Physics-constrained Deep Recurrent Neural Models of Building Thermal Dynamics

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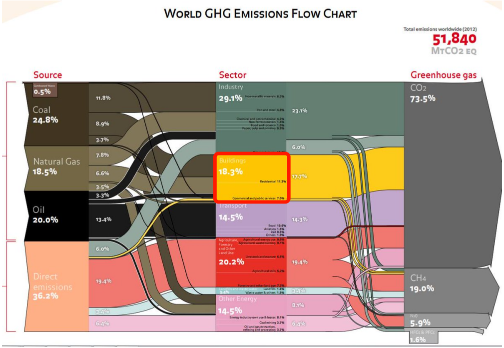
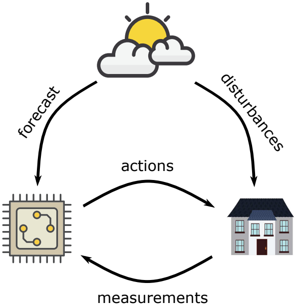
Motivation

Problem[1]



Inefficient controls

Solution[2]

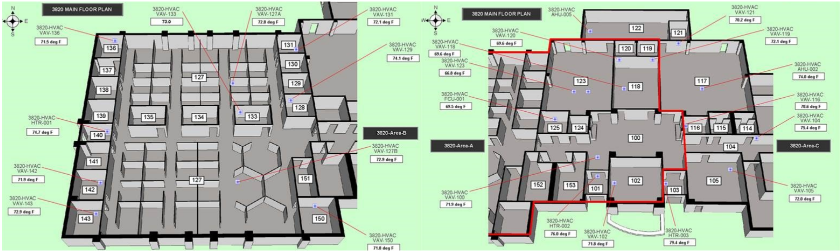


Model predictive control

[1] Edit by Ecofys (now part of Navigant Consulting), original by World Resources Institute (WRI).

[2] Advanced optimal control can save energy and cut the building's emissions by almost 30%. Gyalistras et al., Analysis of Energy Savings Potentials for Integrated Room Automation. RHEVA World Congress 2010.

Building's facade.

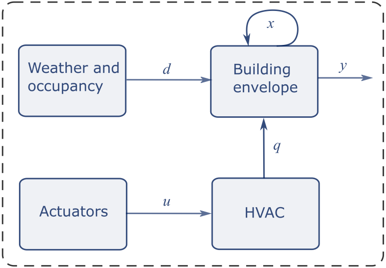


Building's zone layout.

Physics-based Model

$$\mathbf{x}_{t+1} = A\mathbf{x}_t + B\mathbf{q}_t + f_d(\mathbf{d}_t),$$
$$\mathbf{y}_t = C\mathbf{x}_t,$$
$$\mathbf{q}_t = \dot{\mathbf{m}}_t cp \Delta \mathbf{T}_t,$$

Building model structure

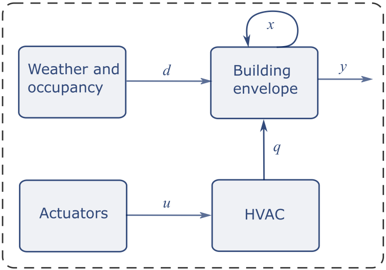


Modeling of Building Thermal Dynamics

Physics-based Model

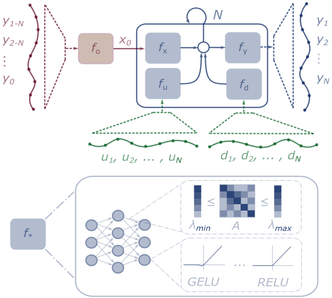
$$\mathbf{x}_{t+1} = A\mathbf{x}_t + B\mathbf{q}_t + f_d(\mathbf{d}_t),$$
$$\mathbf{y}_t = C\mathbf{x}_t,$$
$$\mathbf{q}_t = \dot{\mathbf{m}}_t cp \Delta \mathbf{T}_t,$$

Building model structure



Physics-structured Neural Model

$$\mathbf{x}_{t+1} = f_x(\mathbf{x}_t) + f_u(\mathbf{u}_t) + f_d(\mathbf{d}_t)$$
$$\mathbf{y}_t = f_y(\mathbf{x}_t)$$
$$\mathbf{x}_0 = f_o([\mathbf{y}_{1-N}; \ldots; \mathbf{y}_0])$$



Deep Learning with Physics-inspired Constraints

Eigenvalue constraints for dissipative dynamics:

$$\mathbf{M} = \lambda_{\text{max}} - (\lambda_{\text{max}} - \lambda_{\text{min}})\sigma(\mathbf{M}')$$

$$\tilde{\mathbf{A}}_{i,j} = \frac{\exp(\mathbf{A}'_{ij})}{\sum_{k=1}^{n_x} \exp(\mathbf{A}'_{ik})}\mathbf{M}_{i,j}$$

Penalty constraints for confined trajectories:

$$p(\mathbf{y}_t, \underline{\mathbf{y}}_t): \ \underline{\mathbf{y}}_t \leq \mathbf{y}_t + \mathbf{s}_t^{\underline{y}} \quad \cong \quad \mathbf{s}_t^{\underline{y}} = \max(0, \ -\mathbf{y}_t + \underline{\mathbf{y}}_t)$$

$$p(\mathbf{y}_t, \overline{\mathbf{y}}_t): \ \mathbf{y}_t - \mathbf{s}_t^{\overline{y}} \leq \overline{\mathbf{y}}_t \quad \cong \quad \mathbf{s}_t^{\overline{y}} = \max(0, \ \mathbf{y}_t - \overline{\mathbf{y}}_t)$$

Multi-term Loss Function:

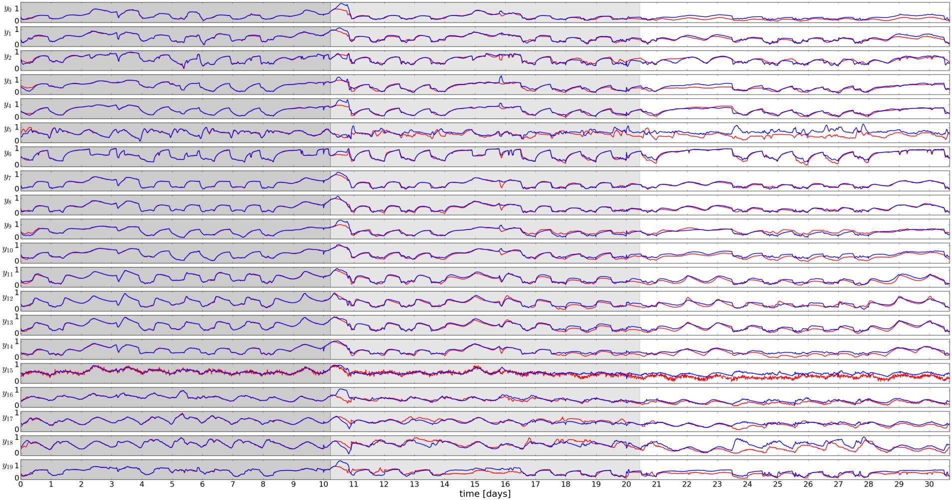
$$\mathcal{L}_{\text{MSE}}(\mathcal{Y}^{\text{ref}}, \mathcal{Y}|\Theta) = \frac{1}{N}\sum_{t=1}^{N} ||\mathbf{y}_t^{\text{ref}} - \mathbf{y}_t||_2^2 + Q_{\text{dx}}||\mathbf{x}_t - \mathbf{x}_{t-1}||_2^2 +$$

$$Q_{\text{ineq}}^{\mathbf{y}}||\mathbf{s}_t^{\mathbf{y}}||_2^2 + Q_{\text{ineq}}^{\mathbf{u}}||\mathbf{s}_t^{f_u}||_2^2 + Q_{\text{ineq}}^{\mathbf{d}}||\mathbf{s}_t^{f_d}||_2^2$$

Dataset:

$$D = \{(\mathbf{u}_t^{(i)}, \mathbf{d}_t^{(i)}, \mathbf{y}_t^{(i)}), (\mathbf{u}_{t+\Delta}^{(i)}, \mathbf{d}_{t+\Delta}^{(i)}, \mathbf{y}_{t+\Delta}^{(i)}), \ldots, (\mathbf{u}_{t+N\Delta}^{(i)}, \mathbf{d}_{t+N\Delta}^{(i)}, \mathbf{y}_{t+N\Delta}^{(i)})\}$$

Open-loop Trajectories of Multi-zone Thermal Dynamics

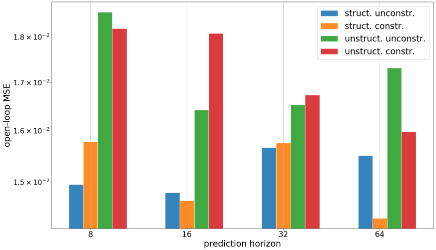


Open-loop trajectories of the learned (blue) and ground truth (red) multi-zone building thermal dynamics.

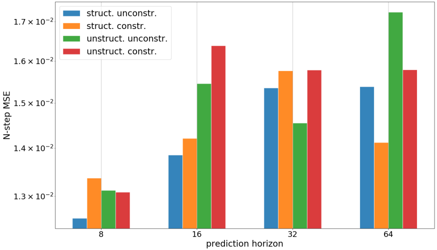
Experimental Case Study Results

Test set MSE of structured constrained, and unstructured unconstrained model.

Structure	Constrained	N	N-step [K]	Open-loop [K]
Structured	Y	64	0.4811	0.4884
Unstructured	N	16	0.5266	0.5596



Open-loop MSE



N-step MSE

More than 50% reduction in error compared to state of the art[3].

[3] Typical MSE of state of the art methods reported in the literature is around 1K.

Conclusions

- Generic case-agnostic data-driven modeling of building thermal dynamics
- Physically coherent and interpretable
- Sampling efficient and control-oriented
- Significant reduction in error against state of the art in the literature
- Future work: design of advanced predictive control with proposed models

Acknowledgements

This work was funded by the Physics Informed Machine Learning (PIML) investment at the Pacific Northwest National Laboratory (PNNL).

Implementation in PyTorch: `https://github.com/pnnl/neuromancer/tree/NeurIPS2020`