CityLearn Challenge 2023 - Forecast Track

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Introduction

Background

- PhD student at the University of Washington
- Data Scientist at Shifted Energy

Challenges

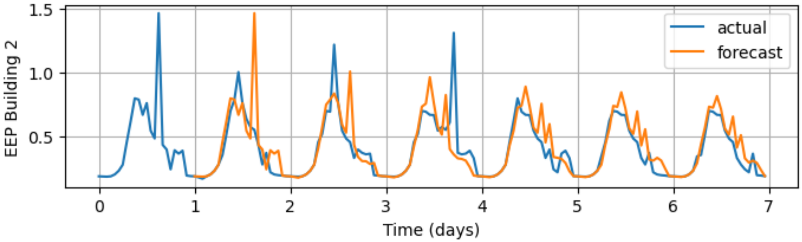
- Cold Start Problem (new buildings have no data)
- Small-Data Regime
  - 720 observations for each building (1 month of data)
  - 30 "hour of the day" observations (12am, 1am, ...)
  - 4 "hour of the week" observations (Mo 12am, Mo 1am, ...)

Seasonal Average - Incremental Formula

For each hour of the day (or week)

$$\bar{x}_n = \frac{\text{total}}{\text{count}} = \frac{1}{n}\sum_{k=1}^{n} x_k$$

$$= \underbrace{\frac{n-1}{n}\cdot \bar{x}_{n-1} + \frac{1}{n}\cdot x_n}_{\text{convex combination}} = \bar{x}_{n-1} + \frac{1}{n}\cdot \underbrace{(x_n - \bar{x}_{n-1})}_{\text{update}}$$



Improvements

All forecasts use the seasonal average with improvements:

(1) initialization

(2) filter out large values (not clipping)

(3) blend with the most recent observation

(4) load-type specific ideas

For example,

1. EEP: seasonal average + (1) + (2)
2. Emissions: seasonal average + (1) + (3)

Improvements (1) - Initialization

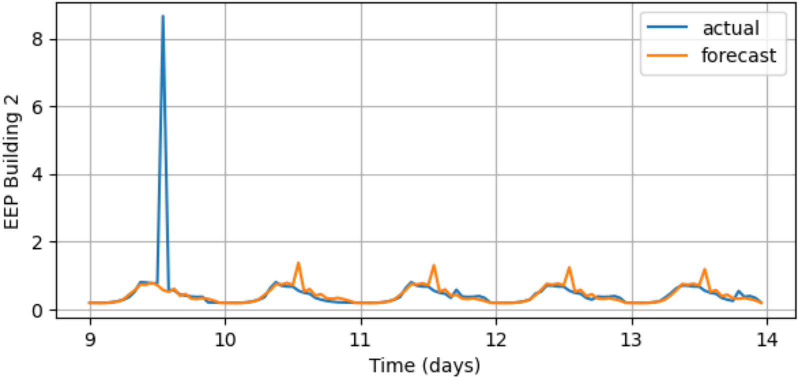
Let x_0 be prior estimate, τ be prior weight

$$
\begin{aligned}
\tilde{x}_n &= \frac{\text{total} + \tau x_0}{\text{count} + \tau} = \frac{1}{n+\tau}\left(\tau x_0 + \sum_{k=1}^{n} x_k\right) \\
&= \underbrace{\frac{n+\tau-1}{n+\tau} \cdot \tilde{x}_{n-1} + \frac{1}{n+\tau} \cdot x_n}_{\text{convex combination}} = \tilde{x}_{n-1} + \frac{1}{n+\tau} \cdot \underbrace{(x_n - \tilde{x}_{n-1})}_{\text{update}} \\
&= \frac{n}{n+\tau} \cdot \bar{x}_n + \frac{\tau}{n+\tau} \cdot x_0
\end{aligned}
$$

Derive x_0 from training data or schema, τ is a hyperparameter.

Improvements (2) - Filtering

Filter large spikes from EEP and DHW.

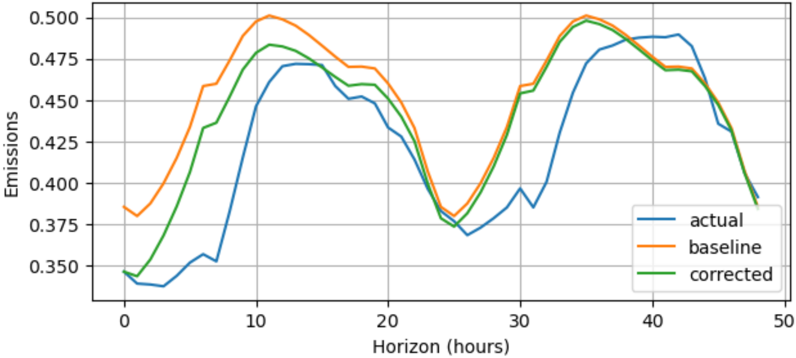


Improvements (3) - Blend most recent observation

Correct the level of the forecast

$$\hat{x}_{n+h} = \bar{x}_{n+h} + \alpha^h(x_n - \bar{x}_n)$$

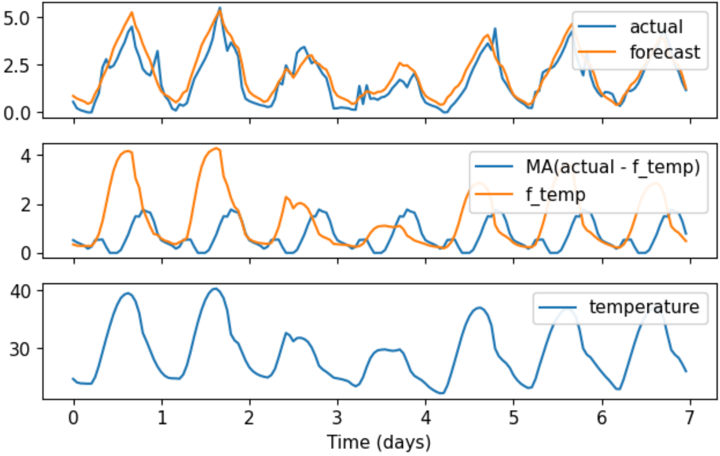
where h is the horizon and α is the blending weight (roughly 0.93).



Improvements (4) - Cooling

Decompose into temperature-dependent and time-dependent parts

```
f_temp = c * gumbel(a * temperature + b)
forecast = MA(actual - f_temp) + f_temp
```

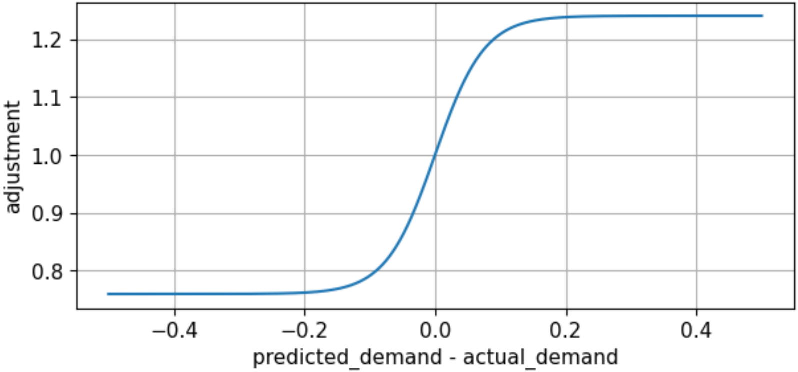


Improvements (4) - Domestic Hot Water Heating

Adjust forecast depending on cumulative daily demand:

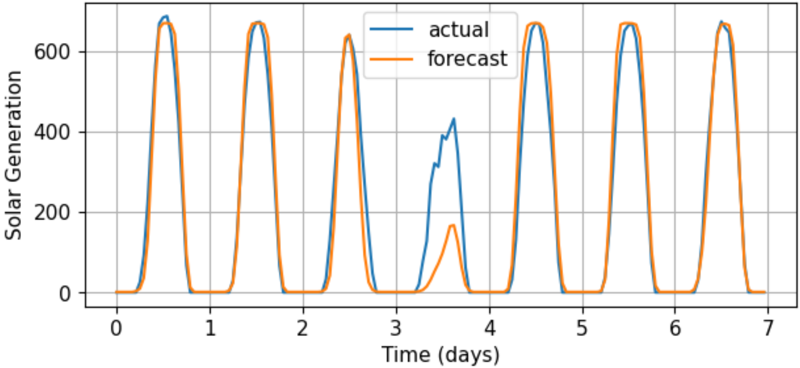
- if demand is **higher** than normal, then **decrease** forecast
- if demand is **lower** than normal, then **increase** forecast

```
1 + a*tanh(b*(predicted_demand - actual_demand))
```



Improvements (4) - Solar

- First 24 hours: 1-layer NN with irradiance forecast
- Next 24 hours: blend 24-hour ahead forecast with the average



References

Hansen, N., Akimoto, Y., and Baudis, P. (2019). CMA-ES/pycma on Github. Zenodo, DOI:10.5281/zenodo.2559634.

Nweye, K., Nagy, Z., Mohanty, S., Chakraborty, D., Sankaranarayanan, S., Hong, T., Dey, S., Henze, G., Drgona, J., Lin, F., Jiang, W., Zhang, H., Yi, Z., Zhang, J., Yang, C., Motoki, M., Khongnawang, S., Ibrahim, M., Zhumabekov, A., May, D., Yang, Z., Song, X., Zhang, H., Dong, X., Zheng, S., and Bian, J. (2022). The citylearn challenge 2022: Overview, results, and lessons learned. In Ciccone, M., Stolovitzky, G., and Albrecht, J., editors, *Proceedings of the NeurIPS 2022 Competitions Track*, volume 220 of *Proceedings of Machine Learning Research*, pages 85–103. PMLR.