Modeling and Optimization of Complex Building Energy Systems with Recurrent Neural Networks

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Building electricity consumption

Buildings consumes around 70% of the total electricity generated in US.

UW campus pays $1 million per month in electricity bill!
Building control

\[
\min_{\text{input } (t, \ldots, t+T)} \sum_{t}^{t+T} \text{electricity}
\]

s.t. \( \text{Electricity} = f(\text{input}) \)

\( TL \leq \text{Temp} \leq TH \)

Challenges:

• Complex building dynamics: lighting, HVAC…

• Long temporal dependencies: current inputs affect future
Modeling of buildings

Detailed physics model

- Takes significant effort
- Hard to use in optimization

Simplified model

\[
\begin{align*}
\min_{\text{input } (t, \ldots, t+T)} & \sum_{t}^{t+T} \text{electricity} \\
\text{s.t.} & \quad \text{Electricity} = f(\text{input}) \\
& \quad TL \leq \text{Temp} \leq TH
\end{align*}
\]

Are there other options?
Data-driven building models

- Available data: sensors, weather forecasting...

- More data starting to come...
Tradeoff in data-driven models

- **Accurate**deep neural networks
- **Trackable**linear model, regression trees

**Our model: Recurrent neural network (RNN)**

- Capture the temporal dynamics
- Powerful representation
- Can we use it for control?
Contributions

• RNN model for buildings: easy to train (130s) & accurate (RMSE 0.076)

• Control/optimize: gradient descent (respect to inputs)
How to model a building by RNN?
How to model a building by RNN?

• What is RNN?

- $P_t$ is the output at time $t$: electricity usage
- $x_t$ is the input at time $t$: temperature set-point, environment (temp, humidity...), occupancy, temp measurement
- $s_t$ is the “state” at time $t$, $s_t = f(x_t, s_{t-1}) = f(x_t, x_{t-1}, ..., x_{t-T})$
Optimizing electricity usage

Close the loop by optimizing **controllable inputs**!
Building control

Building optimization/control:

Objective:

\[
\min_{x_t^i, x_{t+1}^i, \ldots, x_{t+T}^i} \sum_{\tau=t}^{t+T} (P_\tau - \hat{P}_\tau)^2
\]

Constraints:

- Upper, lower bound: \(\overline{x}_t, \underline{x}_t\)
- Input-Output: \(P_t = RNN(x_{t-T}, \ldots, x_{t-1}, x_t)\)
- Controllable-non controllable: \(x_t^{nc} = f(x_{t-T}, \ldots, x_{t-1}, x_t^c)\)
Optimization algorithm

Optimization problem:

\[
\min_{x_t^c, x_{t+1}^c, \ldots, x_{t+T}^c} L(\cdot) = \sum_{\tau=t}^{t+T} (P_{\tau} - \hat{P}_{\tau})^2 - \lambda \left[ \sum_{\tau} \log(x_{\tau} - \bar{x}_{\tau}) + \sum_{\tau} \log(\bar{x}_{\tau} - x_{\tau}) \right]
\]

Gradient descent:

1. Initialize \( x_t, x_{t+1}, \ldots, x_{t+T} \)
2. Update \( x_t^c, x_{t+1}^c, \ldots, x_{t+T}^c \) by gradient descent
3. Update \( x_{\tau}^{nc} = f(x_{\tau-T}, \ldots, x_{\tau-1}, x_{\tau}^c), \tau = t, t+1, \ldots, t+T \)
4. Implement \( x_t \) and proceed to time \( t+1 \)
Example building

• **Ground truth model:** Energyplus

• A 12-storey high building in Seattle

• 16 zones

• 55 inputs: 16-zone temp set-points, 16-zone real-time temperature measurements, 16-zone occupancy, 7 outdoor weather features

• “Memory” length: 4 hours

• Output: electricity usage
RNN model of building

- 1 year data, 10 minutes resolution
- 2.5 GHz Intel Core i7 Macbook: training time 130 seconds

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Y_{i,pred} - Y_{i,true})^2}
\]

RMSE : 0.076

\[
\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{Y_{i,pred} - Y_{i,true}}{Y_{i,true}} \right|
\]

MAPE: 8.2% for weekdays
Building optimization results

- Electricity usage reduction under different conditions: unconstrained, 18-26°C, 19-24°C

![Graph showing electricity usage reduction over time under different conditions. The graph compares measurements with simulations for 9 times 10^8 J over the course of a day. The legend includes lines for Measurements, L19H24, L18H26, and Unconstrained.]
Temperature set points: 18-26°C

basement

bottom_core

top_core

top_sub4
RNN V.S. RC model

- **Fitting performance**: Energyplus generates a 12-storey building data in Seattle for 1 year

\[
\text{RMSE (normalized)} \\
\text{RNN: 0.076} \\
\text{RC: 0.214}
\]
RNN V.S. RC model

- **Optimization performance**: 18-26°C

Electricity usage:
- RNN: 69.26%
- RC: 95.93%
  (w.r.t. original usage)
Conclusions & future works

Conclusions:

• Use RNNs to model the complex dynamics of building
• Optimize building electricity usage by taking gradient with respect to RNN inputs while satisfying comfort constraints

Future works:

• Optimization on RNN
• Test on real building systems