Physics-inspired Deep Learning and Reinforcement Learning for building control

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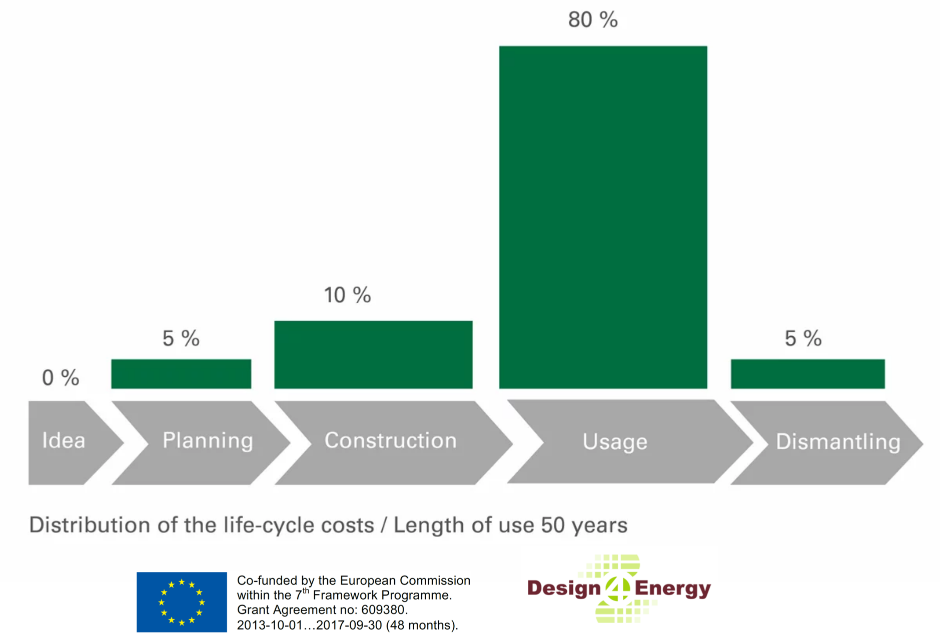
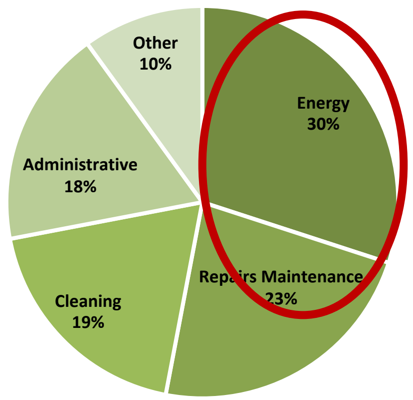
The importance of building control

- Buildings are **large energy consumers**
- **3 main ways** to tackle this issues

Design → **Control** → **Retrofit**



http://www.design4energy.eu/



OPEX of office buildings

https://www.chappleelectric.com/images/Commercial-Buildings-Costs.png

The importance of building models

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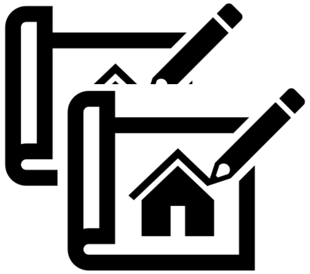

Models

of the **temperature** evolution to understand how much energy
is needed to matintain the comfort of the occupants

Issues of classical models

- Classically, people use **physics-based models**, built from first principles
  - Follow the **laws of physics**
  - Large **engineering overhead**

… ***but each building is different!***

… ***can we leverage data in black-box methods?***

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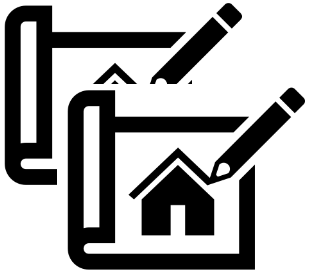

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Agenda

Introduction

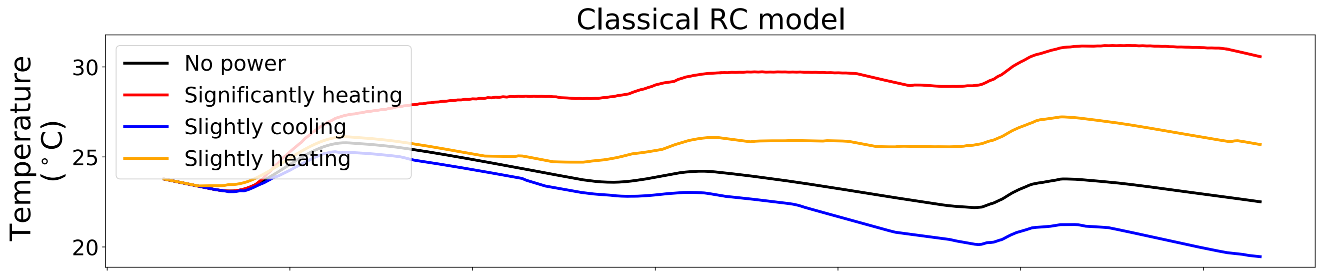
Deep Learning for building models

Deep Reinforcement Learning for building control

Conclusion

Physics-based vs Neural Network models

- Classical RC model from first principles

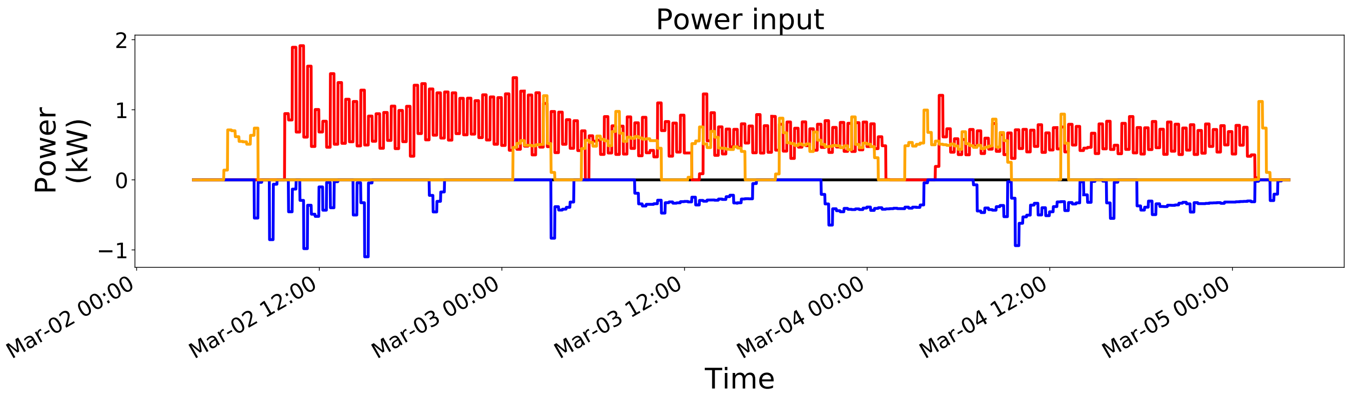


- **Neural networks (LSTM)**
  - **Great accuracy** during training
  - More than **50% more accurate**

Physically Consistent Neural Networks (PCNNs)

Retain physical consistency while being more accurate than physics-based models

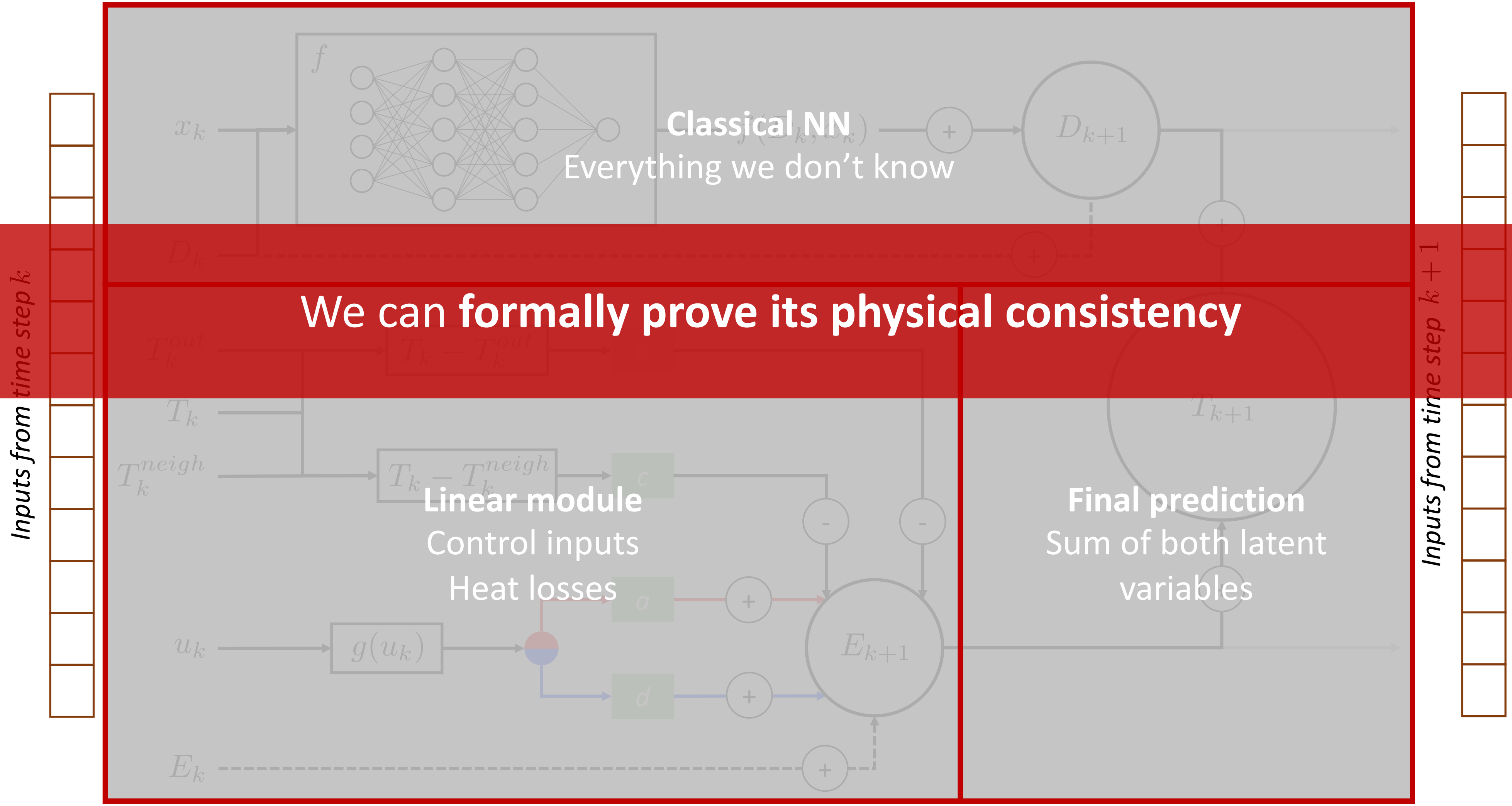
- **Generalization issue**, because of the poor **data coverage**
  - Buildings are inhabited and hence operated **following rules**



- **Not acceptable** in control application

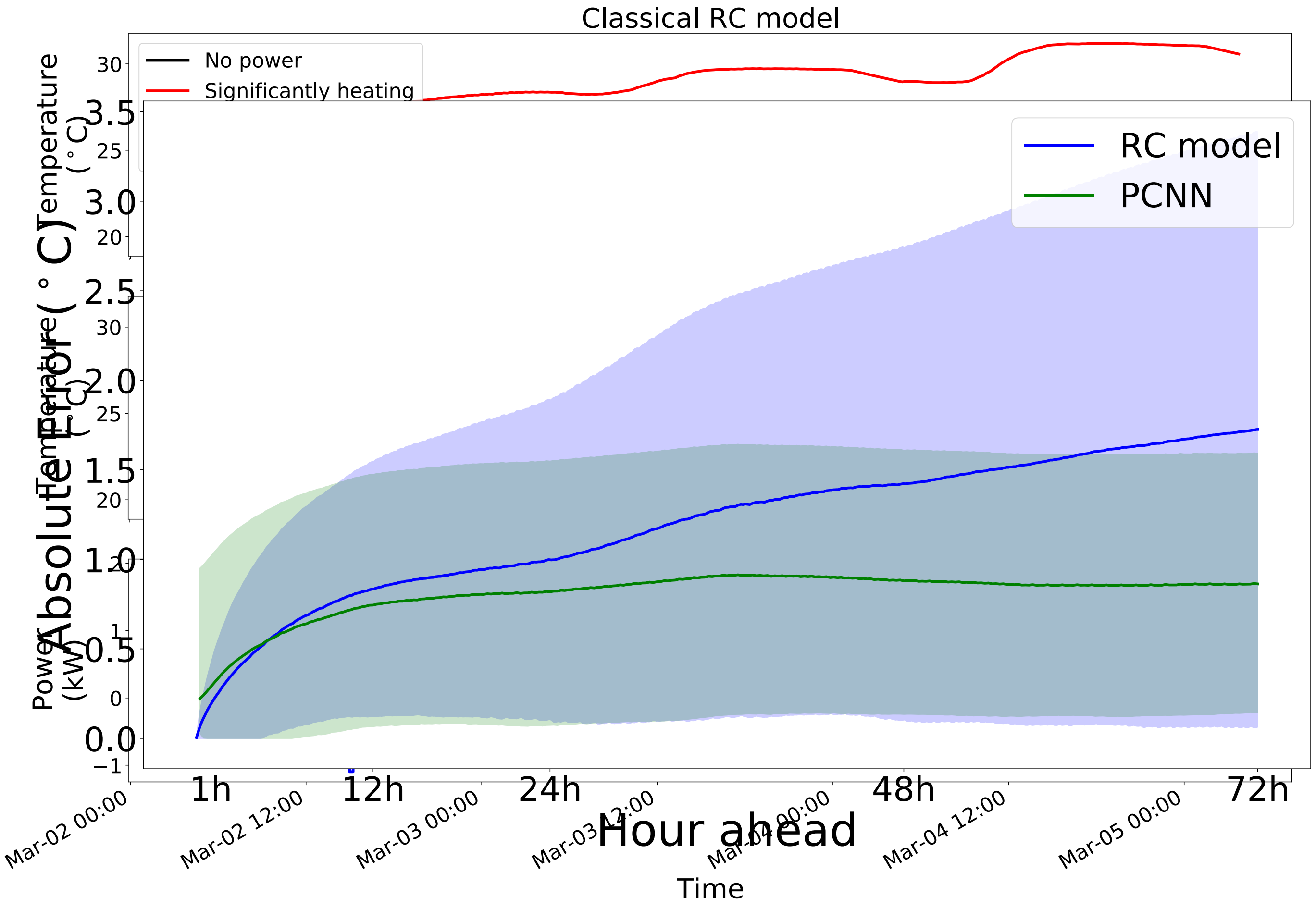
… Let's go back to what we know to counter this issue !

PCNNs



We can **formally prove its physical consistency**

Physical consistency



- From the eye, we can see **both have a similar physical behavior**

… PCNNs are indeed following the underlying physical laws despite relying on NNs

But PCNNs **fit the data better than RC models** – they are more accurate

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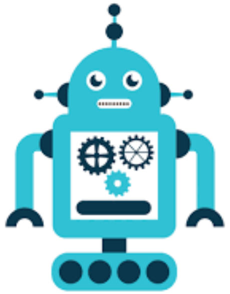
(Deep) Reinforcement Learning

$$R(s_t, a_t)$$

$$R_t = -\max\{0, T_t - U_t\} - \max\{0, L_t - T_t\} - \lambda E_t$$

$$s_t$$

$$s_t = \{T_{t-h:t}, W_{t-h:t}, L_t, U_t, t, \ldots\}$$

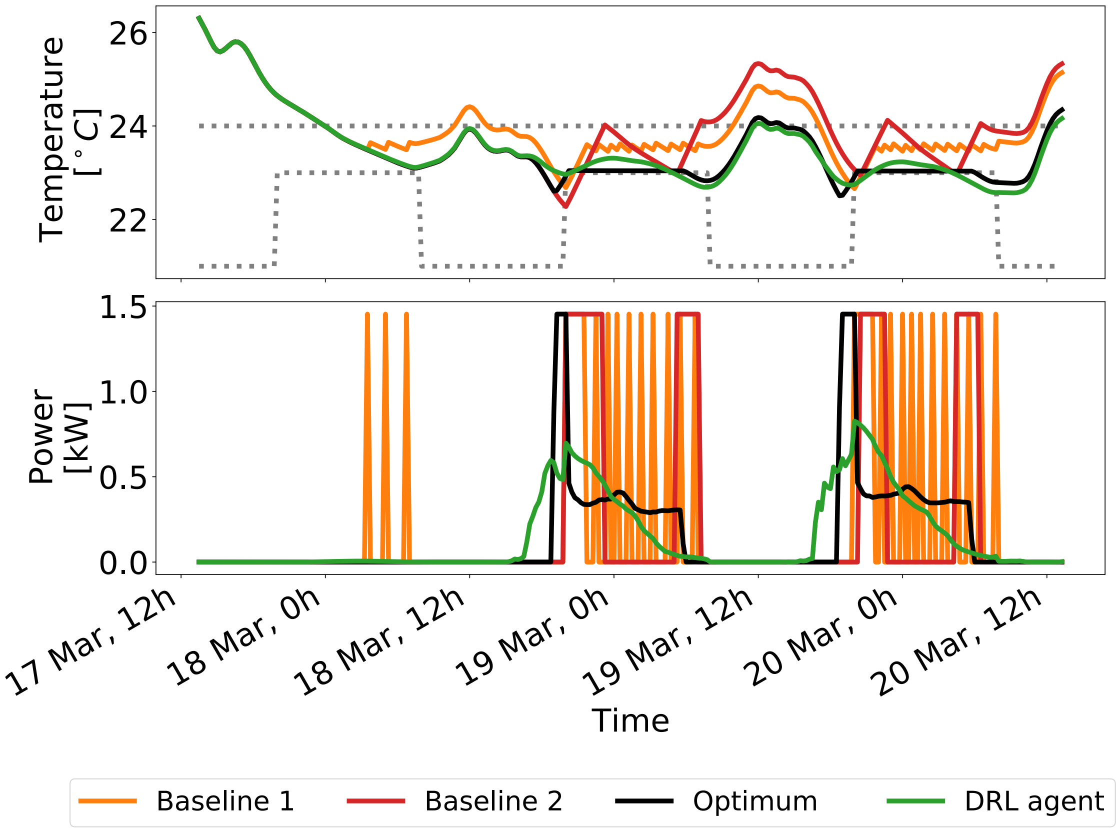


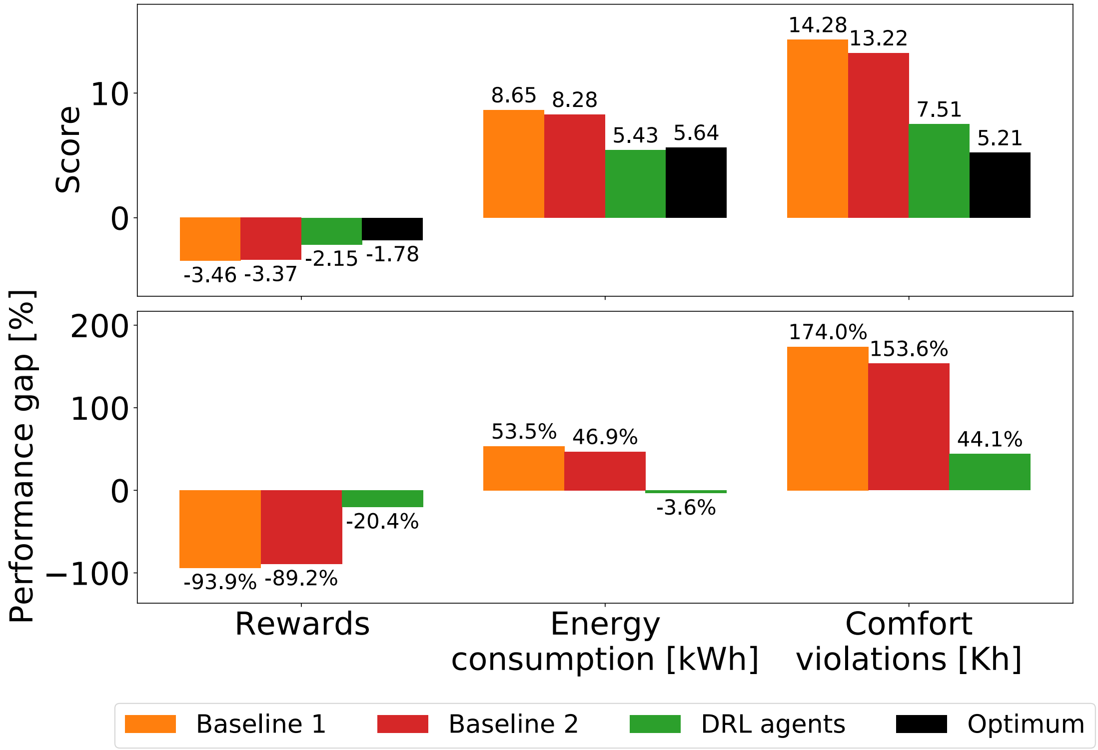
$$a_t$$

$$a_t = \text{heating/cooling}$$

Simulation

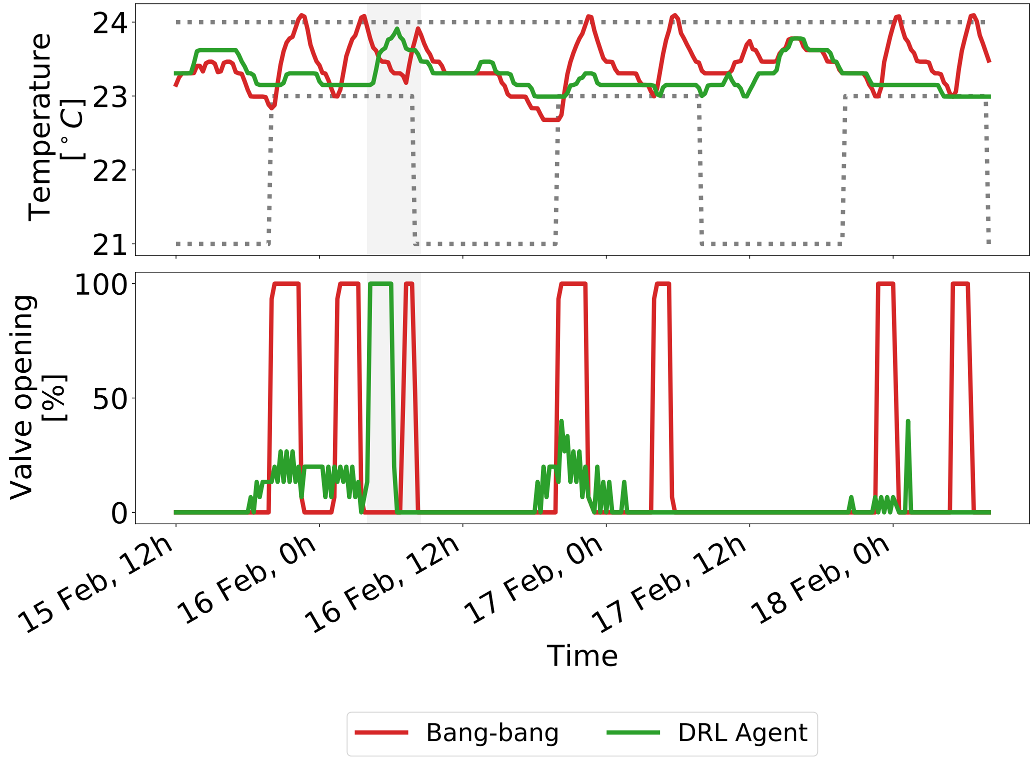
- DRL agents **converge to behaviors similar to the optimal trajectories** (computed *a posteriori*)
  - Confirmed by **statistical analysis** over 2000 3-day long sequences





Experiment

- We deployed a DRL agent and one baseline
- **Very similar results** to what could be seen in simulation
  - **Preheating** behavior
  - Close to the lower bound
- Connection issue in grey
- The DRL agent opened the valves **63% less often** with virtually **no comfort violations**



Discussion & Conclusion

- Building control **will be necessary** in the energy transition
  - Deep Learning methods can be applied when data is available
- **Black-box models can be misleading**, even if they fit the data well
  - PCNNs as a **potential solution - easy to scale**

→ ***Avoid tedious engineering***

- **Deep Reinforcement Learning** provides good results when coupled with PCNNs

→ ***Energy savings of ~40%***
→ ***Comfort of the occupants improved***

- Fully **black-box pipeline from data to control policies**

→ ***"Plug & Play" controllers***

- Outlook: Expansion of PCNNs
  - Model entire buildings
  - **Couple PV panel production, battery storage, …**

→ ***Buildings as prosumers***

Thank you for your attention!

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References

- **Physically Consistent Neural Network Building Models: Theory and Analysis.** L. Di Natale, B. Svetozarevic, P. Heer and C.N. Jones (2021). *Manuscript submitted to Applied Energy.* https://arxiv.org/abs/2112.03212.
- **Near-optimal Deep Reinforcement Learning Policies from Data for Zone Temperature Control.** L. Di Natale, B. Svetozarevic, P. Heer and C.N. Jones (2022). *Manuscript submitted to IEEE ICCA 2022.* https://arxiv.org/abs/2203.05434.