Learning Indoor Temperature Predictions for Optimal Load Ensemble Control

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Introduction

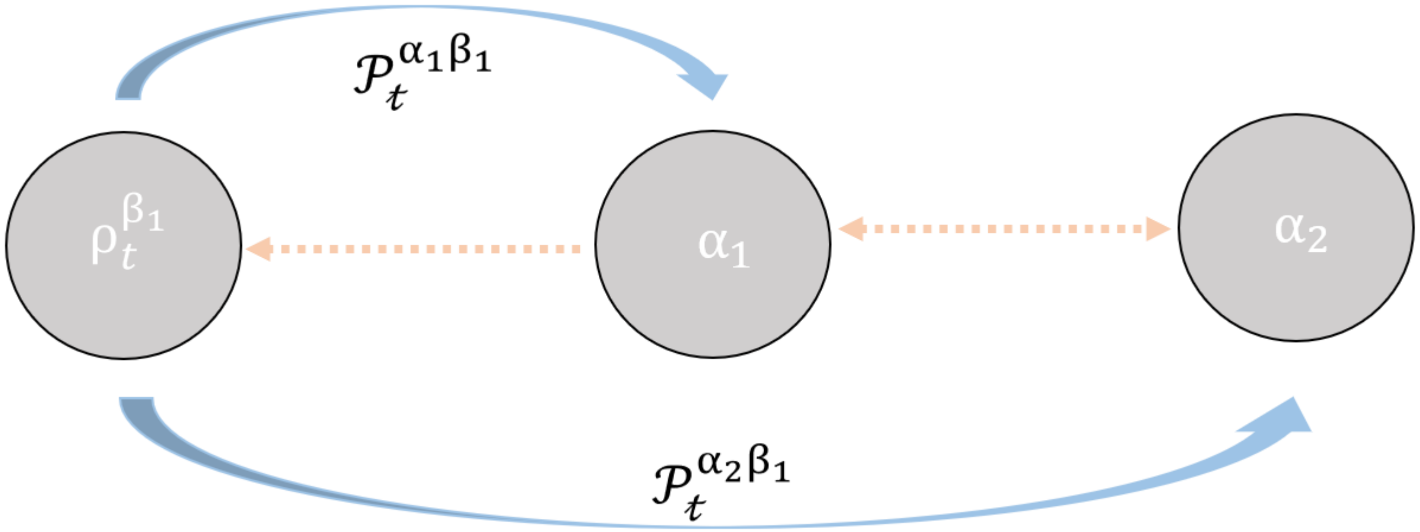
- Constantly increasing penetration levels of renewable energy sources
- Increased need for active consumers
- Trade-off between users' comfort and system flexibility needs
- Motivation: we need to **learn users' default behavior** to provide flexibility to the power system while **keeping their comfort satisfied**

How do we plan to achieve this?

- A lot of end-users needed to see an impact
- Easier access to information for building managers and aggregators
- Temperature preferences kept satisfied = keeping the comfort intact
- Avoiding **direct** participation of every consumer → learning from the previous behavior
- Physics-aware machine learning
  - Physical equations added to the loss function
  - Type of regularization

The process modeling (1/2)

- Behavior of an ensemble controlled by an aggregator is modeled as the Markov Process



$$\min_{\rho,\mathcal{P}} \sum_{t\in\mathcal{T}} \sum_{\alpha\in\mathcal{A}} E_{\rho_{t+1}^{\alpha}} \left(-U_{t+1}^{\alpha} + \sum_{\beta\in\mathcal{A}} \gamma_t^{\alpha\beta} \cdot log \frac{\mathcal{P}_t^{\alpha\beta}}{\overline{\mathcal{P}}_t^{\alpha\beta}} \right)$$

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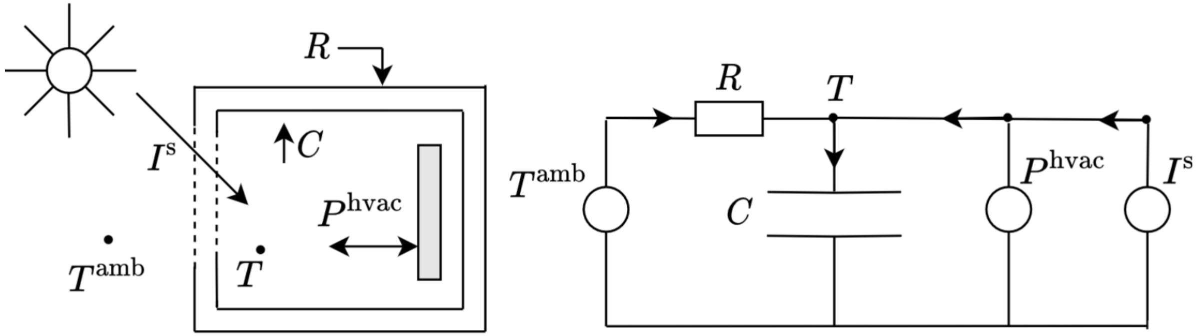
The process modeling (2/2)



- Modeling room temperature with lumped parameter model

$$\frac{dT}{dt} = -\frac{1}{R \cdot C} \cdot T + \frac{1}{R \cdot C} \cdot T^{\text{amb}} + \frac{1}{C} \cdot \left(P^{\text{hvac}} + A^{\text{w}} \cdot I^{\text{s}}\right)$$

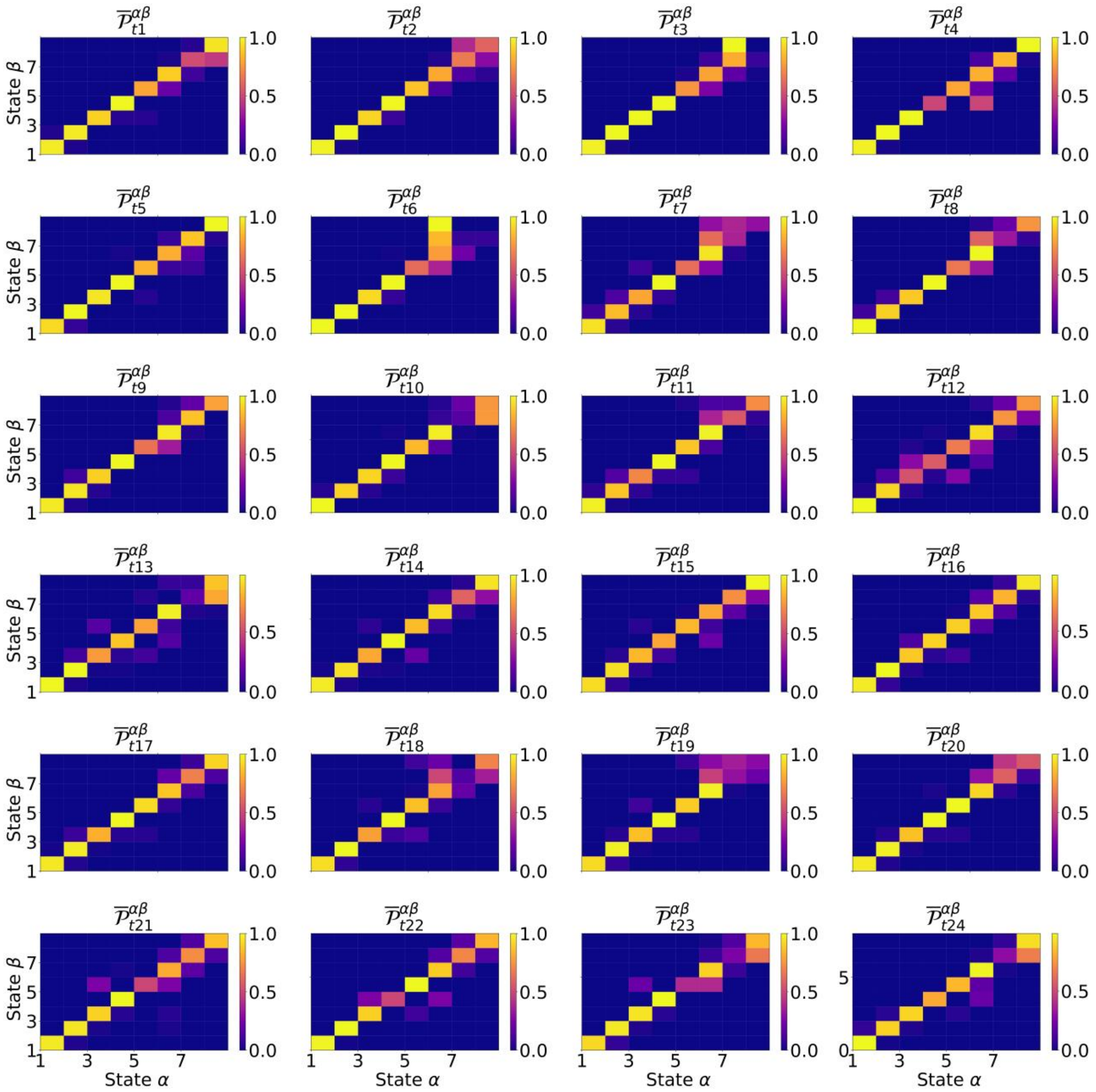
$$T_{t+\tau} = A \cdot T_t + (1 - A) \cdot T_t^{\text{amb}} + (1 - A) \cdot R \cdot \left(P_t^{\text{hvac}} + A^{\text{w}} \cdot I^{\text{s}}\right)$$

$$A = e^{-\frac{\tau}{R \cdot C}}$$

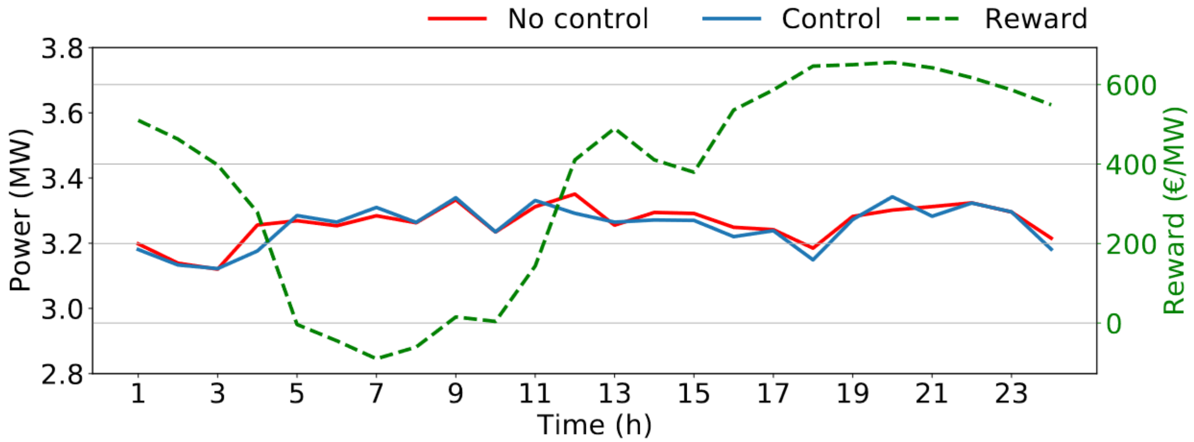
- Dealing with time series → LSTM
- Penalty method

Input preparation

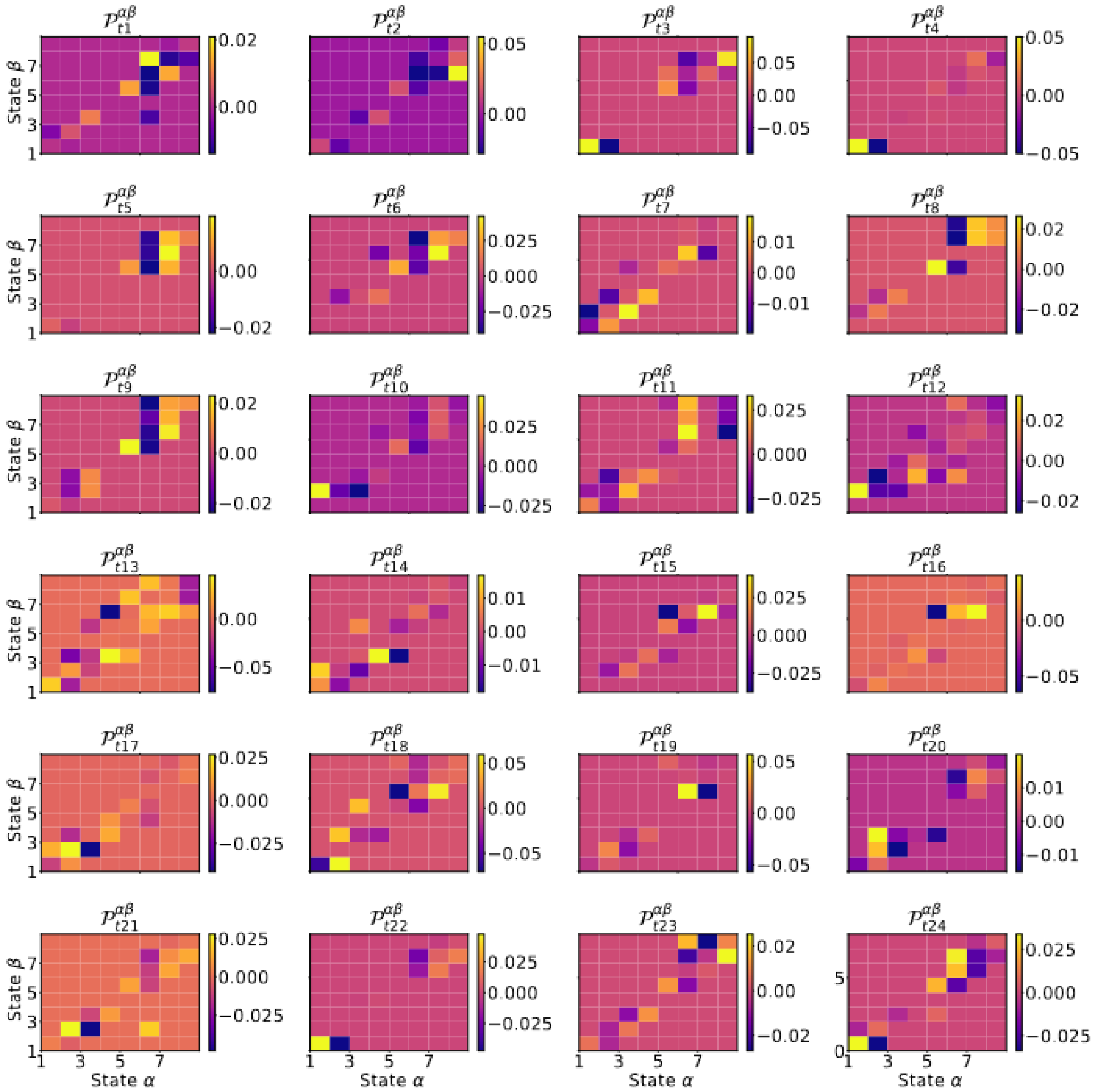
- Available data on outdoor and indoor temperatures, as well as HVAC consumption and solar irradiance
- The whole house is represented as one temperature zone
- Data was discretized into 3 categories each, which resulted in 81 combinations (only 8 were left in the end)



Results



No control
Control
Reward
Power (MW)
Reward (€/MW)
Time (h)



$\mathcal{P}^{\alpha\beta}_{t1}$ … $\mathcal{P}^{\alpha\beta}_{t24}$
State β
State α

Conclusion

- A model for the thermally controllable load was created while considering user preferences and comfort
- Consumption changes depending on reward signals
- Controlled consumption is kept similar to the default user consumption

Future work

- Improvement of this model: hyperparameters optimization, learning R and C parameters (finding proper initialization method)
- Making the problem continuous
- Multi-zone modeling
- Modeling multiple houses/objects separately
- New method, possible more explainable → RL?

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Thank you for the attention!