BEEM: Data-driven Building Energy bEnchMarking for Singapore

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Building energy performance benchmarking

It is the practice of measuring and comparing the energy performance of a building with its peer groups. There are several benefits:

- ✓ Identifying energy saving opportunities
- ✓ Prioritizing retrofits and upgrades
- ✓ Increasing awareness

Energy performance benchmarking has been proven to reduce energy usage by up to 7% [1].

Background and Motivation

Many factors affect the building energy consumption:

1. Physical: geometry, orientation, facades, etc.
2. Operational: occupancy, schedule, electrical and mechanical fixtures, etc.
3. External: meteorological variables

Building energy usage should be normalized for these differences to enable a fair benchmarking. Further, the benchmarking approach should be scalable to a large number of buildings, e.g., at city scale.

Current approaches

Using Key Performance Indicators (KPI) of energy usage such as Energy Use Intensity (kWh/m^2/year):

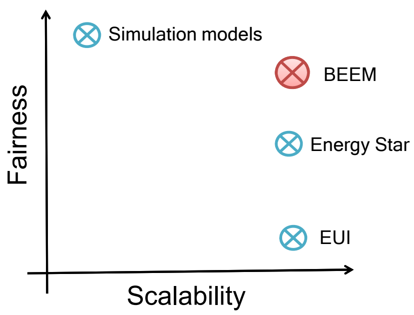
- It is simple and easy to use
- But it overlooks other factors, such as occupancy, thus EUI is a unfair measure

Whole building energy simulation models:

- It can account for many influencing factors
- But it is very tedious in terms of time, effort and expertise required - limits scalability

Contemporary approaches such as Energy Star [2]:

- Poor accuracy in modelling the variations in the energy usage (using linear models), resulting in inconsistent scores



Our approach (BEEM): Fair and scalable comparison between buildings by leveraging advanced machine learning methods!

Our approach - BEEM

1. Data preparation

- BCA's energy disclosure dataset (1145 samples)
- Define peer groups and apply data limitation filters

2. Model development

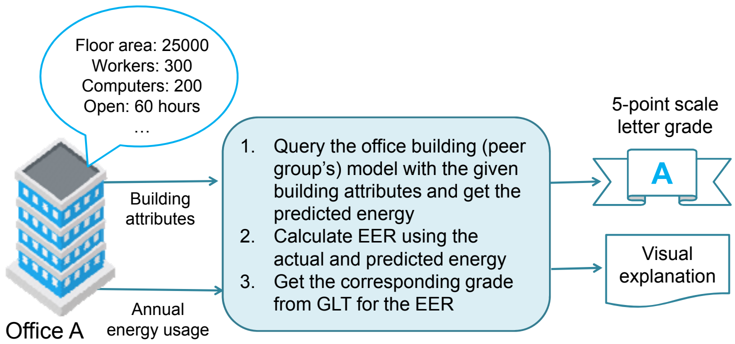
- Fit nonlinear models between energy usage and building characteristics using XGBoost algorithm

3. Measure energy efficiency ratio

- $EER = \frac{Actual\ energy}{Predicted\ energy}$

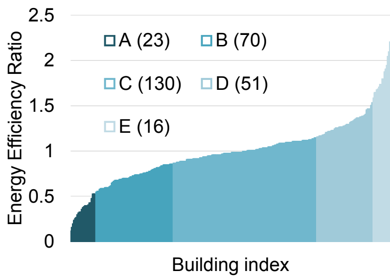
4. Generate Grade Lookup Table (GLT)

- Apply univariate clustering algorithm to the sorted EER list
- Map the cluster boundaries to the 5 point scale letter grades (A to E)



Results

Grade distribution of office buildings

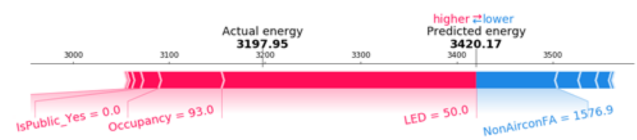


Model performance comparison

Building type	R-squared		NRMSE	
	MLR	XGB	MLR	XGB
Office	80.3	95.0	45.5	21.8
Hotel	93.5	97.6	39.2	23.4
Retail	83.3	95.6	40.4	14.4
Average	85.7	96.1	41.7	19.8
Improvement	+10.4 (12.2%)		-21.9 (52.5%)	

XGB: Our proposed nonlinear model;
MLR: Multiple Linear Regression (the baseline) model that has been used in [2 & 3]

An example visual explanation of a model prediction using SHAP values



References:

1. US Environmental Protection Agency (EPA), U.S. EPA Portfolio Manager Data Trends 2012 Technical Brief, Technical Report, 2012.
2. Energy Star - Buildings & Plants https://www.energystar.gov/buildings
3. Siew Eang Lee and Priyadarsini Rajagopalan. 2008. Building energy efficiency labelling programme in Singapore. Energy Policy 36, 10 (2008), 3982–3992.

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