Integrating Deferrable Demand in Electricity Markets

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Innovation in Energy Management – Make Green Efficient!

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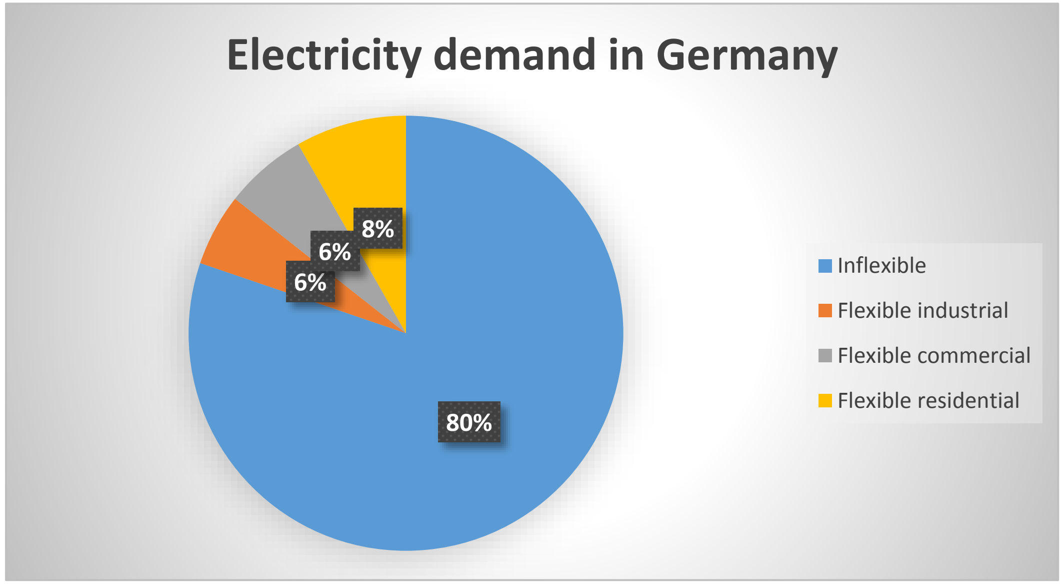
Motivation

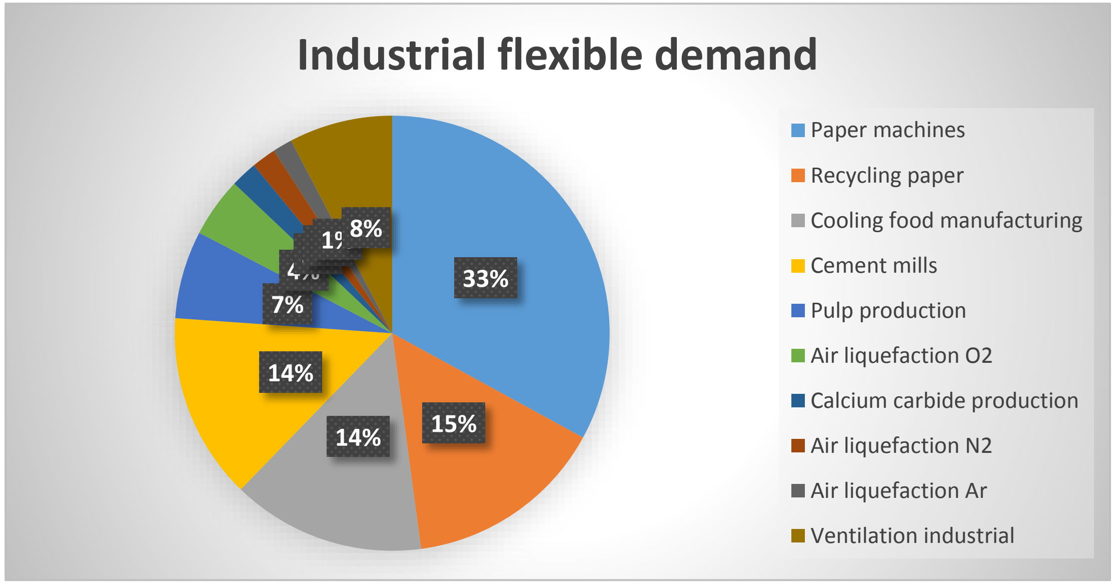
Flexibility

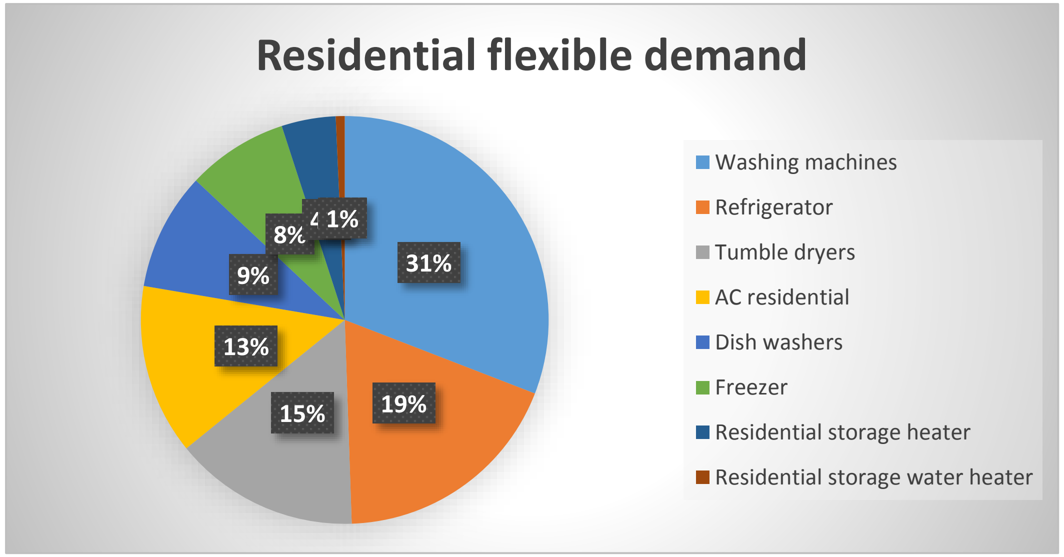
Demand response paradigms

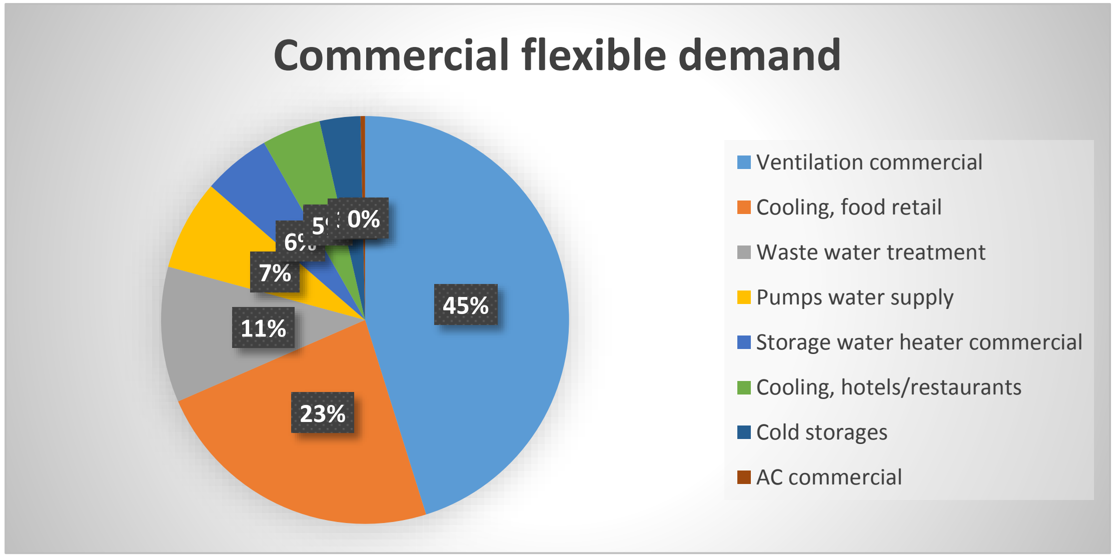
Electricity market models with DR

Flexibility in Germany (Gils, 2014)



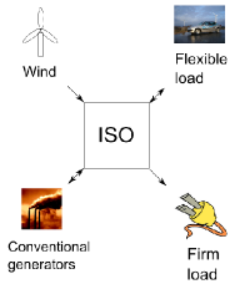




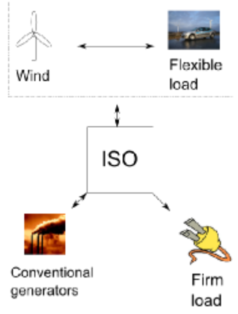


Demand Response Paradigms

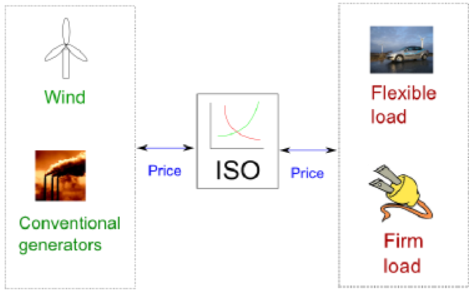
- *Boiteux, 1960*: time of use pricing
- *Schweppe, 1988*: real-time pricing
- *Gedra and Varaiya, 1993*: interruptible service via callable forward contracts
- *Chao et al., 1986*: priority service pricing
- *P and Oren, 2011*: coupling renewable supply with deferrable demand



System operator control



Coupling renewables with deferrable demand

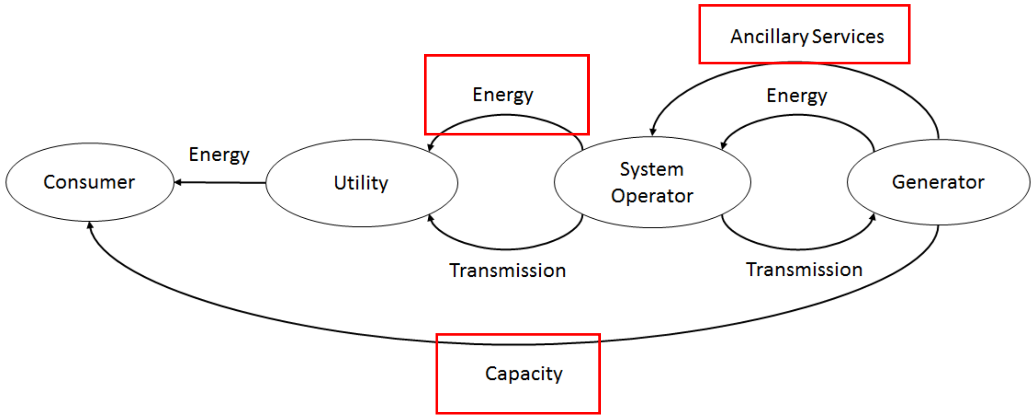


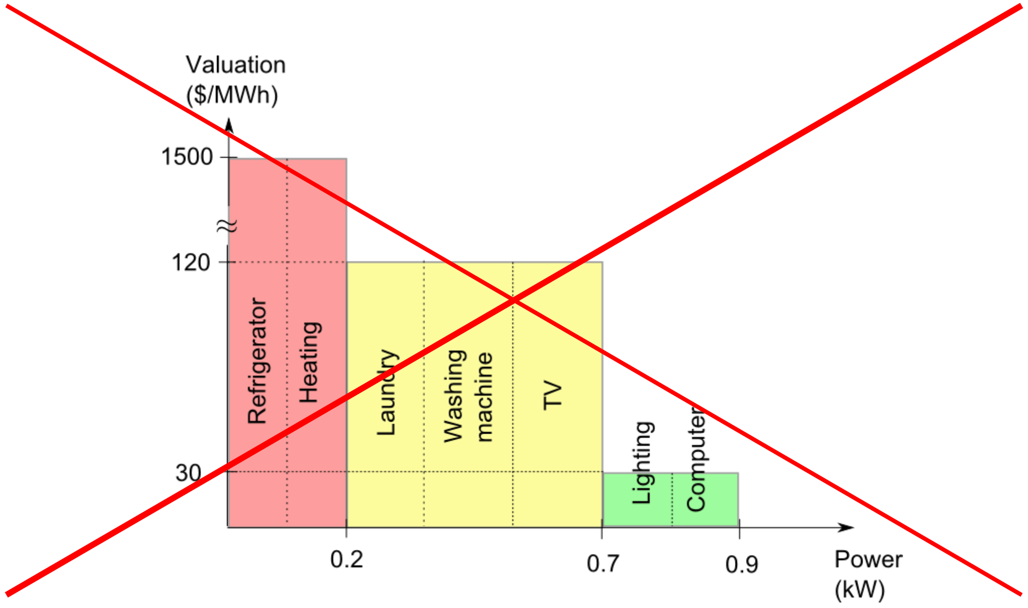
Price-responsive demand

Centralized → Decentralized

Modeling Electricity Markets with Demand Response

- Demand response can valorize flexibility in a number of markets:
  - Energy (price arbitrage, buy low – sell high)
  - Ancillary services (already offers asymmetric up primary reserve, tertiary reserve)
  - Capacity
- Goal of this research: <u>closed-loop</u> electricity models with DR, while accounting for:
  - Uncertainty of renewable supply
  - Temporal evolution of consumer elasticity
  - Equilibrium between suppliers and consumers
- Our target model should quantify:
  - Operating costs and system dispatch
  - Capacity requirements
  - Electricity prices





Methodology

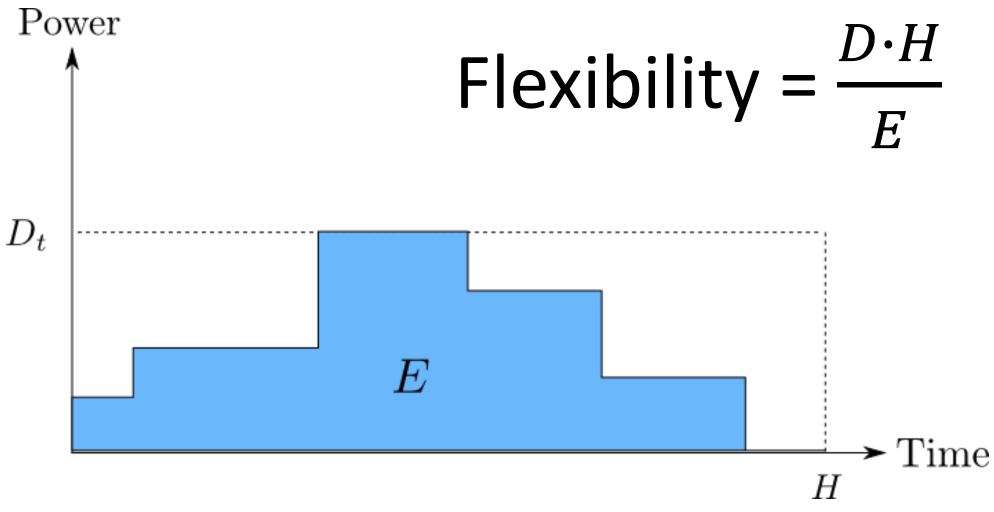
An elementary model of deferrable demand

Stochastic programming

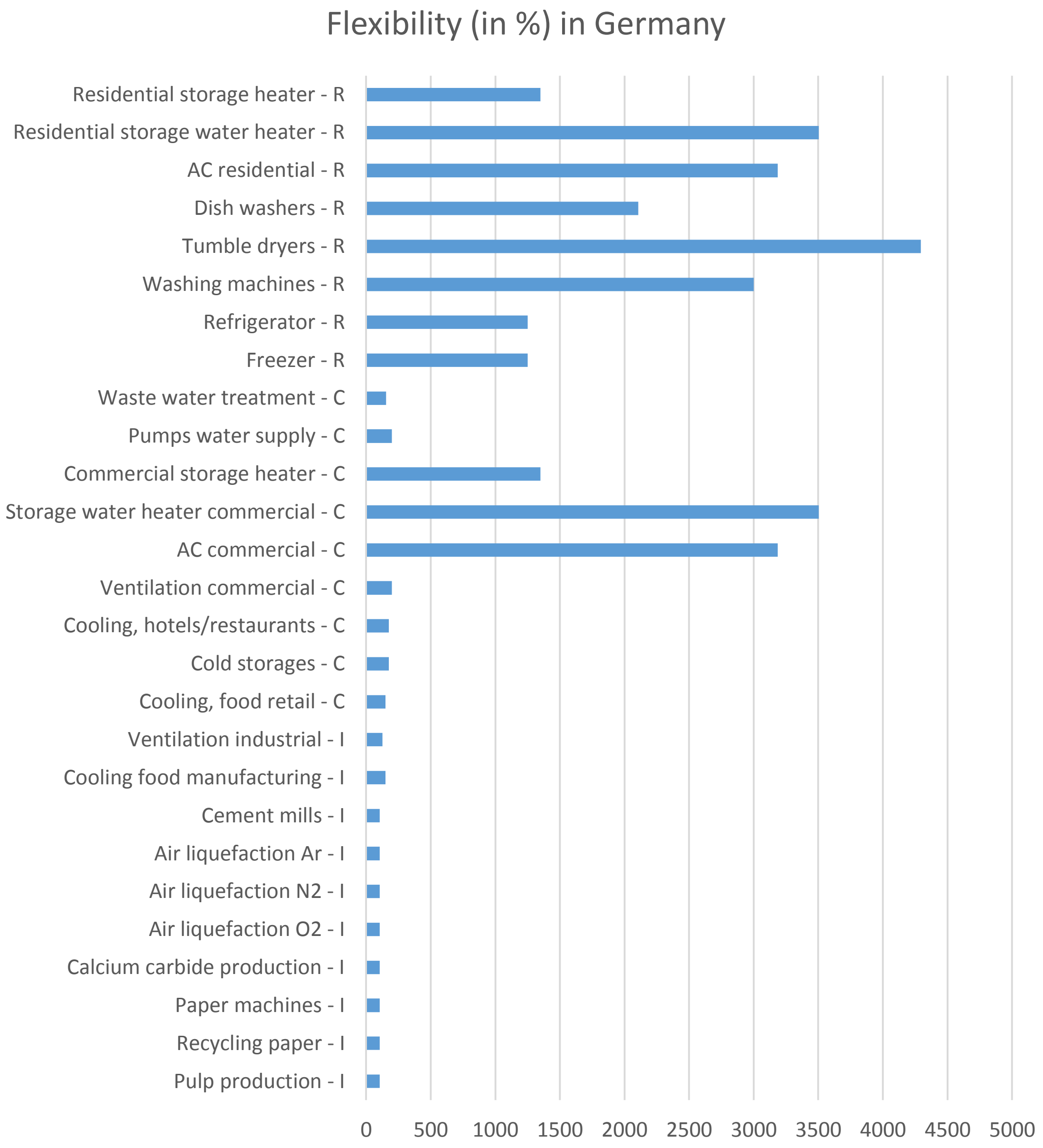
Stochastic Dual Dynamic Programming (SDDP)

Flexibility

- Deferrable demand behaves much like storage
  - H: time window for completing task
  - E: energy required for task
  - D: max rate of consumption

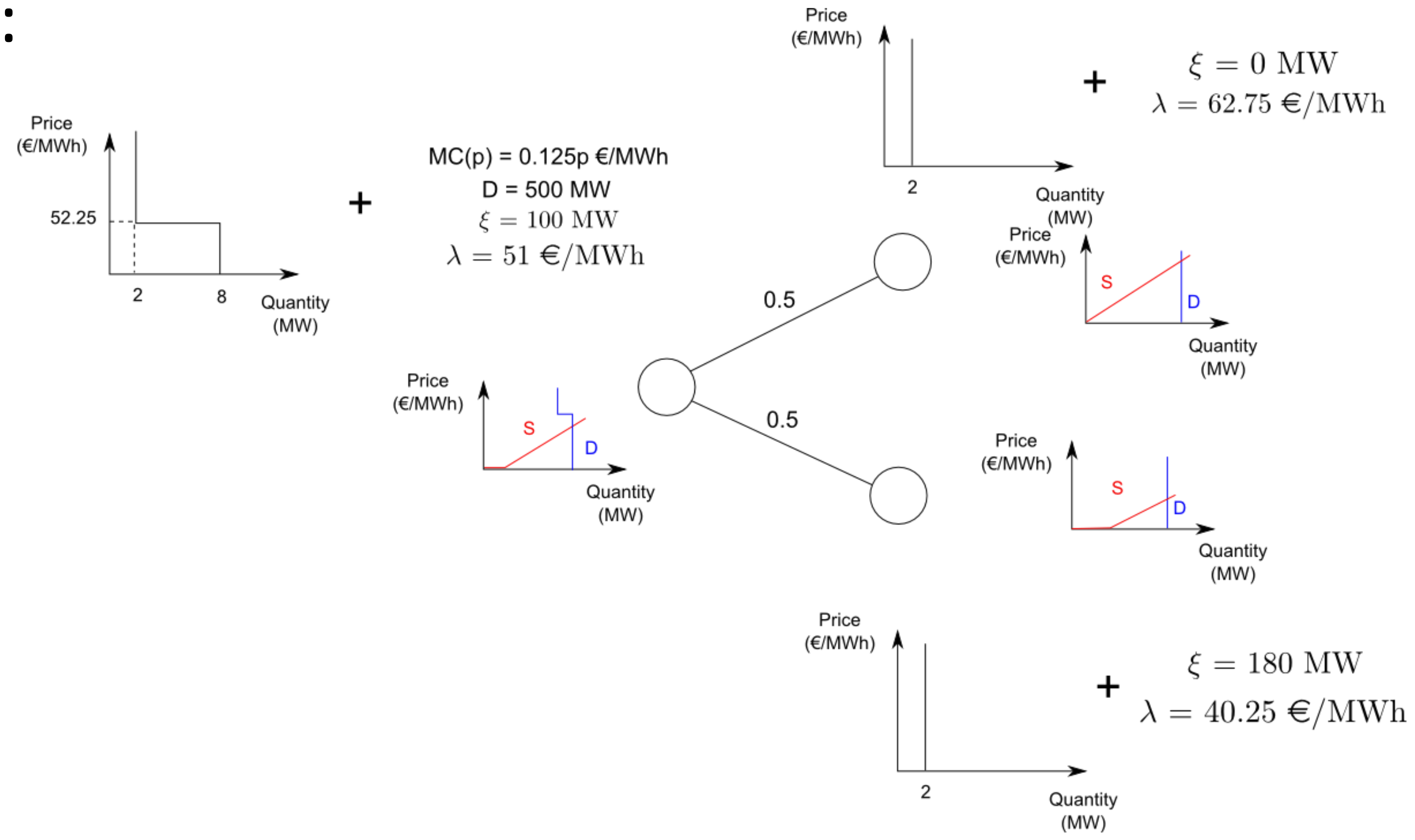


$$\text{Flexibility} = \frac{D \cdot H}{E}$$



A Stochastic Programming Approach

- Consider a market over 2 periods:
  - Uncertain wind ξ
  - Conventional generator with marginal cost $MC(p) = 0.125$ €/MWh
  - Inflexible demand $D = 500\ MW$
  - One deferrable consumer ($E = 10$ MWh, $\mathrm{P} = 8$ MW)
- Not a *coincidence*: market equilibrium ⇔stochastic programming optimal solution



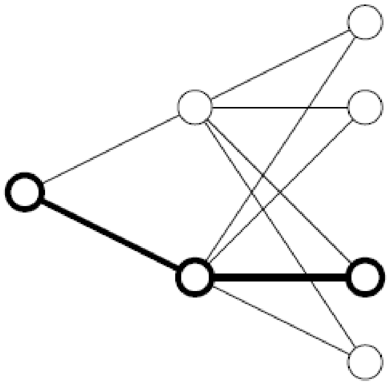
Stochastic Dual Dynamic Programming (SDDP)

- Our target model is a stochastic program that
  - captures uncertainty
  - captures balance between suppliers/consumers
  - captures the role of *time* in flexibility …
- … but it is a multi-stage (e.g. 24 stages/hours) stochastic program → **enormous** number of variables/constraints
- The energy industry has solved this problem in context of hydrothermal planning through *SDDP*
  - Multi-stage (e.g. 12 stages/months) planning of hydro reservoirs
  - Uncertainty of rainfall
  - Role of *time* in level of water in hydro reservoirs
- Advantages
  - SDDP has proven itself as a commercially viable tool
  - Parallelizable
  - The algorithm generates <u>electricity price distributions</u> as a by-product
- Disadvantages
  - There is a long-standing debate about convergence*
  - Unclear if it is appropriate for DR

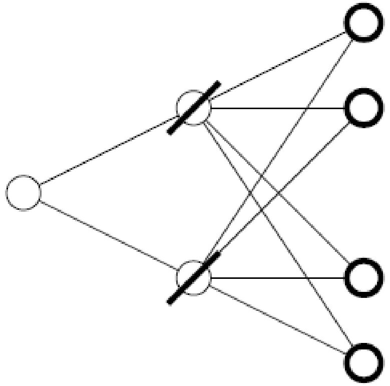
* See upcoming session: MVF Pereira, A Shapiro, ´*Computational Challenges in Energy*´, CORE 50th anniversary, May 26, 2016

The Idea of SDDP

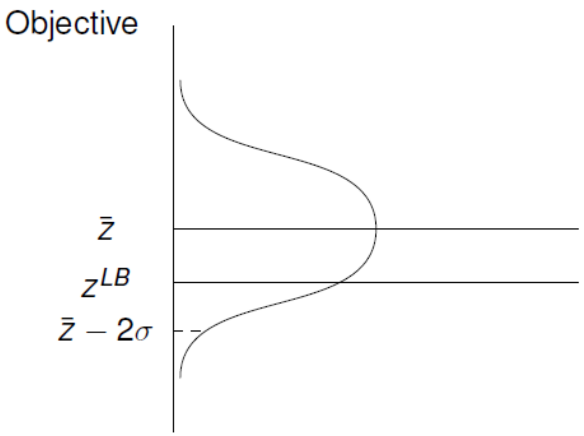
- SDDP relies on two 'tricks'
  - *Simulate* scenarios, instead of *enumerating* → forward pass → upper bound
  - Share information among states of the world that are in the same period → backward pass → lower bound
- These tricks come with restrictions:
  - Serial independence: the future looks the same, no matter what we have observed so far
  - Probabilistic upper bounds (and ensuing debate)



Forward pass



Backward pass



Probabilistic upper bound

Case Study

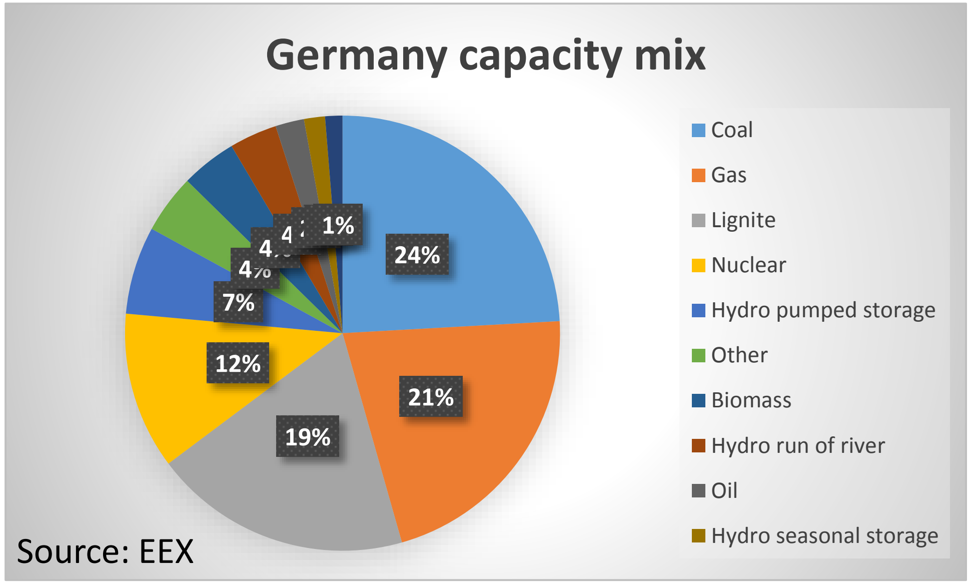
Model setup

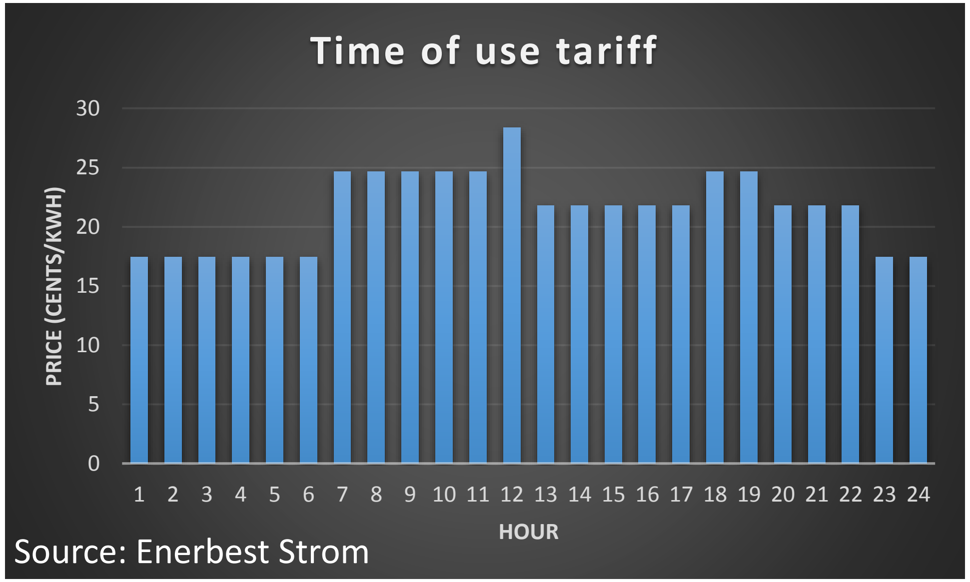
Convergence results

Operating efficiencies of demand response

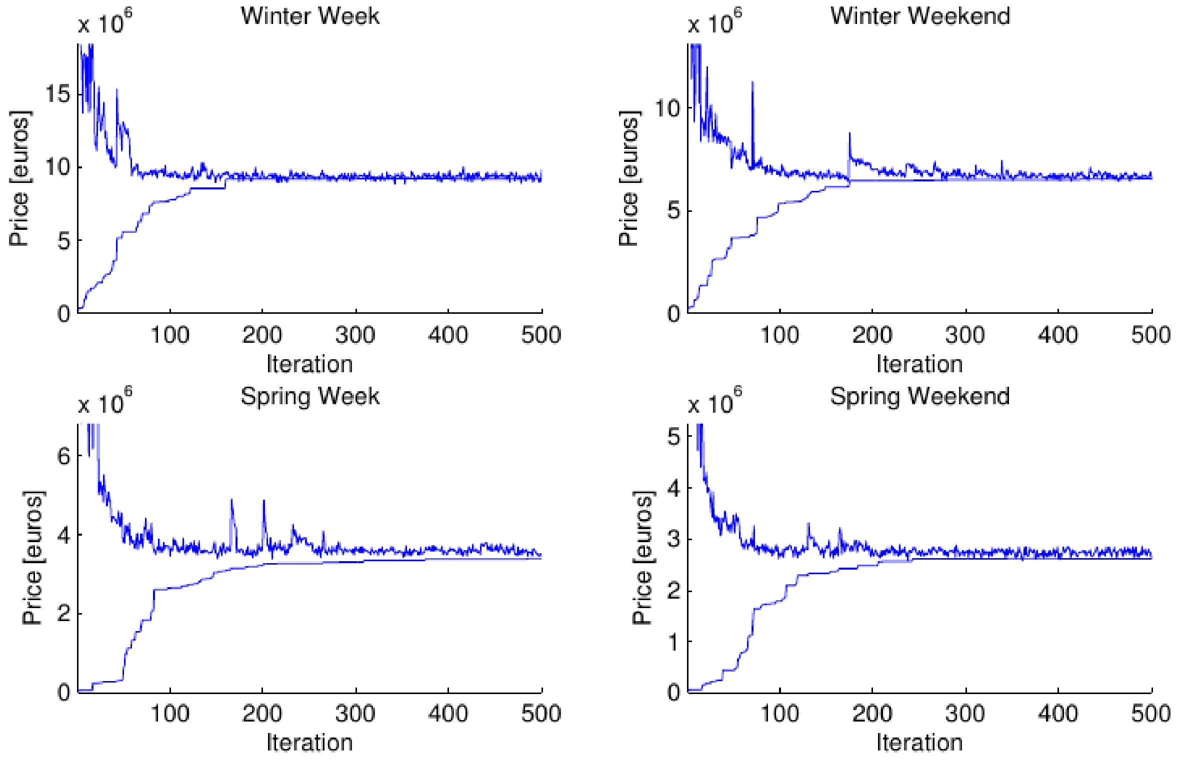
Focus on Germany, 2013

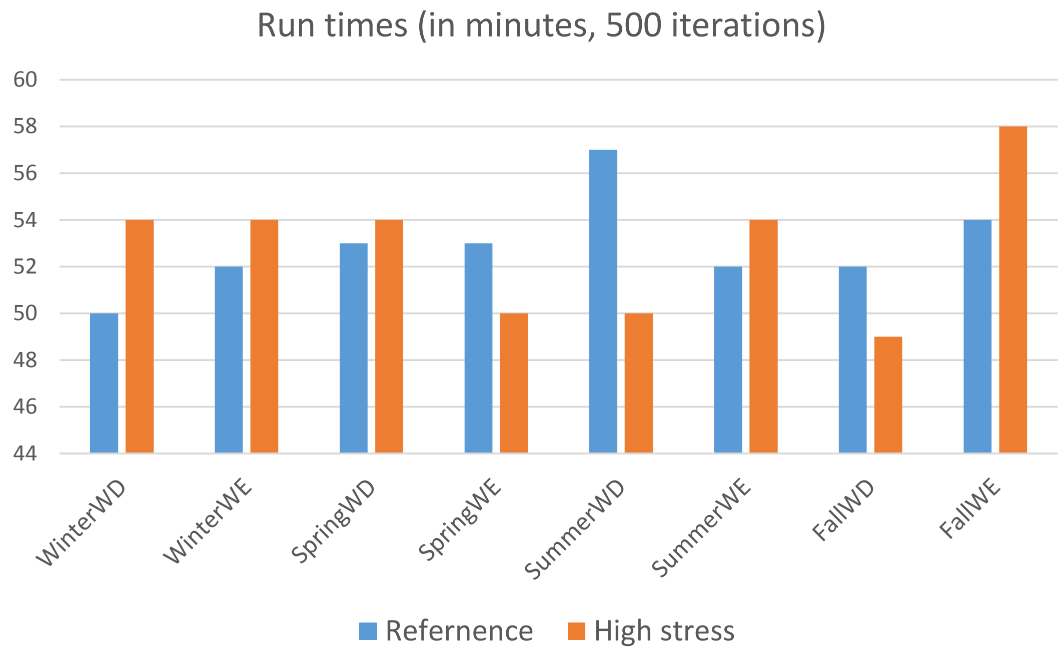
- Demand data: ENTSO-E
- Wind and solar power data: EEX transparency platform
- Flexible load data: (Gils, 2014)
- 24 stages, 2 outcomes per stage → extended form problem with 33.8 billion variables, 19 billion constraints
- Compare four models
  - Perfect foresight
  - Real-time-pricing
  - Time of use pricing
  - Inflexible demand
- Compare two scenarios
  - Reference case
  - High stress case
    - Decommissioning of nuclear capacity
    - Exports of 20 GW for *all* hours of the day



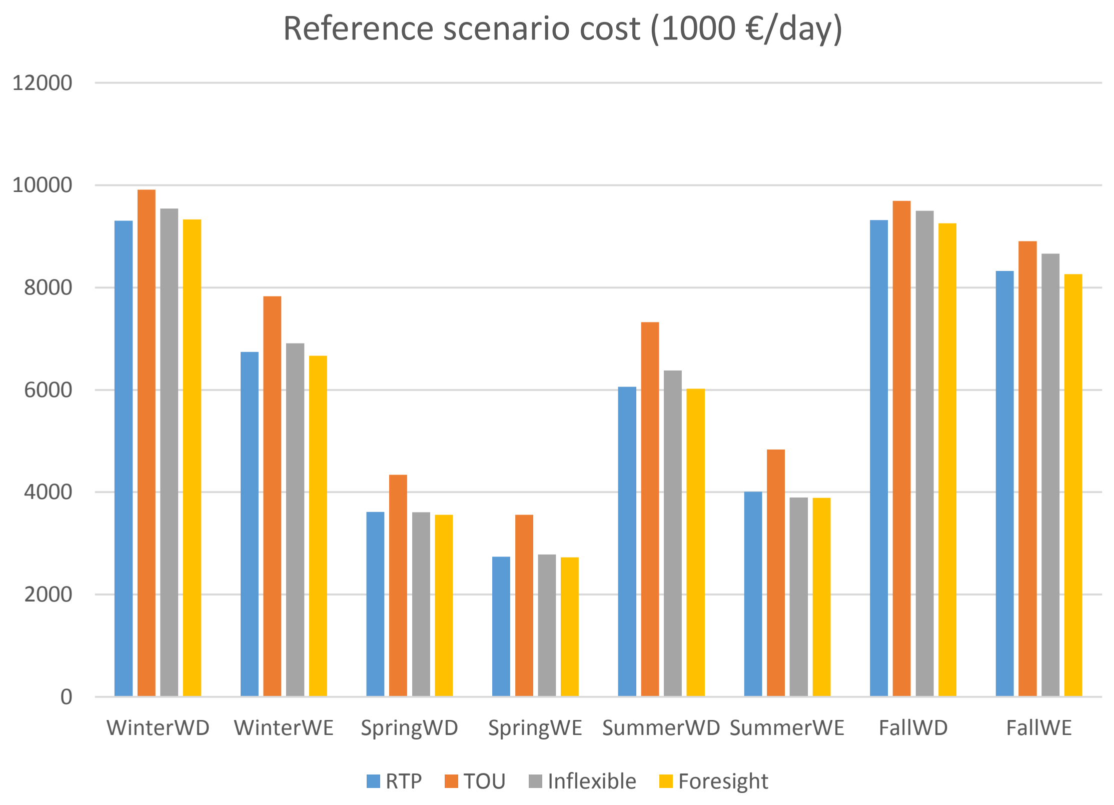


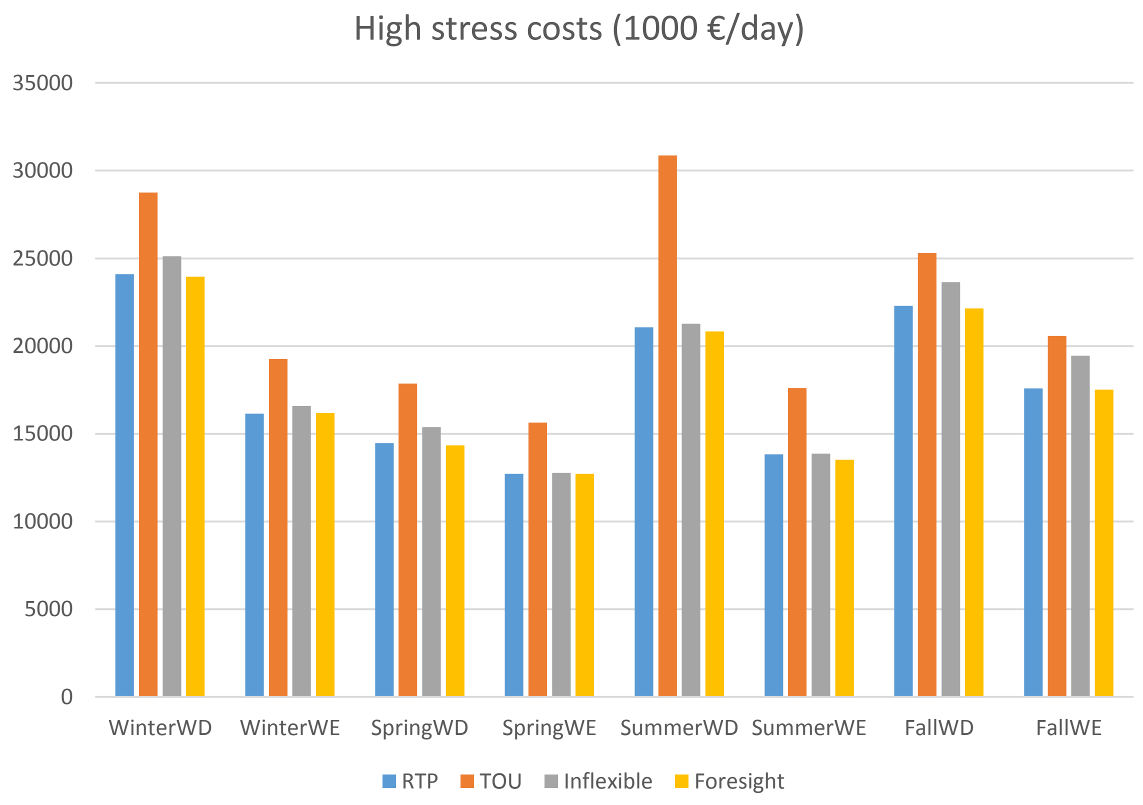
Convergence and Run Times





Policy Comparison





Conclusions and Perspectives

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- Conclusions
  - Stochastic programming can be used as a first approximation of market models with DR
  - SDDP seems capable of tackling closed-loop market models with simple represntation of DR
- Perspectives
  - Detailed modeling of DR constraints
  - Aggregator business models based on priority service pricing
  - **ColorPower** project (sponsor: Electrabel, colaborator: Zome)

Green = Price Sensitive

Yellow = Reliability Responsive

Red = Opt Out