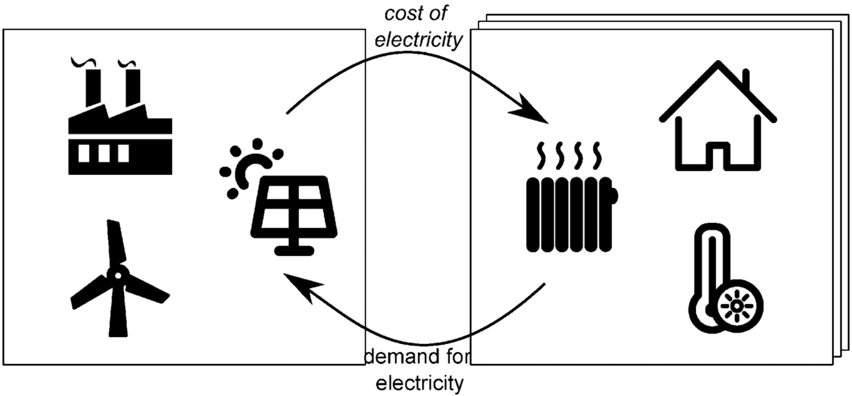
Valuing demand response controllability: a system and aggregator perspective

K. Bruninx

Thanks to: D. Patteeuw, C. Protopapadaki, A. Arteconi, G. Reynders, L. Helsen, D. Saelens, H. Le Cadre, H. Pandžić, Y. Dvorkin, D. Kirschen, W. D'haeseleer & E. Delarue

Zagreb, Croatia – June 19, 2018

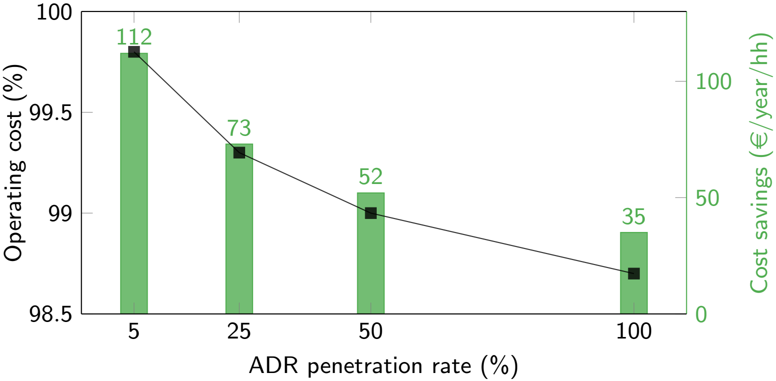
Context



- Thermal inertia allows decoupling the electrical & thermal demand without loss of comfort → opportunity for demand response!

Introduction & motivation

- Many research/policy papers on 'the value of demand response':



Source: A. Arteconi et al., *Active demand response with electric heating systems: Impact of market penetration*, Applied Energy, Vol. 177, 2016, pp. 636–648.

Limiting assumptions in current modeling efforts

- Representation of physical/technical characteristics of the DR resource;
- Non-disruptive end-energy service (e.g. guaranteed thermal comfort);
- Perfectly controllable DR;
- Objective DR provider perfectly aligned with system/aggregator objective;
- Limited heterogeneity in the representation of the DR resource;
- . . .

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- Objective DR provider perfectly aligned with system/aggregator objective;
- Limited heterogeneity in the representation of the DR resource;
- . . .

Research questions

1. **The system perspective:**
   - How can we study the system value (arbitrage & operating reserves) of demand response with thermostatically controlled loads?
   - What is the impact of requiring thermal comfort at all times?
   - What is the impact of limited controllability on the system value?
   - Source: K. Bruninx et al., 'Valuing Demand Response Controllability via Chance Constrained Programming', IEEE Trans. Sustain. Energy, vol. 9, no. 1, 2018.

2. **The aggregator perspective:**
   - How can we study the strategic participation of an aggregator in a market while guaranteeing that all user-defined comfort constraints are met?
   - . . . interaction between an aggregator and its demand response providers?
   - . . . if demand response providers are limitedly controllable?
   - Source: K. Bruninx et al., *On the Interaction between Aggregators, Electricity Markets and Residential Demand Response Providers*, submitted to IEEE. Trans. Power Syst., 2018.

PART 1: The system perspective

Demand response & unit commitment models

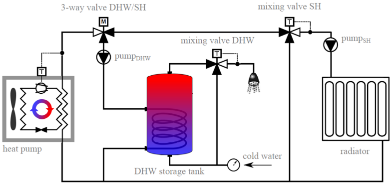
Minimize E[Total Operating Cost]

Subject to

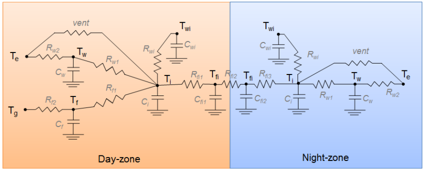
- D + DR = generation + RES;
- Technical constraints of power plants and energy storage systems;
- Limited predictability wind and solar → **Probabilistic reserve requirements**;
- **Physical demand side model.**

Source: D. Patteeuw et al., *Integrated modeling of active demand response with electric heating systems coupled to thermal energy storage systems*, Applied Energy, Vol. 151, 2015, pp. 306–319.

Heating system models



Building (stock) models



User behavior and weather data

Demand response & unit commitment models

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Subject to

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$$\text{Minimize} \sum_{t\in\mathcal{T}} \lambda^{\mathrm{A}}_{h,t}\cdot d^{\mathrm{H}}_{h,t}$$

subject to

$$d^{\mathrm{H}}_{h,t} = p^{\mathrm{HP,SH}}_{h,t} + p^{\mathrm{HP,HW}}_{h,t} + p^{\mathrm{AH,SH}}_{h,t} + p^{\mathrm{AH,HW}}_{h,t}$$

$$p^{\mathrm{HP,SH}}_{h,t} + p^{\mathrm{HP,HW}}_{h,t} \leq \overline{P^{\mathrm{HP}}_{h}}, \qquad p^{\mathrm{AH,SH}}_{h,t} + p^{\mathrm{AH,HW}}_{h,t} \leq \overline{P^{\mathrm{AH}}_{h}}$$

$$\sum_{s\in\mathcal{S}} \dot{q}^{\mathrm{SH}}_{h,s,t} = COP^{\mathrm{SH}}_{h}\cdot p^{\mathrm{HP,SH}}_{h,t} + p^{\mathrm{AH,SH}}_{h,t}$$

$$\dot{q}^{\mathrm{HW}}_{h,t} = COP^{\mathrm{HW}}_{h}\cdot p^{\mathrm{HP,HW}}_{h,t} + p^{\mathrm{AH,HW}}_{h,t}$$

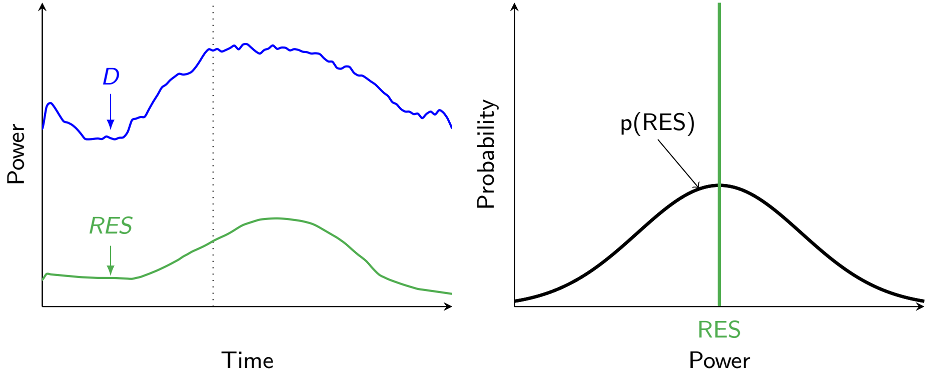
$$T^{\mathrm{SH}}_{h,p,t} = A^{\mathrm{SH}}_{h,p}\cdot T^{\mathrm{SH}}_{h,p,t-1} + \sum_{s\in\mathcal{S}} B^{\mathrm{SH}}_{h,p,s}\cdot \dot{q}^{\mathrm{SH}}_{\mathrm{h,s,t}} + E^{\mathrm{SH}}_{h,p,t}$$

$$\underline{T^{\mathrm{SH}}_{h,p,t}} \leq T^{\mathrm{SH}}_{h,p,t} \leq \overline{T^{\mathrm{SH}}_{h,p,t}}$$

$$T^{\mathrm{HW}}_{h,t} = A^{\mathrm{HW}}_{h}\cdot T^{\mathrm{HW}}_{h,t-1} + B^{\mathrm{HW}}_{h}\cdot \dot{q}^{\mathrm{HW}}_{\mathrm{h,t}} + E^{\mathrm{HW}}_{h,t}$$

$$\underline{T^{\mathrm{HW}}_{h,t}} \leq T^{\mathrm{HW}}_{h,t} \leq \overline{T^{\mathrm{HW}}_{h}}$$

Endogenous probabilistic reserve sizing and allocation in UC models



Source: Bruninx, K., Delarue, E., *Endogenous probabilistic reserve sizing and allocation in unit commitment models: cost-effective, reliable and fast*, IEEE Transactions on Power Systems, vol. 32, no. 4, 2017.

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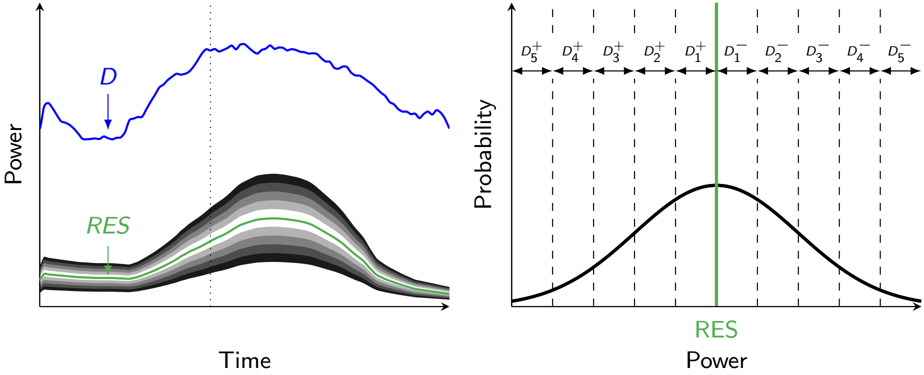

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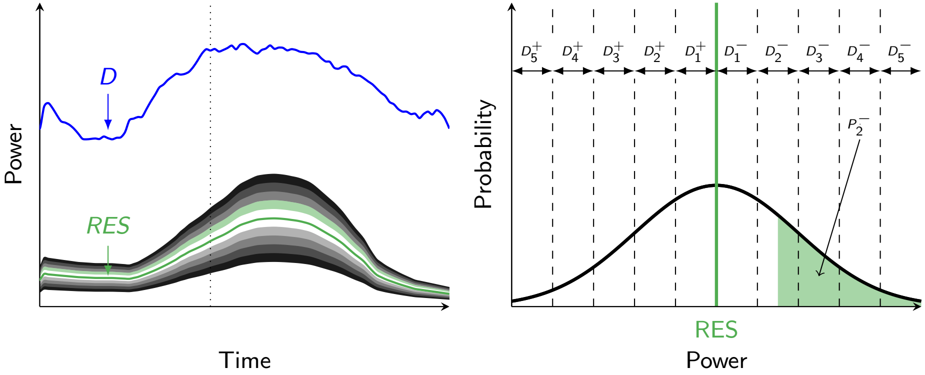

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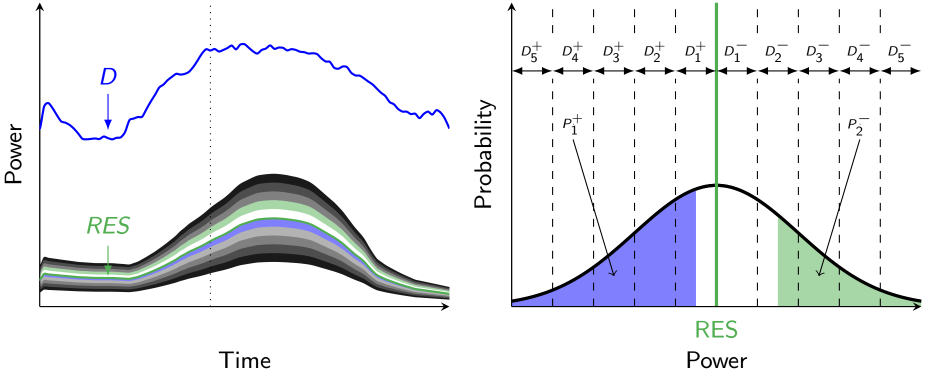

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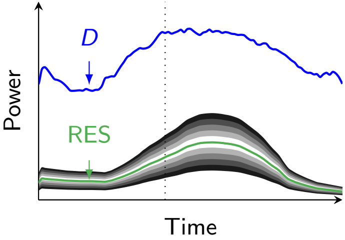
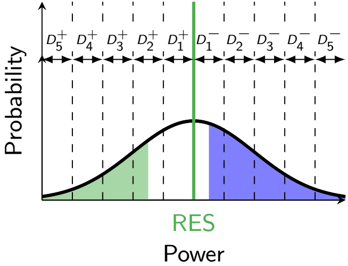
Endogenous probabilistic reserve sizing and allocation in UC models

- + Approximation of **expected deployment costs**, hence endogenous reserve sizing possible and close to optimal UC schedules;
- + **Fast**;
- + Ensured **feasibility** of real-time deployment of energy storage and DR-based regulation;

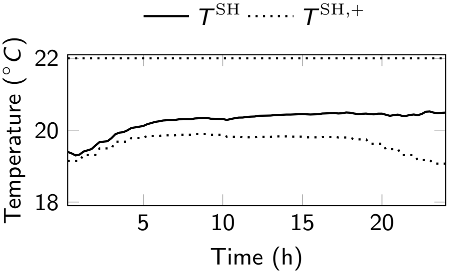
- – **Conservative**, especially for energy storage and DR-based regulation services.

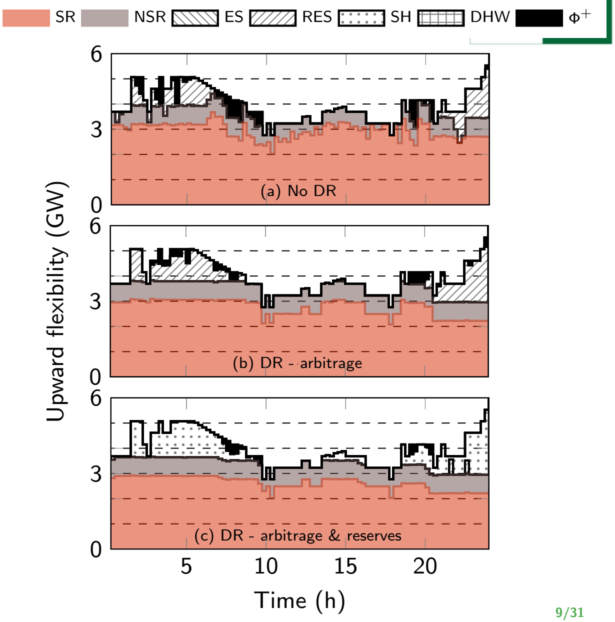




Value of *controllable* DR

- DR-arbitrage → more cost-efficient upward reserve provision;
- DR-reserves → higher uptake RES-based generation, while guaranteeing thermal comfort.





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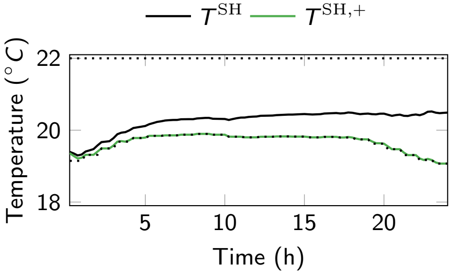

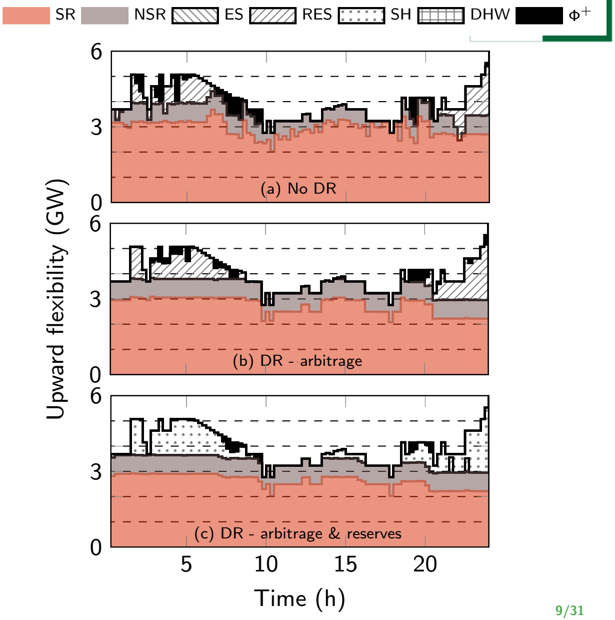

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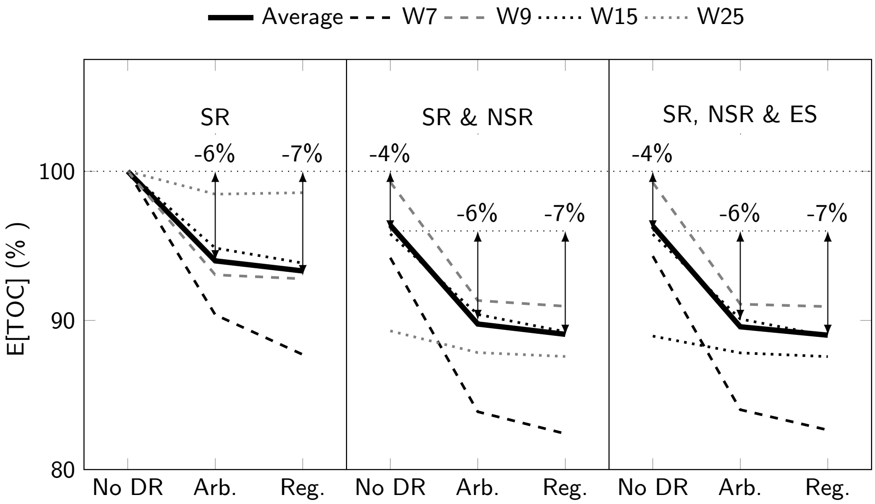
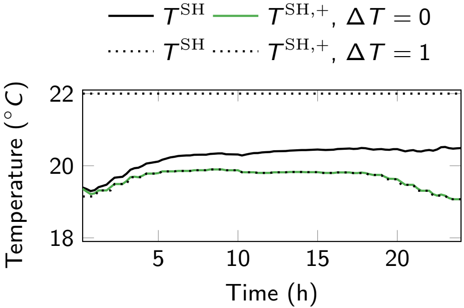
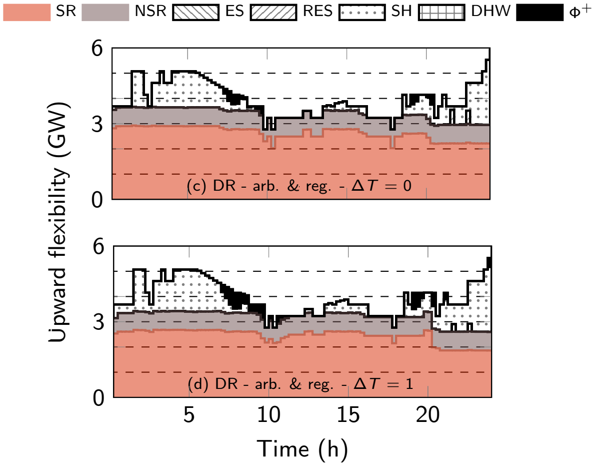


Challenging the guaranteed thermal comfort-assumption





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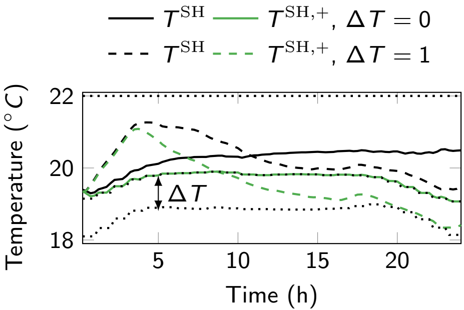
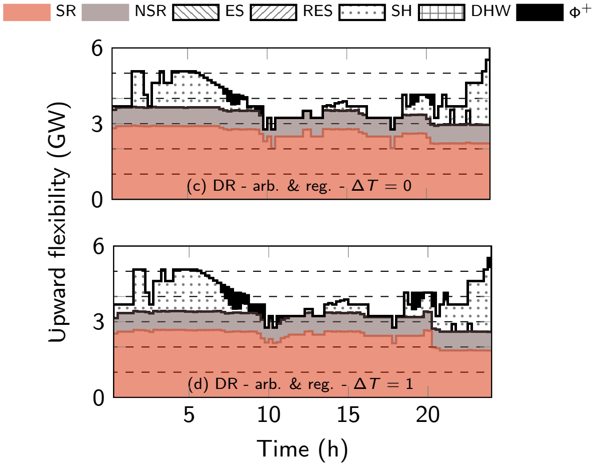
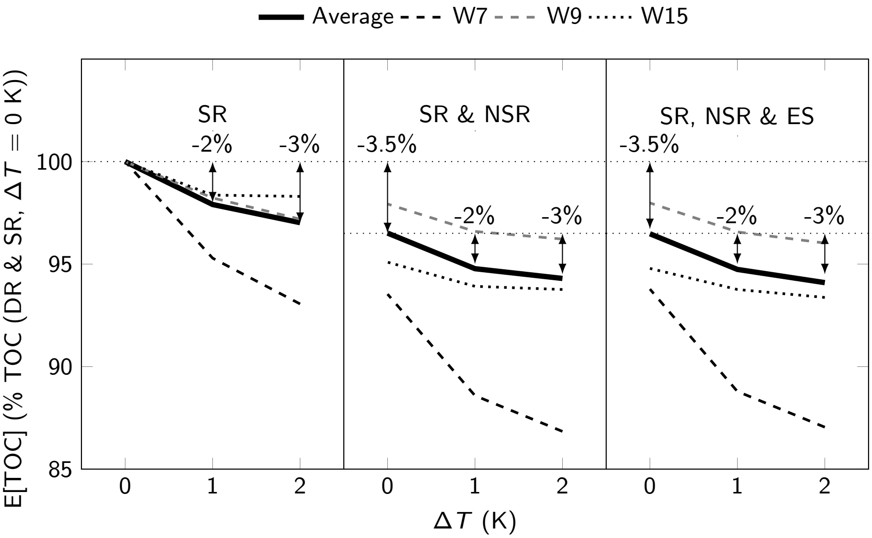




Value of *thermal discomfort*



Challenging the perfectly controllability-assumption

Minimize E[Total Operating Cost]

Subject to

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- Limited predictability wind and solar
  → Probabilistic reserve requirements;
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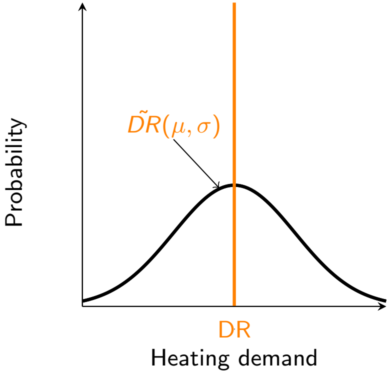
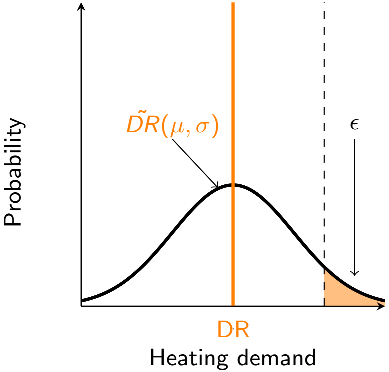


Challenging the perfectly controllability-assumption

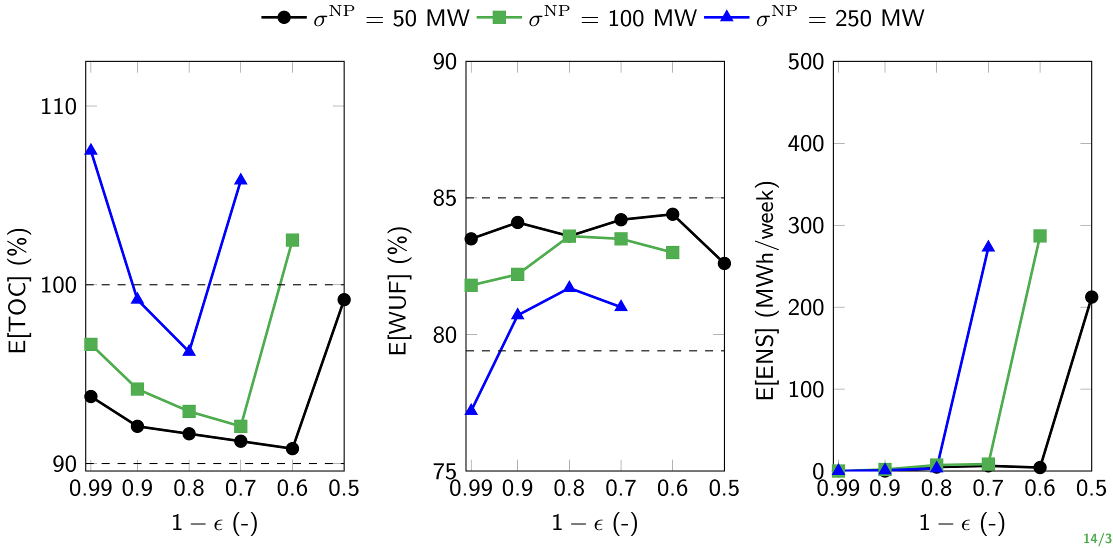
Minimize E[Total Operating Cost]

Subject to

- D + DR = generation + RES
  → $\Pr(\text{D} + \tilde{DR} \leq \text{generation} + \text{RES}) \geq 1 - \epsilon$;
- Technical constraints of power plants and energy storage systems;
- Limited predictability wind and solar
  → Probabilistic reserve requirements;
- Physical demand side model.



Value of *limitedly controllable* DR-based arbitrage



Concluding remarks - the system perspective

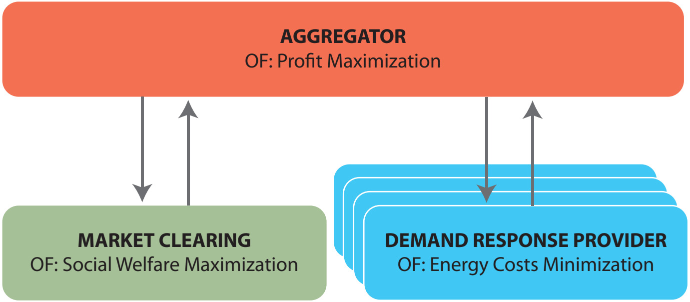
A novel **unit commitment model considering a physical demand response model & RES forecast uncertainty** allows illustrating that

- **significant operating cost reductions** may be attained by leveraging **demand response** with electric heating systems for arbitrage & ancillary services;
- this value can be **increased if thermal discomfort is allowed** to a limited extent;
- **imperfectly controllable demand response** may hold **limited value** for a risk-averse power system operator.

PART 2: The aggregator’s perspective

The aggregator perspective

- How can we study the strategic participation of an aggregator in a market while guaranteeing that all user-defined comfort constraints are met?
- . . . interaction between an aggregator and its demand response providers?
- . . . if demand response providers are limitedly controllable?



AGGREGATOR
OF: Profit Maximization

MARKET CLEARING
OF: Social Welfare Maximization

DEMAND RESPONSE PROVIDER
OF: Energy Costs Minimization

Literature review

Interaction DR aggregator – electricity markets

- Price-taking agent → optimization models (Xu et al., 2017, Mathieu et al., 2015, Zugno et al., 2013);
- Strategic price-maker → Stackelberg Game → bilevel optimization problem/MPEC (Kazempour et al., 2015, Kardakos et al., 2016).

Interaction DR aggregator – DR provider

- Leader-follower → Stackelberg Game → bilevel optimization problem/MPEC (Li et al., 2016, Yu et al., 2016, Zugno et al., 2013);
- Collaboration → Nash Bargaining Game → optimization problem (Contreras et al., 2017, Hoa et al., 2016, Ye et al., 2017)

Limited controllability

- System studies/non-strategic aggregators → chance constrained programming;
- Uncertain availability of DR resources (Li et al., 2015, Zhang et al., 2017);
- Limited controllability (Bruninx et al., 2017).

Methodology: Aggregator's perspective

Objective: maximize operating profit

$$\text{Maximize} \quad \Pi^{\mathrm{A}} = \sum_{t \in \mathcal{T}} \left[R^{\mathrm{A}}(\lambda^{\mathrm{A}}_{h,t}, D^{\mathrm{H}}_t) - \sum_{\omega \in \Omega} \pi_\omega \cdot \lambda_{t,\omega} \cdot q^{\mathrm{agg}}_{t,\omega} \right]$$

- Revenue $R^{\mathrm{A}}(\lambda^{\mathrm{A}}_{h,t}, D^{\mathrm{H}}_t)$, based on retail rate $\lambda^{\mathrm{A}}_{h,t}$ and DR load D^{H}_t;
- Expenses in whole-sale market $\sum_{\omega \in \Omega} \pi_\omega \cdot \lambda_{t,\omega} \cdot q^{\mathrm{agg}}_{t,\omega}$, with $\lambda_{t,\omega}$ the market clearing price.

subject to

$$\mathbb{P}\left(\overline{Q^{\mathrm{agg}}_t} \geq D^{\mathrm{H}}_t, \ \forall t \in \mathcal{T} \right) \geq 1 - \epsilon$$

- Chance constraint: procure sufficient electricity to cover the limitedly controllable DR load D^{H}_t with a probability of $(1-\epsilon) \cdot 100\%$;

$$D^{\mathrm{H}}_t = (1 + \delta^{\mathrm{P}}) \cdot \sum_{h \in \mathcal{H}} NB_h \cdot d^{\mathrm{H}}_{h,t} + \delta^{\mathrm{NP}}, \ \forall t \in \mathcal{T}$$

- Assume δ^{P} and δ^{NP} follow a Gaussian distribution → SOC

Methodology: Market operator's perspective

Objective: maximize total surplus w.r.t. the bids and offers of the market participants

$$\text{Maximize} \sum_{t\in\mathcal{T}} \left[P^{\mathrm{d}} \cdot d_{t,\omega} + P^{\mathrm{agg}} \cdot q^{\mathrm{agg}}_{t,\omega} - \sum_{i\in\mathcal{I}} P^{\mathrm{g}}_i \cdot g_{i,t,\omega}\right]$$

Subject to:

$$\begin{aligned}
-w_{t,\omega} - \sum_{i\in\mathcal{I}} g_{i,t,\omega} + d_{t,\omega} + q^{\mathrm{agg}}_{t,\omega} = 0 \quad (\lambda_{t,\omega}) & \qquad \text{Market clearing condition (price)}\\
0 \leq g_{i,t,\omega} \leq \overline{G_i} & \qquad \text{Generation limit (conventional)}\\
0 \leq d_{t,\omega} \leq \overline{D_t} & \qquad \text{Demand}\\
0 \leq w_{t,\omega} \leq \overline{W_{t,\omega}} & \qquad \text{Generation limit (RES)}\\
0 \leq q^{\mathrm{agg}}_{t,\omega} \leq \overline{Q^{\mathrm{agg}}_t} & \qquad \text{Aggregator bid limit}
\end{aligned}$$

Methodology: Demand Response Provider's perspective

Objective: minimize the cost of electric space heating and hot water production

$$\text{Minimize} \sum_{t \in \mathcal{T}} \lambda^{\mathrm{A}}_{h,t} \cdot d^{\mathrm{H}}_{h,t}$$

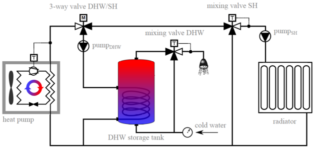
subject to

$$\boldsymbol{\theta_{h,t}} \;-\; \boldsymbol{\theta_{h,t-1}} = \boldsymbol{\mathcal{G}}(d^{\mathrm{H}}_{h,t}, C_h, \overline{P_h}, A_h, E_{h,t})$$

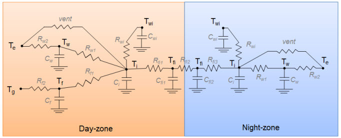
$$\underline{\boldsymbol{\theta_{h,t}}} \leq \boldsymbol{\theta_{h,t}} \leq \overline{\boldsymbol{\theta_{h,t}}}, \;\forall t \in \mathcal{T}$$

Source: D. Patteeuw et al., *Integrated modeling of active demand response with electric heating systems coupled to thermal energy storage systems*, Applied Energy, Vol. 151, 2015, pp. 306–319.

Heating system models



Building models



Consumer behavior

Methodology: Aggregator – Market Interaction

Maximize *Operating profit*

subject to

Chance constraints: $P\left(\overline{Q_t^{\text{agg}}} \geq D_t^{\text{H}},\ t \in \mathcal{T}\right) \geq 1 - \epsilon$

Market clearing: $(\lambda_{t,\omega}, q_{t,\omega}^{\text{agg}}) = \text{argmax}\{\textit{Total surplus} \quad \text{s.t.} \quad \textit{market clearing conditions}\}$

- Assume: aggregator (leader) decides on bid in the wholesale market (follower);
- Bilevel optimization problem → KKT conditions market clearing problem → MPEC → MIQCP

Methodology: Aggregator – Demand Response Provider Interaction

Retailer ∼ *Stackelberg Game*

- flat retail rate $\lambda^{\mathrm{A}}_{h,t} = \lambda^{\mathrm{A}} \rightarrow$ Consumers minimize their energy demand;
- $d^{H}_{h,t}$: parameter in the retailer's problem
- Assume: best possible case for consumer → profit-neutral retailer:

$$\sum_{h \in \mathcal{H}} NB_h \cdot R^{\mathrm{R}}_h = \sum_{t \in \mathcal{T}} \sum_{\omega \in \Omega} \pi_\omega \cdot \lambda_{t,\omega} \cdot q^{\mathrm{agg}}_{t,\omega}$$

Aggregator ∼ *Nash Bargaining Game*, S(*Stackelberg Game*) ∈ S(*Nash Bargaining Game*)

- DR providers collaborate with the aggregator;
- Total benefit of this collaboration:

$$\mathcal{B} = \sum_{h \in \mathcal{H}} NB_h \cdot R^{\mathrm{R}}_h - \sum_{t \in \mathcal{T}} \sum_{\omega \in \Omega} \pi_\omega \cdot \lambda_{t,\omega} \cdot q^{\mathrm{agg}}_{t,\omega}$$

- Division of benefit → Nash Bargaining Game, i.e., contract, not on day-to-day basis;
- Aggregator can only influence $\sum_{t \in \mathcal{T}} \sum_{\omega \in \Omega} \pi_\omega \cdot \lambda_{t,\omega} \cdot q^{\mathrm{agg}}_{t,\omega}$ on day-to-day basis;
- No restrictions on formation retail rate & guaranteed thermal comfort? → S(*Stackelberg Game*) ∈ S(*Nash Bargaining Game*)!

Equivalent MIQCP

Retailer

$$\text{Maximize} \quad -\sum_{t\in\mathcal{T}}\sum_{\omega\in\Omega}\pi_\omega\cdot\lambda_{t,\omega}\cdot q_{t,\omega}^{\mathrm{agg}}$$

s.t. Chance constraint: $P\left(\overline{Q_t^{\mathrm{agg}}}\geq D_t^{\mathrm{H}},\ t\in\mathcal{T}\right)\geq 1-\epsilon$

Profit neutrality: $\sum_{h\in\mathcal{H}} NB_h\cdot R_h^{\mathrm{R}}=\sum_{t\in\mathcal{T}}\sum_{\omega\in\Omega}\pi_\omega\cdot\lambda_{t,\omega}\cdot q_{t,\omega}^{\mathrm{agg}}$

$d_{h,t}^{\mathrm{H}}$ assumed given

Market clearing constraints

Aggregator

$$\text{Maximize} \quad -\sum_{t\in\mathcal{T}}\sum_{\omega\in\Omega}\pi_\omega\cdot\lambda_{t,\omega}\cdot q_{t,\omega}^{\mathrm{agg}}$$

s.t. Chance constraint: $P\left(\overline{Q_t^{\mathrm{agg}}}\geq D_t^{\mathrm{H}},\ t\in\mathcal{T}\right)\geq 1-\epsilon$

Demand response model

Market clearing constraints

Case study

We'll show how ...

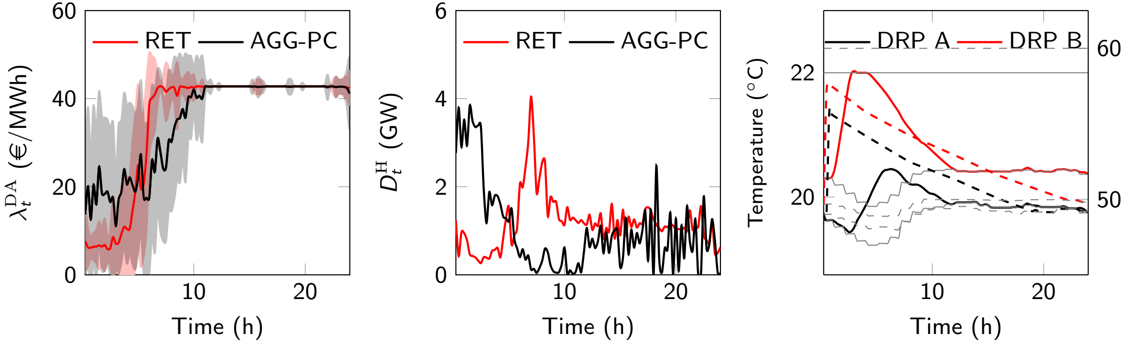
- the aggregator shifts heating demand from high to low price periods, without jeopardizing the thermal comfort of its consumers;
- the benefit of the aggregator - consumer collaboration decreases if demand response loads become less controllable. Liquid intraday and balancing markets limit impact limited controllability.

Data & assumptions

- $\sim$ isolated Belgian power system, additional gas-fired generation to cover electrified heating demand;
- Wind energy $\sim$ 50% of the annual energy demand (excl. electric space heating);
- Number of DR providers $\sum_{h \in \mathcal{H}} NB_h = 10^6$ → average 2030 low-energy building;
- Stochastic occupancy model → equivalent comfort constraints;
- Reference case: retailer serving a perfectly controllable/predictable heating demand;
- Most results for 316$^{\mathrm{th}}$ day of the calendar year (abundant wind power during first hours of the day, median of heating season conditions).

Optimal bidding strategies – Perfectly controllable heating loads

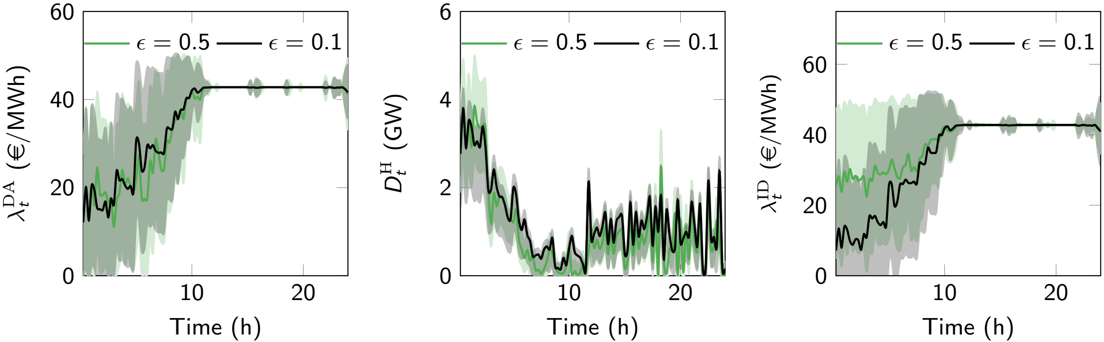
- Aggregator avoids high λ_t^{DA} period by shifting heating demand D_t^{H} to the night;
- Significant pre-heating (space heating) and pre-charging (hot water tanks), but day-zone & hot water temperatures remain within user-specified comfort constraints.



(a) Day-ahead electricity price (b) Heating demand (c) Day-zone (solid) and hot water (dashed) temperatures (AGG)

Optimal bidding strategies – Limitedly controllable heating loads

- Risk-averse aggregator is able to maintain day-ahead price profile λ_t^{DA}, but more procurement during the high price period;
- Procured demand D_t^{H} during the night remains approximately the same, but part of this procured quantity is 'reserved' to deal with unexpected real-time deviations;
- Excess/deficits can be sold/bought in intraday markets: risk-averse aggregator is more likely to sell, but sees lower prices λ_t^{ID}.



(a) Day-ahead electricity price (b) Heating demand (c) Intraday electricity price

Sensitivity analysis w.r.t. ϵ, $\delta^P \sim N(0, \sigma^P)$ and $\delta^{NP} \sim N(0, \sigma^{NP})$

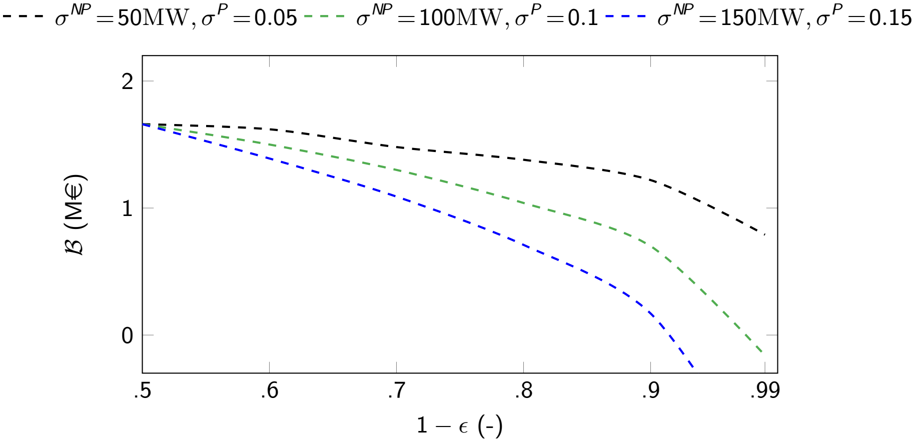


Figure: Change in benefit $\mathcal{B}$ of the consumer-aggregator cooperation for different ϵ, $\delta^P \sim N(0, \sigma^P)$ and $\delta^{NP} \sim N(0, \sigma^{NP})$ values for the 316$^{\mathrm{th}}$ day of the calendar year.

Sensitivity analysis w.r.t. ϵ, $\delta^P \sim N(0, \sigma^P)$ and $\delta^{NP} \sim N(0, \sigma^{NP})$

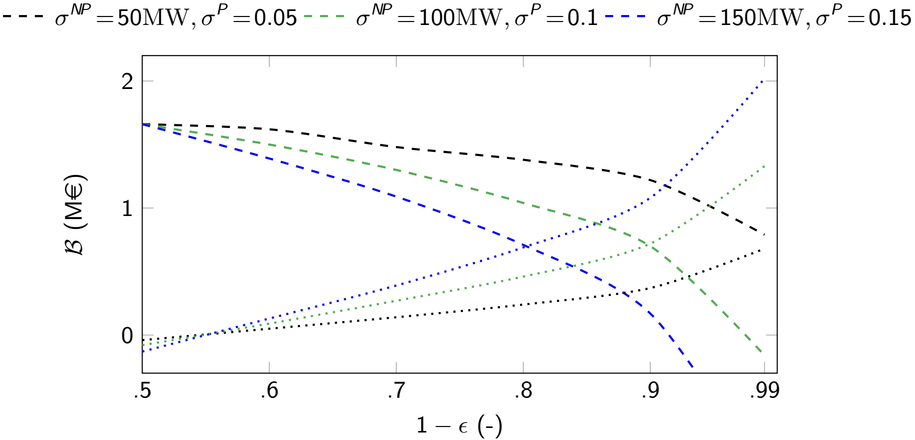


Figure: Change in benefit $\mathcal{B}$ of the consumer-aggregator cooperation for different ϵ, $\delta^P \sim N(0, \sigma^P)$ and $\delta^{NP} \sim N(0, \sigma^{NP})$ values for the 316th day of the calendar year.

Sensitivity analysis w.r.t. ϵ, $\delta^P \sim N(0, \sigma^P)$ and $\delta^{NP} \sim N(0, \sigma^{NP})$

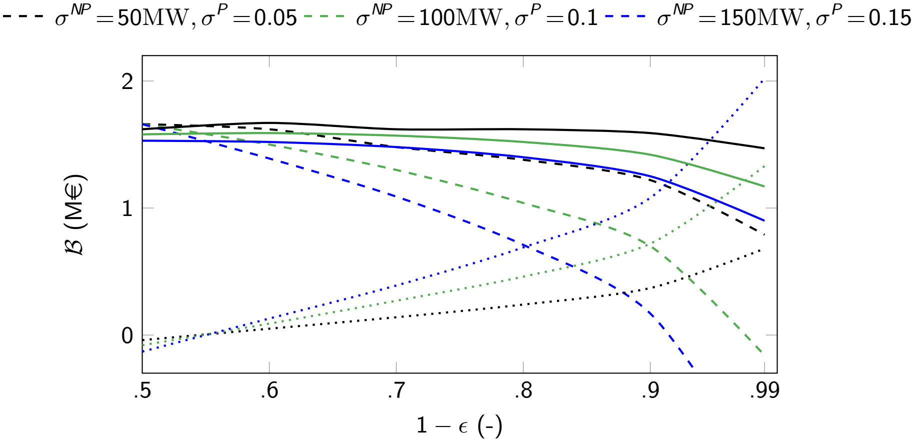


Figure: Change in benefit $\mathcal{B}$ of the consumer-aggregator cooperation for different ϵ, $\delta^P \sim N(0, \sigma^P)$ and $\delta^{NP} \sim N(0, \sigma^{NP})$ values for the 316th day of the calendar year.

Sensitivity analysis w.r.t. heating demand

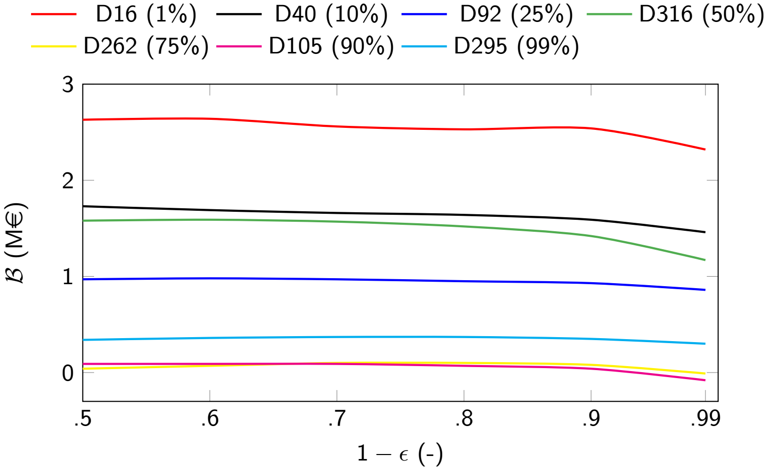


Figure: Change in benefit $\mathcal{B}$ of the consumer-aggregator cooperation for different days of the heating season. σ^P was set to 0.1, σ^{NP} equals 100 MW.

Concluding remarks - the aggregator's perspective

Model

- Strategic interaction aggregator – wholesale market $\sim$ Stackelberg game;
- Cooperation aggregator – DR provider $\sim$ Nash Bargaining game on division benefits, solution equivalent Stackelberg game $\in$ set outcomes of Nash Bargaining Game;
- Limited controllability of DR providers $\rightarrow$ chance constraints.

Case study

- Aggregator may lower wholesale prices by actively managing limitedly controllable resources, respecting consumer's comfort constraints;
- As the DR resource becomes less controllable and the aggregator becomes more risk-averse $\rightarrow$ the aggregator's profit decreases, but impact is limited if intraday markets are sufficiently liquid.

Concluding remarks

To sum up:

- Two different perspective, both illustrating significant benefits in DR with TCLs;
- Violating thermal comfort leads to system-wide savings, but compensation available to consumers may be insufficient;
- Impact limited controllability depends on perspective & model assumptions: system perspective may be too conservative, whereas intraday markets may be represented as too liquid.

Future work:

- Consumer-centric perspective;
- Sub-rational consumer behavior;
- Other aggregator strategies - e.g., risk-aversion;
- . . .

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Publications: `www.mech.kuleuven.be/en/tme/research/energy_environment`

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