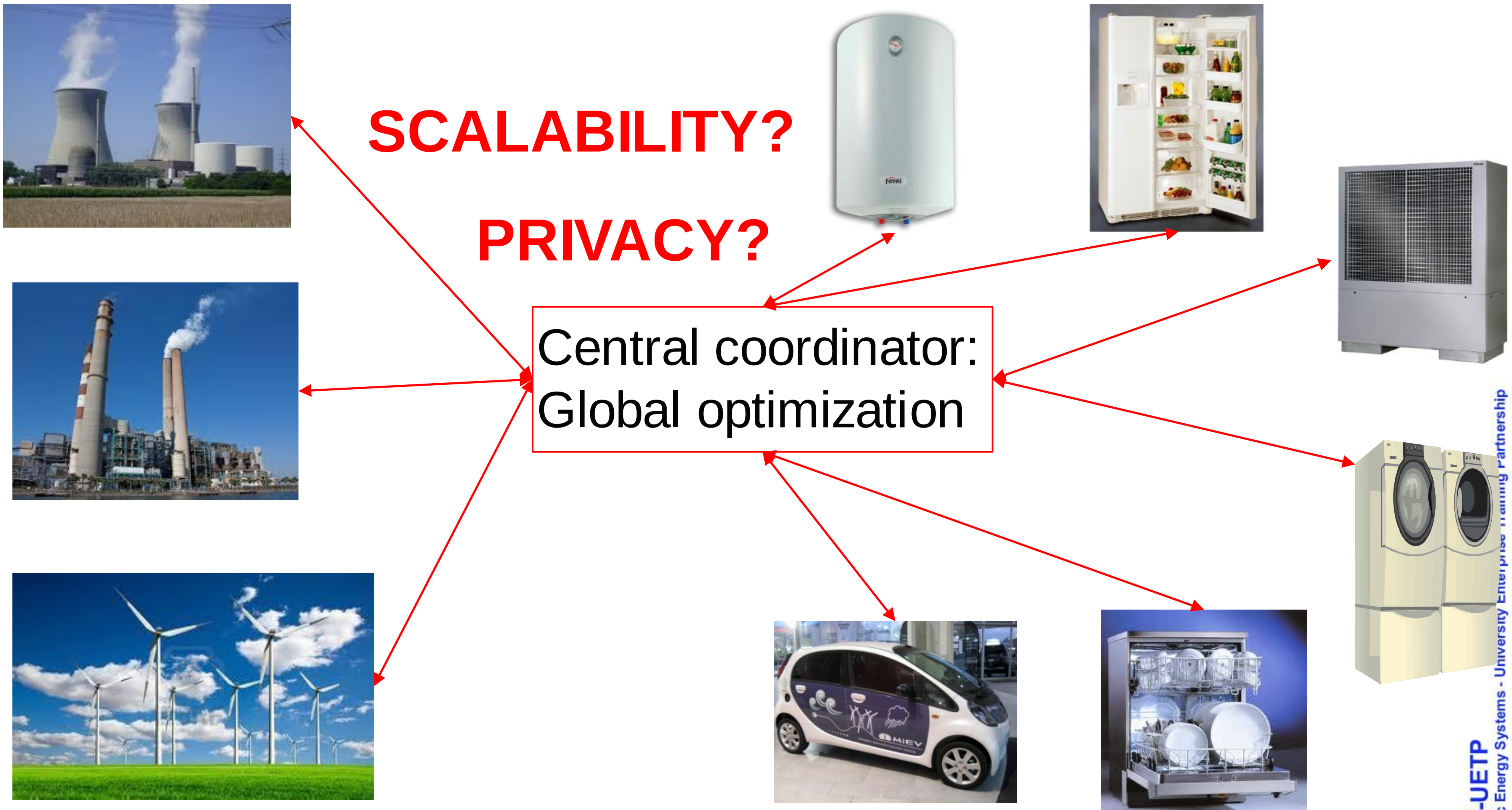
Deferrable cycles



- Flexibility is associated with the maximum cycle delay limit
- Example: dishwashers with delay functionality

System coordination

Traditional, centralized coordination approach



Distributed coordination approach

Defining the challenge

- Develop distributed coordination mechanism
  - ➢Optimally coordinating flexible loads from the system perspective…
  - ➢…without centralized knowledge of their operational parameters
- Mathematical approach
  - ➢Decompose the original global optimization problem to a number of local optimization problems solved independently by the individual participants
  - ➢Dual decomposition provides suitable foundations

Application of dual decomposition

Mathematical structure

Global optimization problem

- Objective function:

$$\min f = \min \sum_{j=1}^{N_J} C_j(\boldsymbol{s}_j)) - \sum_{i=1}^{N_I} B_i(\boldsymbol{d}_i)$$

- Decision variables:

$\boldsymbol{d}_i, \forall i \in I$ $\quad$ $\boldsymbol{s}_j, \forall j \in J$

- Individual constraints:

$\boldsymbol{d}_i \in D_i, \forall i \in I$ $\quad$ $\boldsymbol{s}_j \in S_j, \forall j \in J$

- Coupling constraints:

$$e_t = \sum_{i=1}^{N_I} d_{i,t} - \sum_{j=1}^{N_J} s_{j,t} = 0, \forall t \in T$$

Relax coupling constraints through Lagrangian multipliers

$$L = \sum_{j=1}^{N_J} C_j(\boldsymbol{s}_j) - \sum_{j=1}^{N_I} B_i(\boldsymbol{d}_i) + \sum_{t=1}^{24} \lambda_t \left(\sum_{i=1}^{N_I} d_{i,t} - \sum_{j=1}^{N_J} s_{j,t} \right)$$

Separable w.r.t. each generator / demand

Demand *i* sub-problem:

- Objective function

$$\min (\boldsymbol{\lambda})^T * \boldsymbol{d}_i - B_i(\boldsymbol{d}_i)$$

- Decision variables: $\boldsymbol{d}_i$
- Constraints: $\boldsymbol{d}_i \in D_i$

Generator *j* sub-problem:

- Objective function

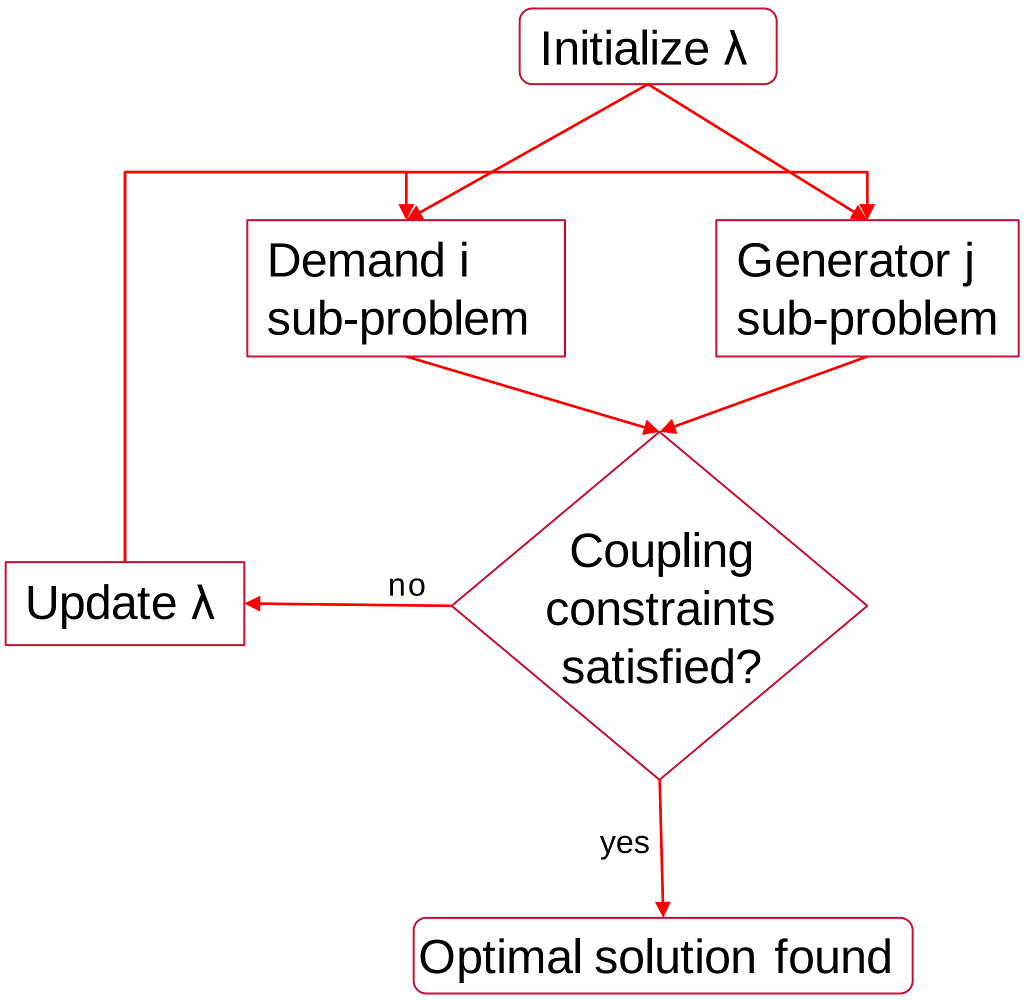
$$\min C_j(\boldsymbol{s}_j) - (\boldsymbol{\lambda})^T * \boldsymbol{s}_j$$

- Decision variables: $\boldsymbol{s}_j$
- Constraints: $\boldsymbol{s}_j \in S_j$

Update Lagrangian multipliers until coupling constraints are satisfied (optimal solution reached)

Application of dual decomposition

Interpretation as a price-based market clearing mechanism



- Interpreted as price-based market clearing mechanism:
  - Lagrangian multipliers represent market prices
  - Sub-problems represent surplus-maximizing actions of independent participants
  - Optimal solution is also a competitive market equilibrium
- Guaranteed to converge to optimal solution of the global problem when:
  - Sub-problems are strictly convex
  - A suitable Lagrangian multipliers update mechanism is employed

Fundamental application challenge

Non-convexities in generation and demand participants sub-problem

- Generation side
  - ➢Unit commitment decisions
  - ➢Fixed and start-up / shut-down costs

- Demand side
  - ➢Discrete power levels
  - ➢Options to forgo demand activities

Fundamental application challenge

A very simple demand non-convexity

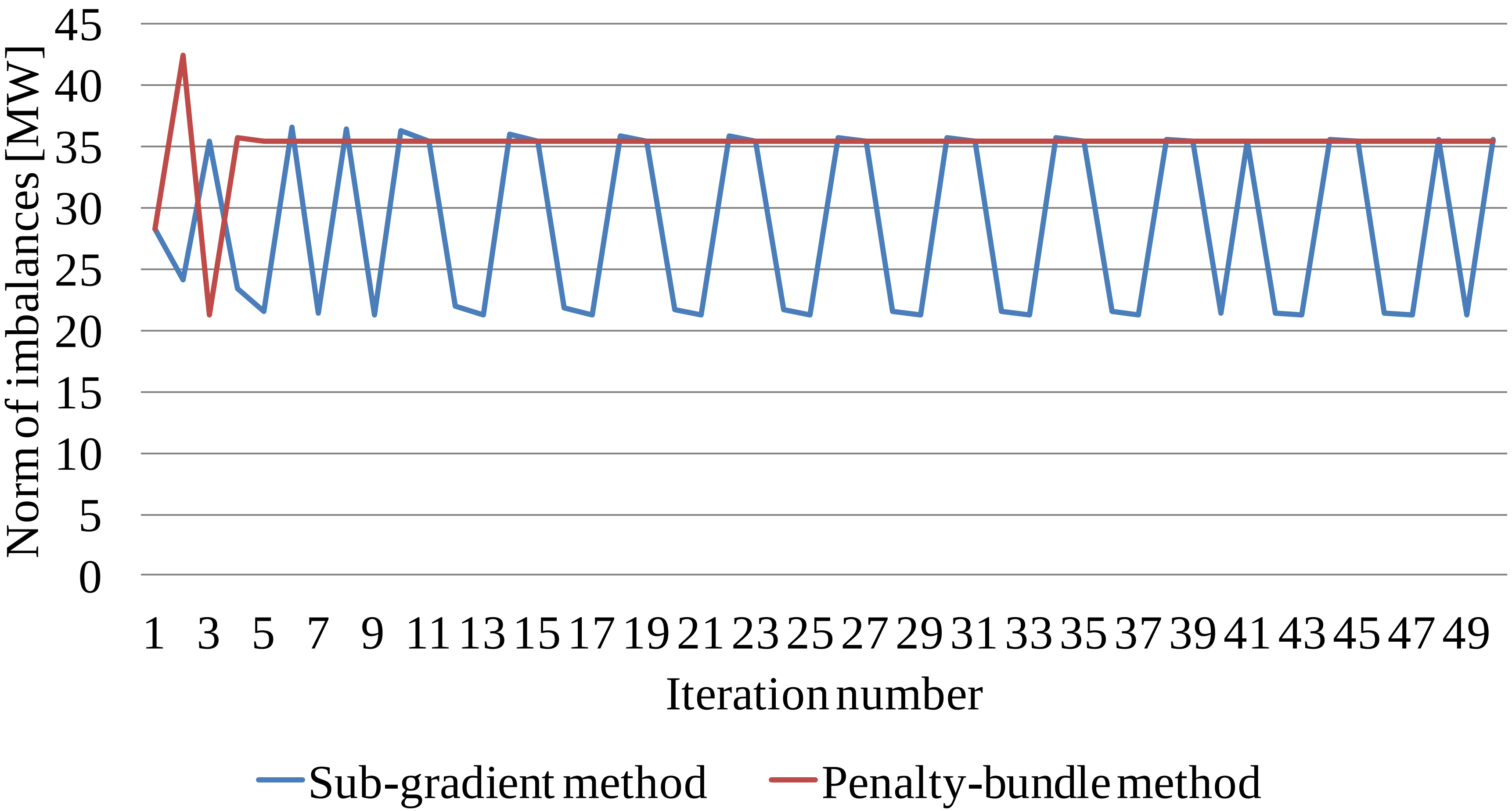
- Example: Flexible demand which requires a total energy E over time periods 1 and 2, and is indifferent to (its benefit / satisfaction does not depend on) the specific time period the required energy is obtained:
  - Decision variables: $d(1)$, $d(2)$
  - Constraint: $d(1)+d(2)=E$ > convex
  - Objective function: $\min [\lambda(1)*d(1)+\lambda(2)*d(2)]$ > linear and thus not strictly convex

- Optimal response function of this flexible demand is discontinuous:
  - $d(1)=E$, $d(2)=0$ if $\lambda(1)<\lambda(2)$
  - $d(1)=0$, $d(2)=E$ if $\lambda(1)>\lambda(2)$
  - $d(1)=?$, $d(2)=?$ if $\lambda(1)=\lambda(2)$

Fundamental application challenge

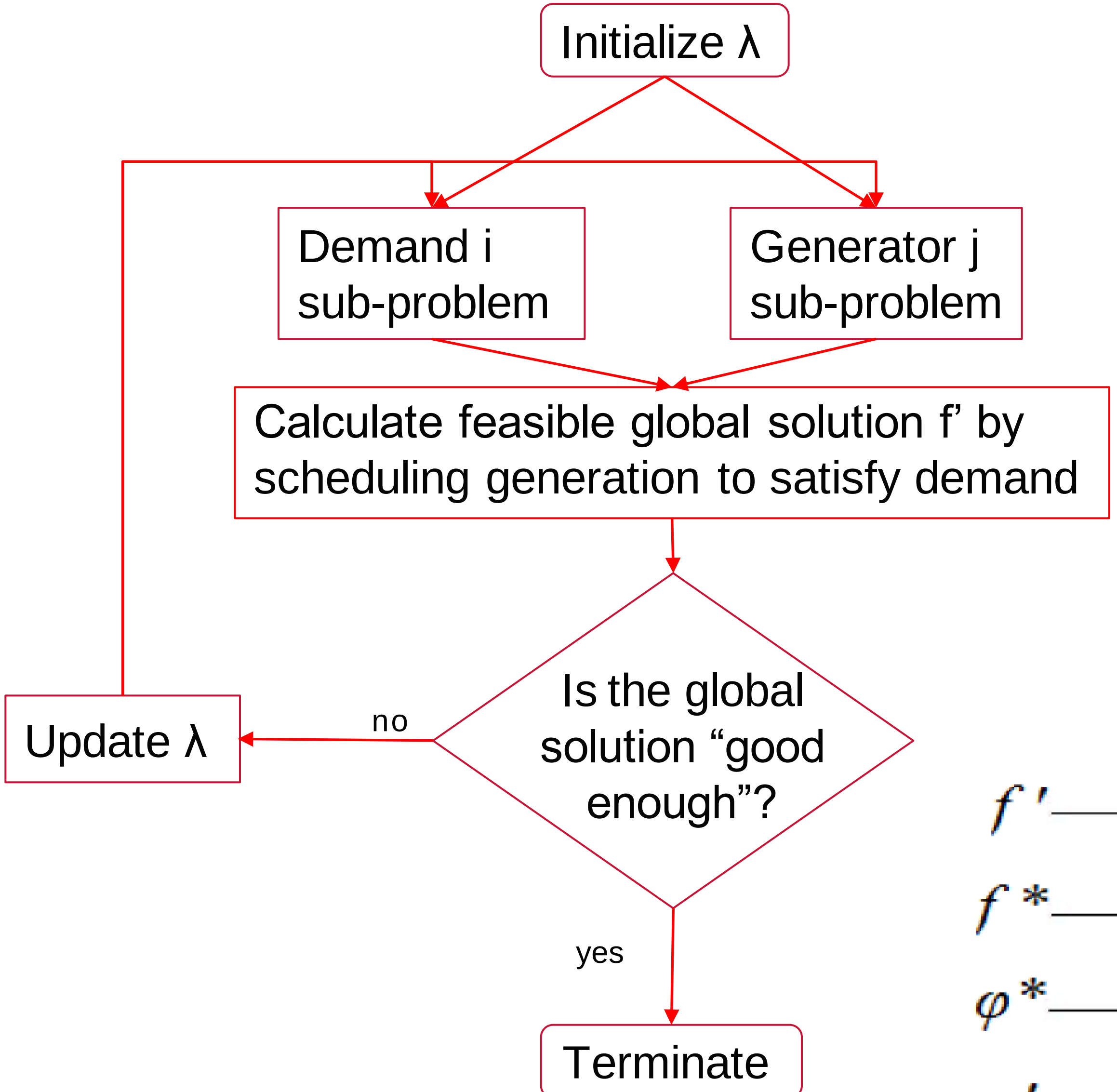
Illustration of solution infeasibility

- A feasible solution (satisfying the demand-supply balance constraints) cannot be reached irrespectively of the umber of iterations and the Lagrangian multipliers' update method !

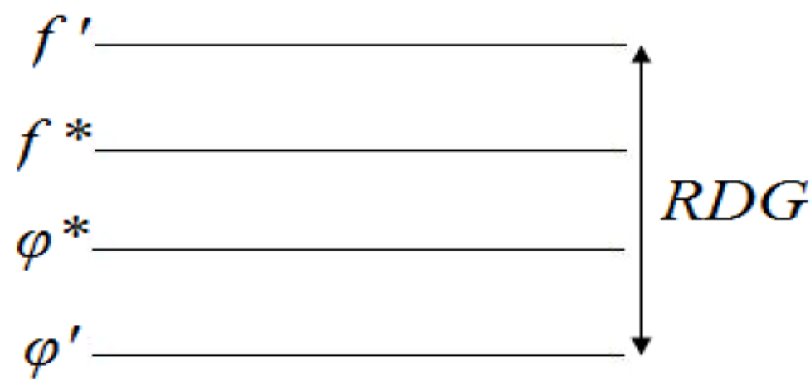


Forcing feasibility…

A simple LR heuristic approach

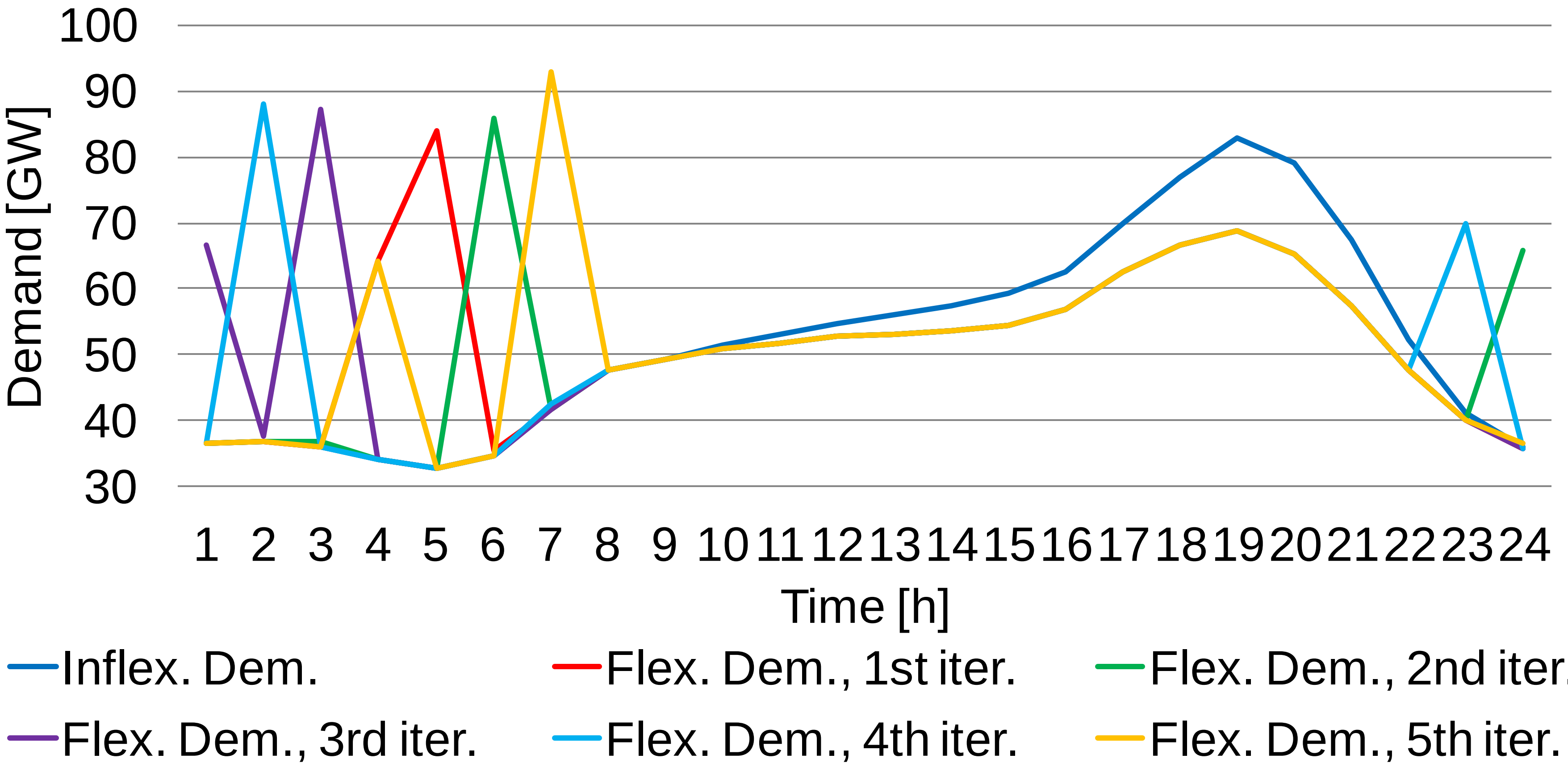


- Interpreted as dynamic pricing scheme:
  - ➢Demand side is exposed to certain tariff (retail sector)
  - ➢The resulting demand levels need to be satisfied by the generation side (wholesale sector)
- We have disturbed the natural structure of LR > the feasible solutions are not necessarily optimal



…but response discontinuities are still there !

Instead of infeasibility, we are now facing sub-optimality !

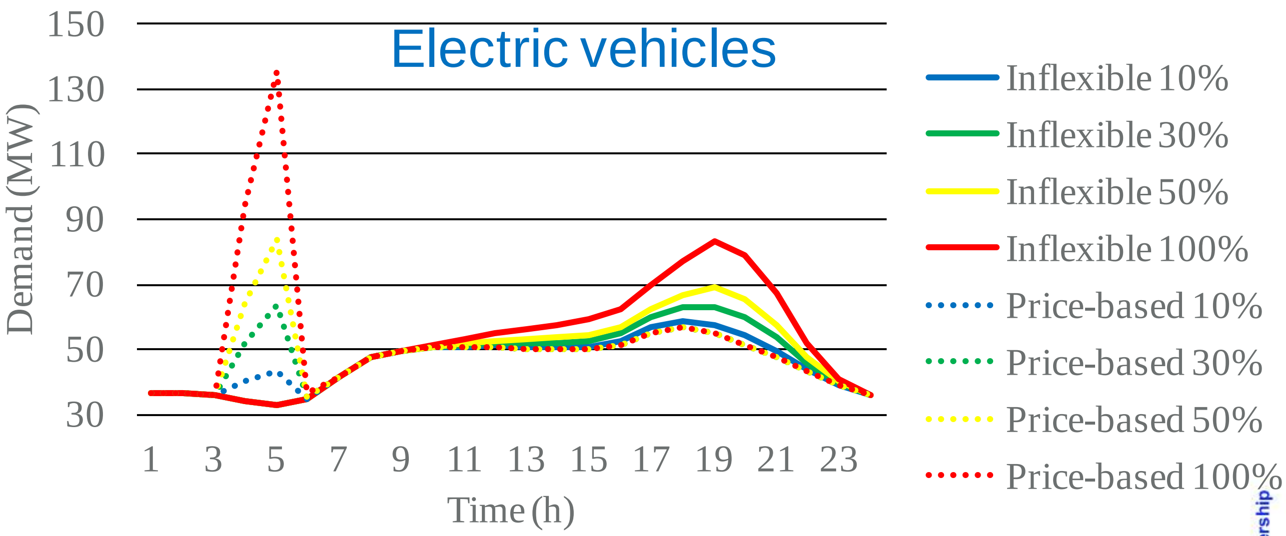


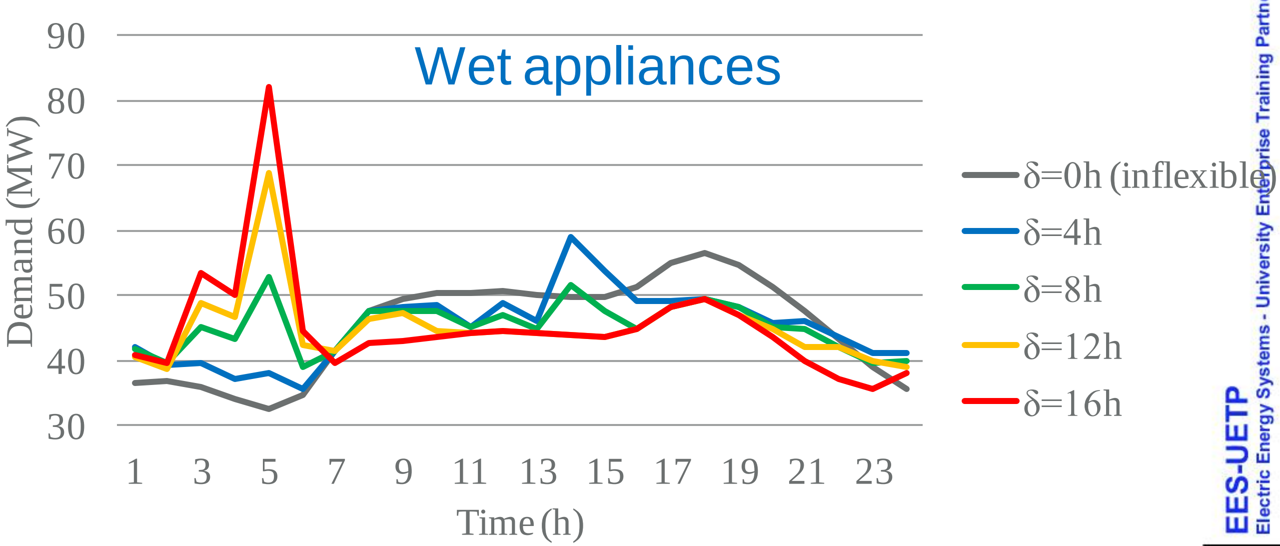
SHOULD DYNAMIC PRICING SCHEMES BE TRUSTED?

Demand response concentration effect

Particularly probable if demand response is automated

- Flexible loads' response is concentrated at the lowest-priced periods
  - ➢ New demand peaks, higher costs, higher network losses
  - ➢ Concentration effect enhanced with higher number, higher flexibility and lower diversity of flexible loads





How to avoid demand response concentration?

Directly limit the flexibility of loads to shift at the lowest-price periods

- The size of the demand response concentration effect depends on the flexibility extent of the loads…
  - Loads with continuously adjustable power: maximum power limit d_{max}
  - Loads with deferrable cycles: maximum cycle delay limit δ_{max}

- …so can we mitigate the concentration effect by imposing flexibility limits?
  - Determining suitable absolute flexibility limits is practically impossible for feasibility and fairness reasons, since information on loads' properties is not available

- Impose relative flexibility restriction $\omega \in (0,1]$
  - Loads with continuously adjustable power: $d_{max} >>> \omega * d_{max}$
  - Loads with deferrable cycles: $\delta_{max} >>> \omega * \delta_{max}$

- Concern: consumers might not accept direct restriction of their flexibility

How to avoid demand response concentration?

Penalise the flexibility utilized by the loads

- Apply flexibility price (penalty) α (different than traditional linear prices)
  - Loads with continuously adjustable power: penalty term $\alpha * d^2$
  - Loads with deferrable cycles: penalty term $\alpha * \delta$

- Concern: the more complex signals are difficult to interpret?

How to avoid demand response concentration?

Send differentiated prices to different loads

- The size of the demand response concentration effect depends on the diversity of flexible loads…

- …so can we mitigate the concentration effect by introducing diversity in the price signals?

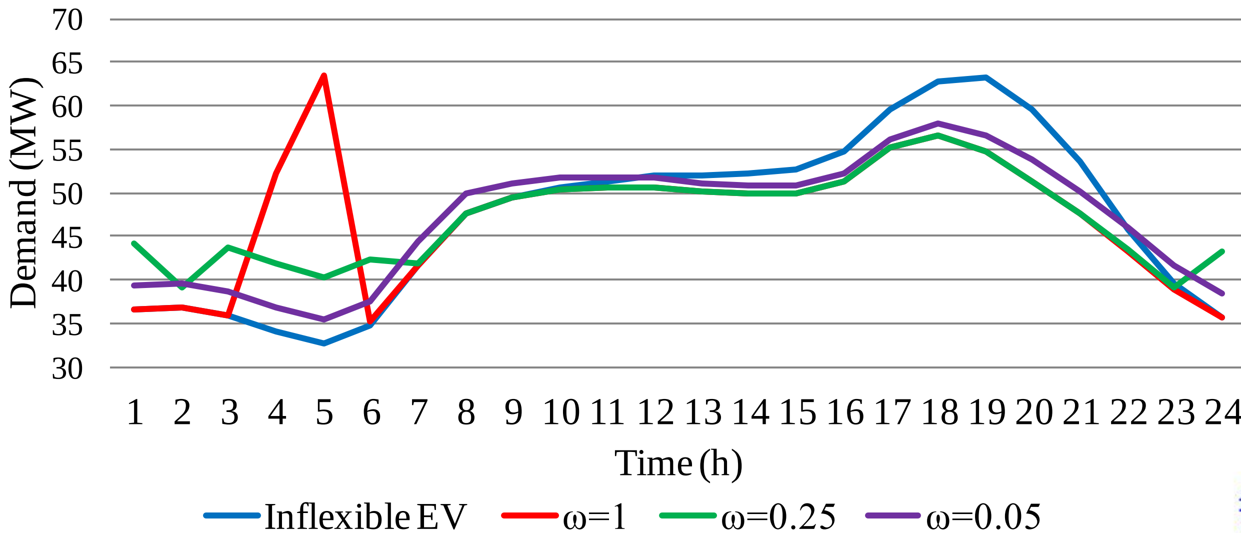
- Information on loads properties is not available, so we apply randomization of price signals
  - Randomize single non-linear price α instead of multiple linear prices λ_t
  - Employ normal distribution with mean α and deviation σ
  - $\alpha_i^{rand} = \alpha + \sigma * x_i$

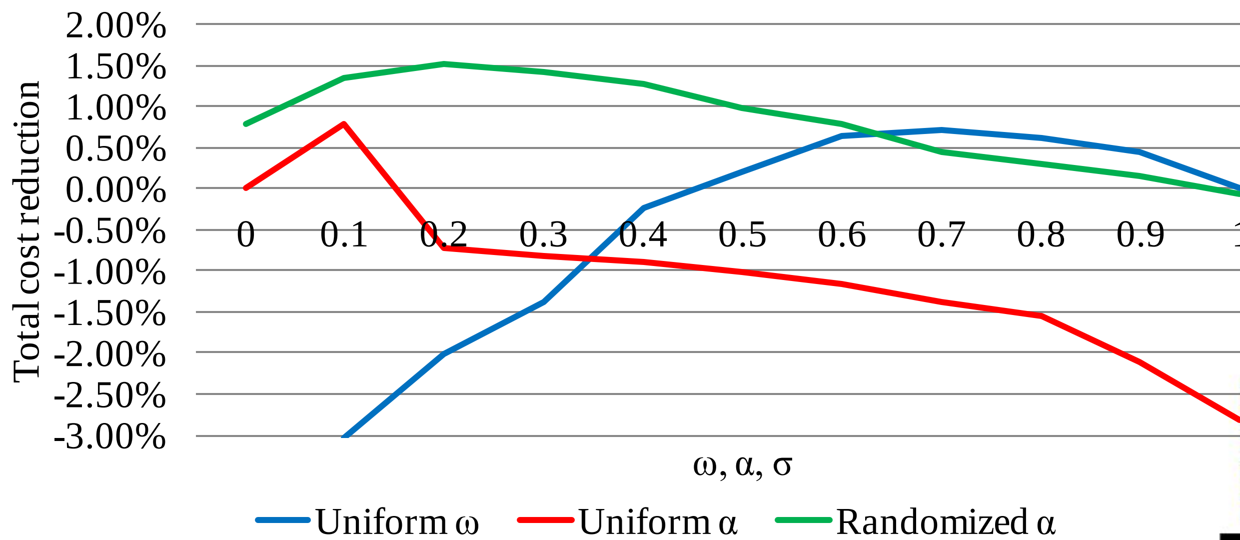
- Concern: are differentiated prices fair to different consumers?

Tuning the parameters of these smart strategies

The selected values will significantly affect the emerging solutions

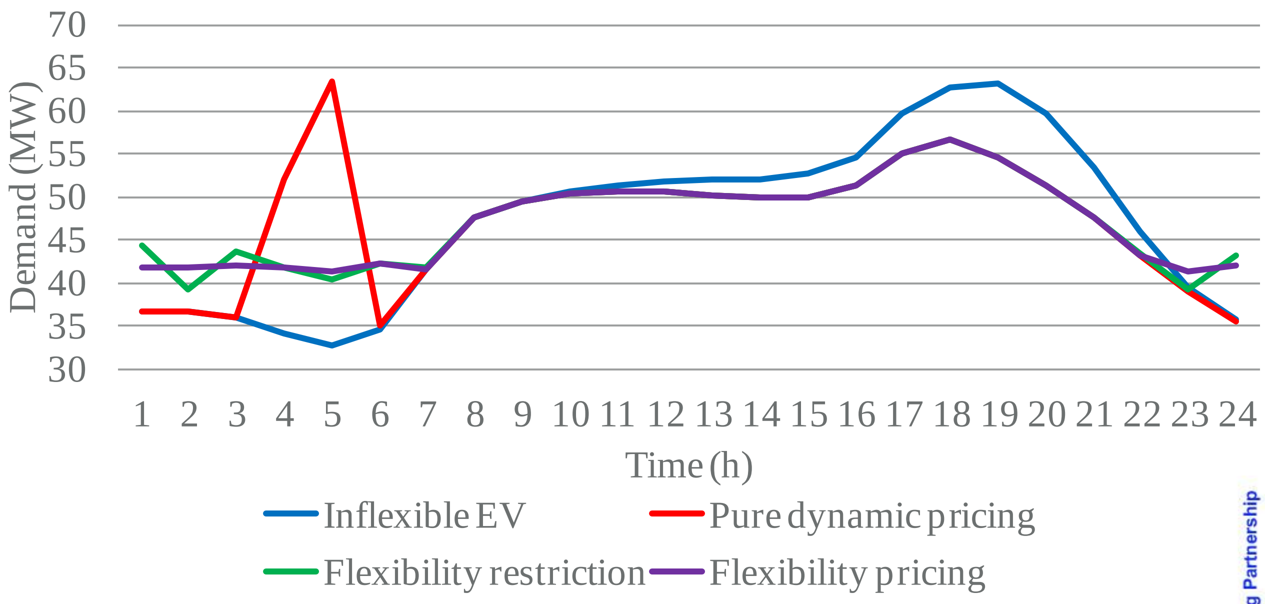
- Trade-off between:
  - Avoiding demand response concentration
  - Filling the off-peak valleys





Application to distributed coordination of electric vehicles

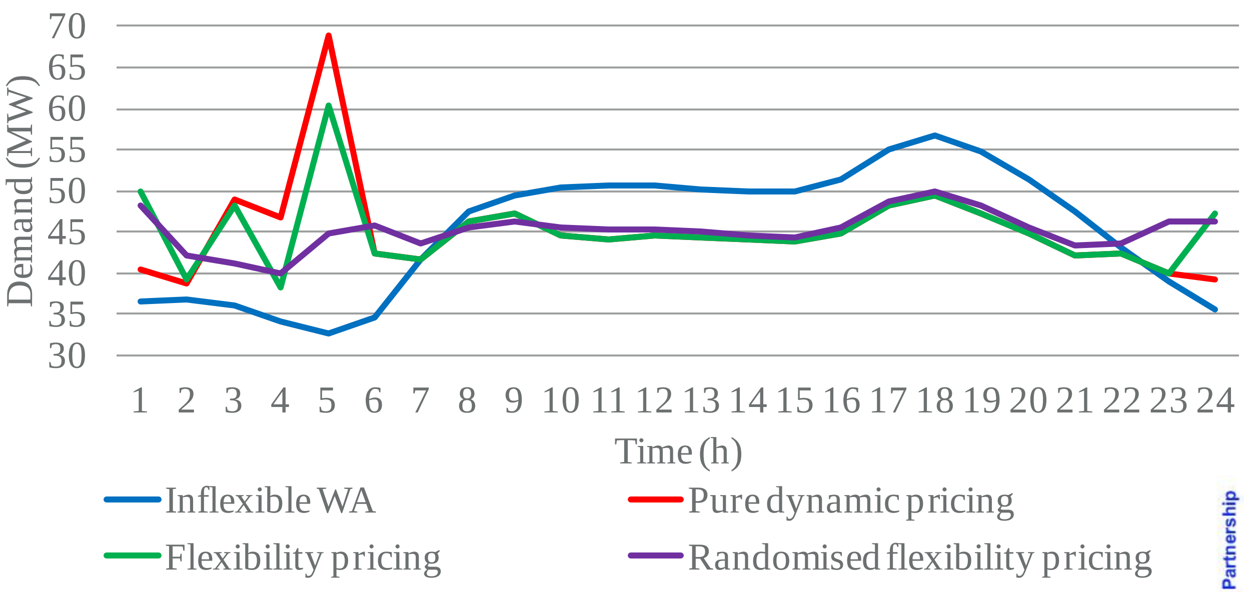
- Flexibility pricing slightly outperforms flexibility restriction
- Randomised pricing does not bring additional benefits



EV penetration	Flexibility restriction		Flexibility pricing		Randomised pricing	
	ω*	Benefit	α* (£/kW^2)	Benefit	σ* (£/kW^2)	Benefit
10%	0.35	0.15%	0.001	0.15%	0	0.15%
30%	0.25	10.01%	0.004	10.27%	0	10.27%
50%	0.20	29.17%	0.008	29.72%	0	29.72%
100%	0.15	57.40%	0.023	57.70%	0	57.70%

Application to distributed coordination of wet appliances

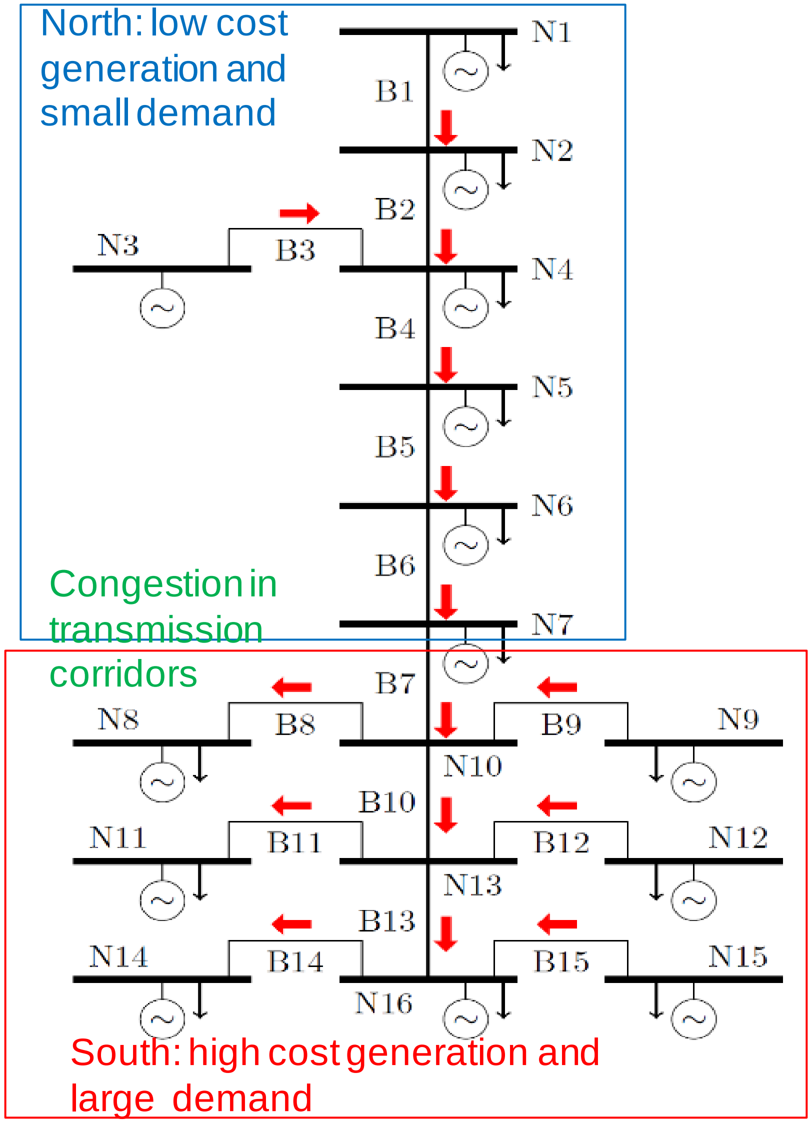
- ➢Flexibility restriction and flexibility pricing have similar performance
- ➢Randomised pricing brings significant additional benefits

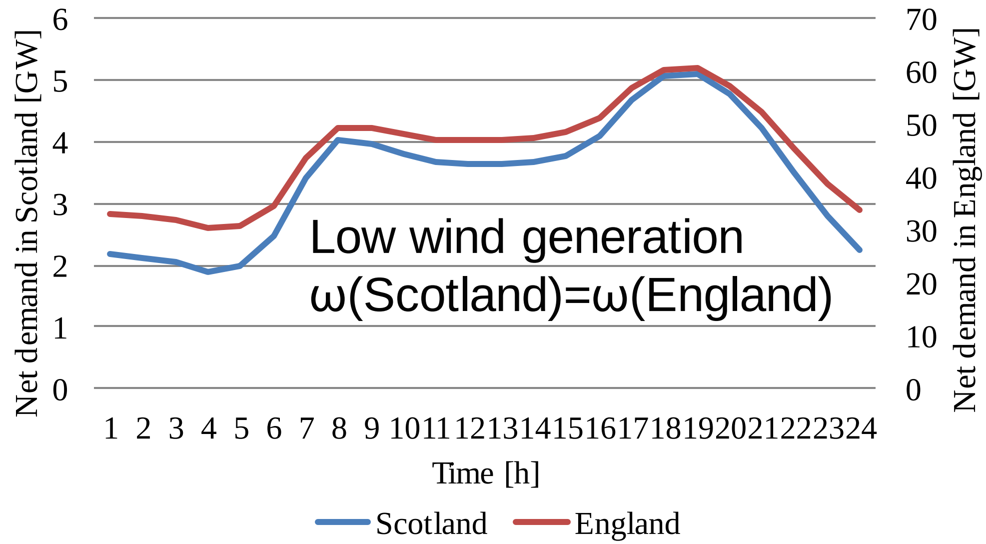


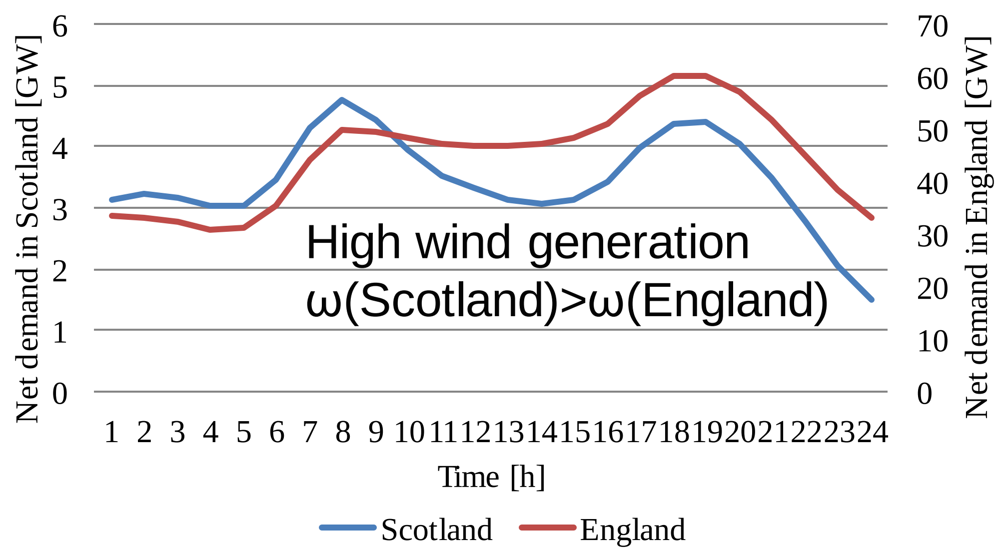
Maximum cycle delay	Flexibility restriction		Flexibility pricing		Randomised pricing	
	ω*	Benefit	α* (£/h)	Benefit	σ* (£/h)	Benefit
4h	1	0%	0.001	0.34%	0.001	1.29%
8h	1	0%	0.001	0.52%	0.002	2.96%
12h	0.7	1.79%	0.001	0.93%	0.007	8.53%
16h	0.5	5.00%	0.002	4.09%	0.009	19.06%

Effect of network congestion and losses

Location-specific parameters could improve the obtained solutions







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Current research challenge

How to tune the strategies' parameters given uncertainties on flexible loads' properties?

- Heuristic approach: Try out a large number of alternative values > high communication requirements

Scenario	N_ω=2	N_ω=5	N_ω=10
Low DR	0.12%	0.14%	0.15%
Medium DR	0.52%	0.70%	0.76%
High DR	1.18%	1.56%	1.70%

- Analytical approach: Optimize parameters considering uncertainty in DR characteristics > high computational requirements

TRADE-OFF ???

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Relevant publications

- D. Papadaskalopoulos and G. Strbac, “Decentralized Participation of Flexible Demand in Electricity Markets – Part I: Market Mechanism,” *IEEE Transactions on Power Systems*, November 2013.
- D. Papadaskalopoulos, G. Strbac, P. Mancarella, M. Aunedi and V. Stanojevic, “Decentralized Participation of Flexible Demand in Electricity Markets – Part II: Application with Electric Vehicles and Heat Pump Systems,” *IEEE Transactions on Power Systems*, November 2013.
- D. Papadaskalopoulos, D. Pudjianto and G. Strbac, “Decentralized Coordination of Microgrids with Flexible Demand and Energy Storage,” *IEEE Transactions on Sustainable Energy*, October 2014.
- Y. Ye, D. Papadaskalopoulos and G. Strbac, “Factoring Flexible Demand Non-Convexities in Electricity Markets,” *IEEE Transactions on Power Systems*, July 2015.
- D. Papadaskalopoulos and G. Strbac, “Non-linear and Randomized Pricing for Distributed Management of Flexible Loads,” *IEEE Transactions on Smart Grid,* March 2016.
- D. Papadaskalopoulos, Y. Ye and G. Strbac, “Location-Specific Signals for Distributed Control of Flexible Loads,” submitted.