BEEM: Towards more Accurate and Explanatory Building Energy Benchmarking for Singapore

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Joint work with
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Energy benchmarking

What is energy benchmarking?

- It is a practice of measuring energy efficiency (relative to peer group) of the building stock and assigning a rating (point/grade)

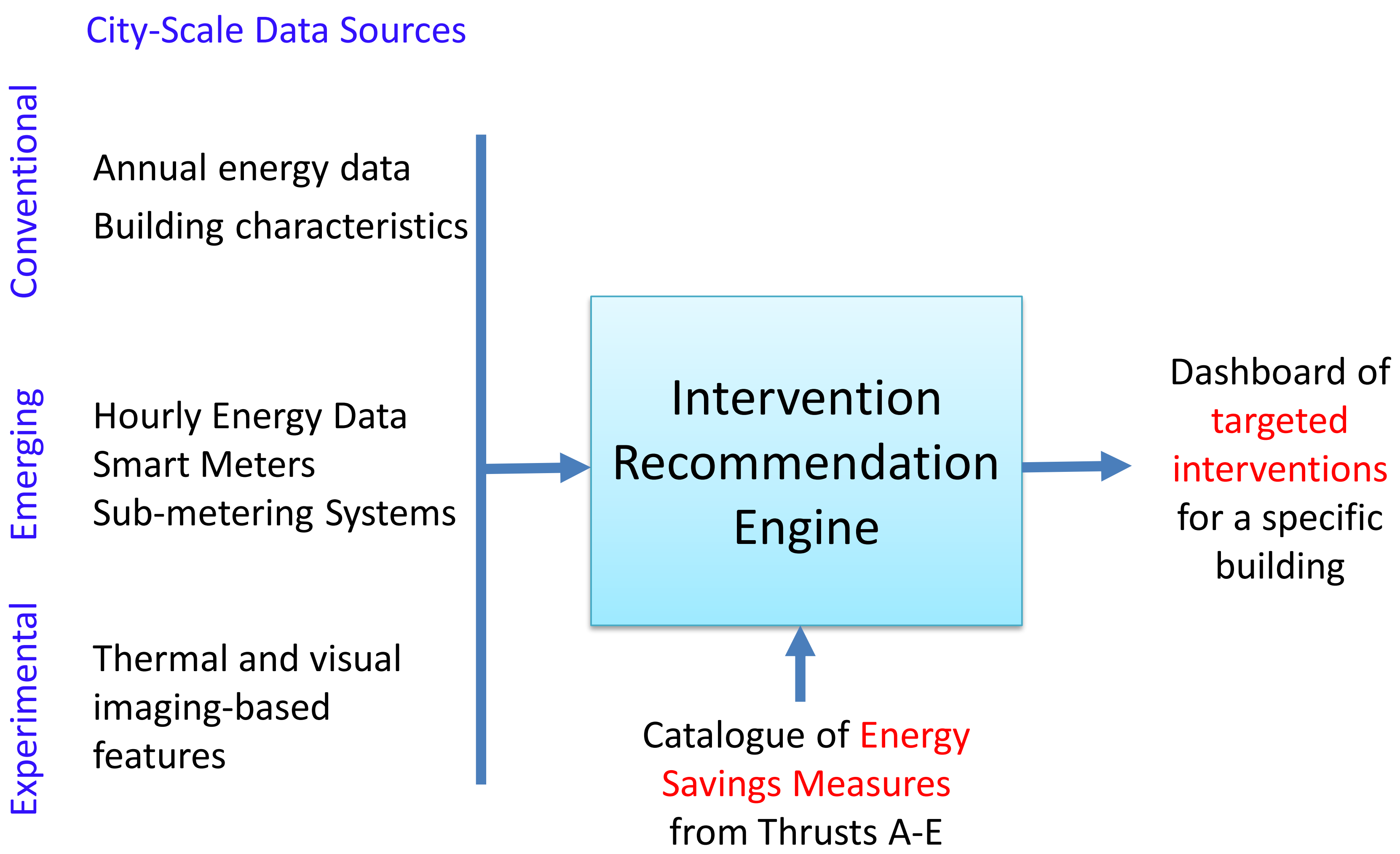
Why do this?

- Identifying energy saving opportunities
- Setting targets for improvement
- Prioritizing retrofit plans
- Increasing awareness

Up to 7% decrease in energy use [1]

[1] US Environmental Protection Agency (EPA), U.S. EPA Portfolio Manager Data Trends 2012 Technical Brief, Technical Report, 2012.

A Platform for Targeting Buildings for Specific Interventions

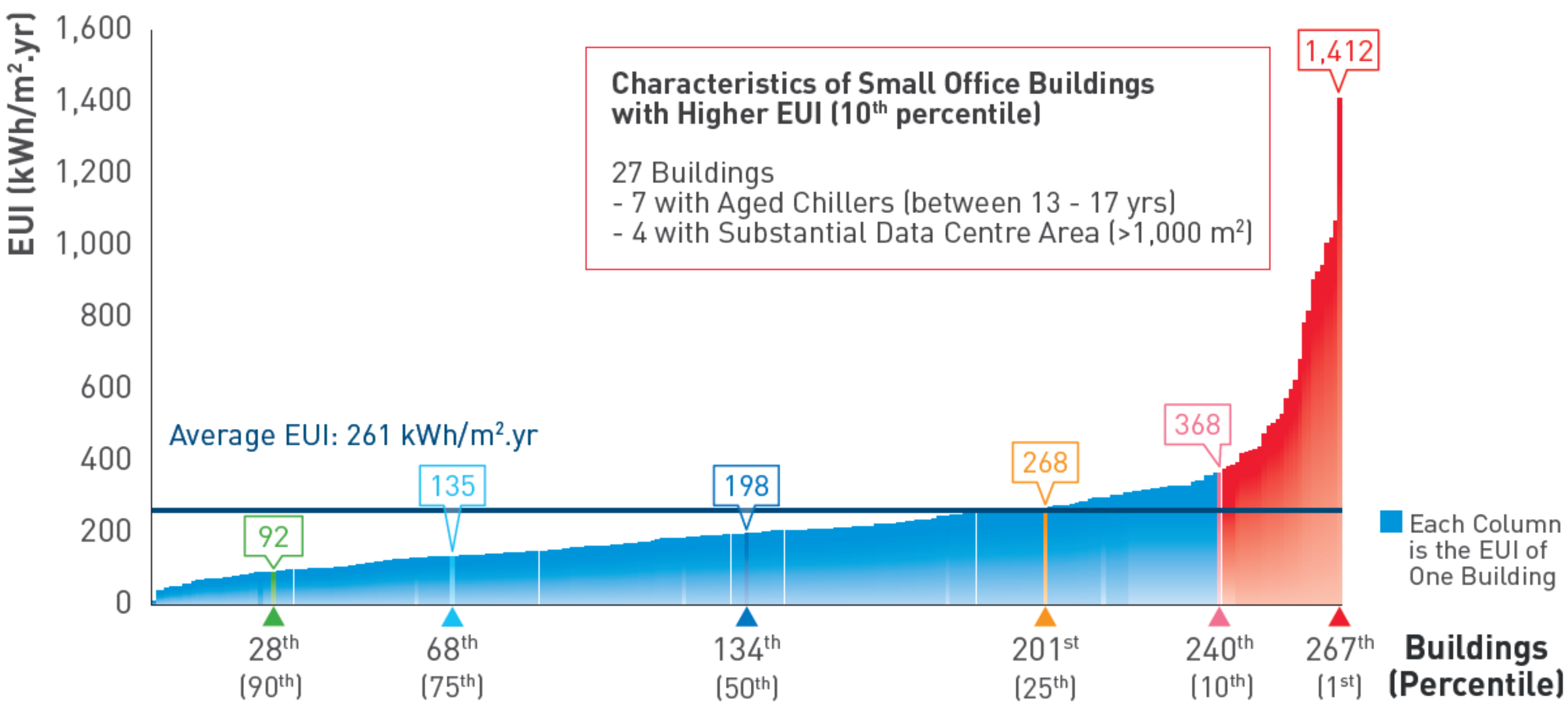


Our goal: Benchmarking Singapore buildings to drive intervention recommendations

Existing approaches

$$\text{Energy Use Intensity (EUI)} = \frac{\text{Total energy usage}}{\text{Square footage}}$$

BCA Building Energy Benchmarking Report 2018 - EUI of 267 Small Office Buildings



Existing approaches

BCA Green Mark Scheme

- A point based rating system that focuses on overall sustainability

Existing approaches

Using data-driven prediction models

- ENERGY STAR Portfolio Manager in the USA and Canada (1-100 score)
- An earlier labelling program in Singapore [1]

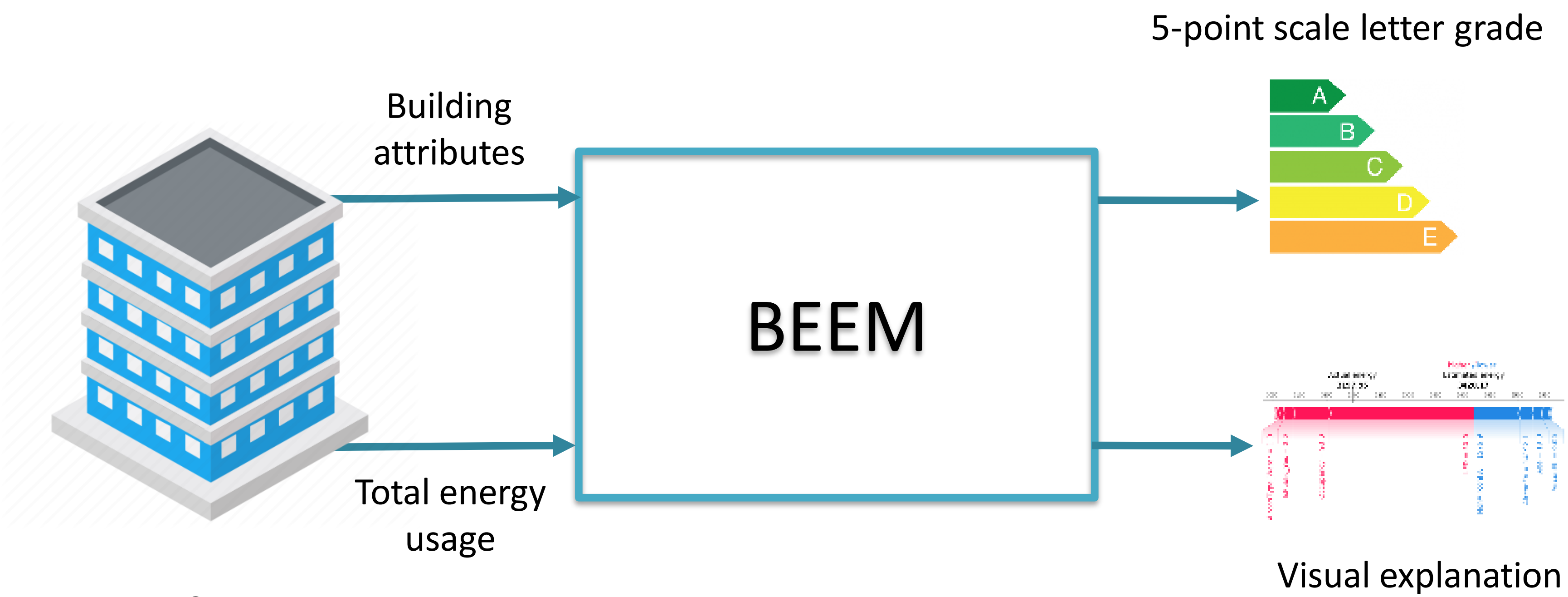
Limitations:

- Inaccurate models using Multiple Linear Regression (MLR)
- Whole model interpretation (average influence on energy usage)

Approach	Normalization factor(s)	Accuracy	Scalable	Complexity
Energy Use Intensity (EUI) kWh/m^2	Gross Floor Area	Low	High	Low
Whole building energy simulation models (EnergyPlus)	Almost all factors	High	Low	High
Energy Star and other contemporary approaches	5-10 most significant factors	Medium	High	Medium to High

[1] Siew Eang Lee and Priyadarsini Rajagopalan. 2008. Building energy efficiency labelling programme in Singapore. Energy Policy 36, 10 (2008), 3982–3992.

Overview of BEEM



Unique features:

- Account for multiple factors (size, age, occupancy, Aircon type, etc.)
- Highly accurate – using nonlinear models (XGBoost algorithm)
- Explainable – local model interpretation (using SHAP values)
    - Which factors influence the energy usage in individual building?
- 5-point scale letter grade (for easy understanding)

Overview of BEEM

CREATE Tower
(Office building)

Overview of BEEM

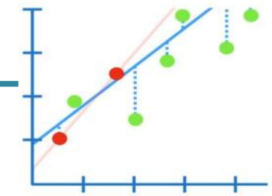
Floor area: 25,000
Workers: 200
Computers: 300
Open: 90 hrs/week
…

CREATE Tower
(Office building)

Building attributes

1. Estimate the energy usage

Peer group's energy usage model



How much energy this building would have consumed?

Overview of BEEM

Floor area: 25,000
Workers: 200
Computers: 300
Open: 80 hrs/week
…

CREATE Tower
(Office building)

Building attributes

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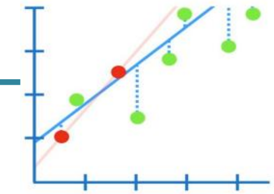
Peer group's energy usage model



Actual energy usage

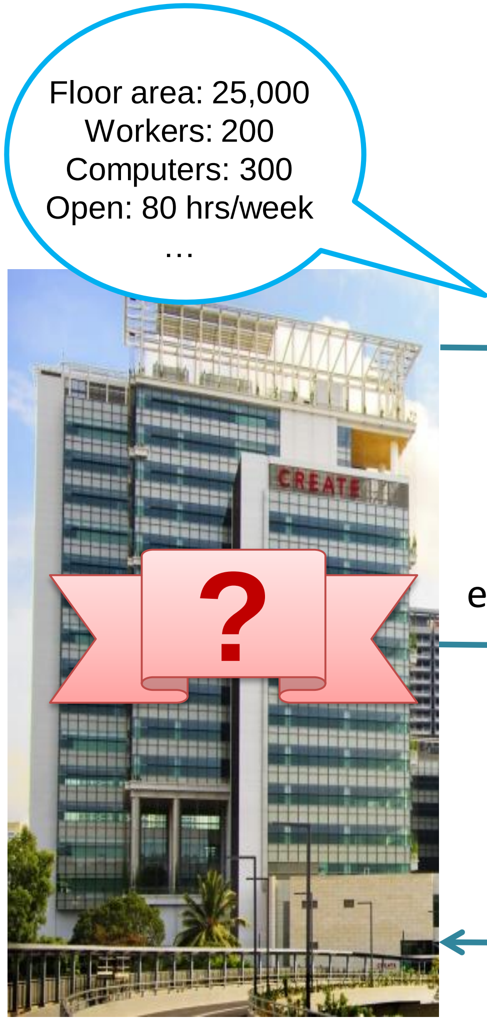
2. Measure relative energy efficiency

$$EER = \frac{Actual}{Estimated}$$

Actual < Estimated => EER < 1 => energy efficient

Actual > Estimated => EER > 1 => energy inefficient

Overview of BEEM

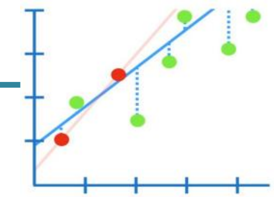


CREATE Tower
(Office building)

Building attributes

1. Estimate the energy usage

Peer group's energy usage model



Actual energy usage

2. Measure relative energy efficiency

$$EER = \frac{Actual}{Estimated}$$

Grade

3. Grading
(based on EER)

EER	Grade
< 0.5	A
0.5 – 0.9	B
0.9 – 1.2	C
1.2 – 1.5	D
> 1.5	E

Grade Lookup Table

Overview of BEEM

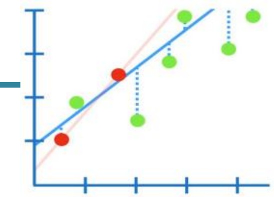
Floor area: 25,000
Workers: 200
Computers: 300
Open: 80 hrs/week
…

CREATE Tower
(Office building)

Building attributes

1. Estimate the energy usage

Peer group's energy usage model



1000

Actual energy usage

800

2. Measure relative energy efficiency

$$EER = \frac{800}{1000} = 0.8$$

Grade

3. Grading (based on EER)

EER	Grade
< 0.5	A
0.5 – 0.9	**B**
0.9 – 1.2	C
1.2 – 1.5	D
> 1.5	E

Grade Lookup Table

Overview of BEEM

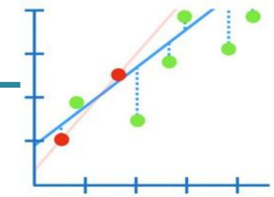
Floor area: 15,000
Workers: 50
Rooms: 200
Open: 168 hrs/week
…

IBIS
(Hotel building)

Building attributes

1. Estimate the energy usage

Peer group's energy usage model



900

Actual energy usage

1200

2. Measure relative energy efficiency

$$EER = \frac{1200}{900} = 1.3$$

Grade

3. Grading
(based on EER)

EER	Grade
< 0.5	A
0.5 – 0.9	B
0.9 – 1.2	C
1.2 – 1.5	**D**
> 1.5	E

Grade Lookup Table

Challenge #1

How to develop an accurate energy usage model for peer group?

Floor area: 15,000
Workers: 50
Rooms: 200
Open: 168 hrs/week
…

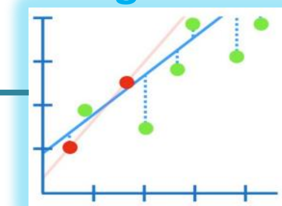
IBIS
(Hotel building)

Building attributes

1. Estimate the energy usage

900

Peer group's energy usage model



Actual energy usage

1200

2. Measure relative energy efficiency

$$EER = \frac{1200}{900} = 1.3$$

Grade

3. Grading (based on EER)

EER	Grade
< 0.5	A
0.5 – 0.9	B
0.9 – 1.2	C
1.2 – 1.5	**D**
> 1.5	E

Grade Lookup Table

Challenge #2

How to create the Grade Lookup Table?

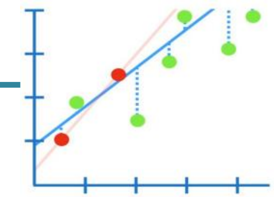
Floor area: 15,000
Workers: 50
Rooms: 200
Open: 168 hrs/week
…

IBIS
(Hotel building)

Building attributes

1. Estimate the energy usage

Peer group's energy usage model



900

Actual energy usage

1200

2. Measure relative energy efficiency

$$EER = \frac{1200}{900} = 1.3$$

Grade

3. Grading
(based on EER)

EER	Grade
< 0.5	A
0.5 – 0.9	B
0.9 – 1.2	C
1.2 – 1.5	**D**
> 1.5	E

Grade Lookup Table

Peer group energy usage model development

Fit a nonlinear model between building attributes and energy usage

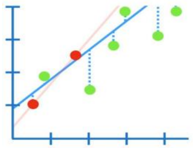
Peer group reference buildings

Detailed building attributes and energy usage

Data cleaning and feature selection

XGBoost algorithm [1]

Hyper-parameter tuning and model selection



Final nonlinear model

Model interpretation

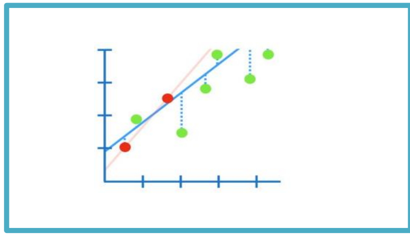
SHAP values [2]

[1] Chen, Tianqi, and Carlos Guestrin. "Xgboost: A scalable tree boosting system." Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining. ACM, 2016.

[2] Lundberg, Scott M., and Su-In Lee. "A unified approach to interpreting model predictions." Advances in Neural Information Processing Systems. 2017.

Grade Lookup Table creation

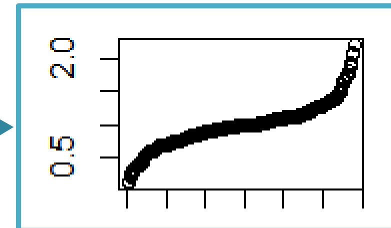
Peer group model



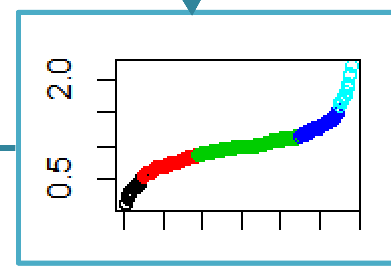
Calculate EER for each reference building

$$EER = \frac{Actual}{Estimated}$$

Distribution of sorted EER



Apply univariate clustering algorithm



Grade Lookup Table

EER	Grade
< 0.5	A
0.5 – 0.9	B
0.9 – 1.2	C
1.2 – 1.5	D
> 1.5	E

Each cluster's boundaries are mapped to a grade

Dataset

BCA Building Energy Benchmarking Data (annual mandatory submission in 2017) - 1145 samples

S.No	Name	Description
1.	AirconFA	Total air-conditioned floor area (m^2)
2.	NonAirconFA	Total non air-conditioned floor area (m^2)
3.	Age	Age of the building
4.	IsPublic	Is public sector building? (Yes/No)
5.	Occupancy	Average monthly occupancy rate (%)
6.	AirconType	Type of air-conditioning system: 1) Water-cooled chilled water plant, 2) Air-cooled chilled water plant, 3) District cooling plant, and 4) Split units or unitary systems
7.	AirconAge	Age of the air-conditioning system
8.	AirconEff	Air-conditioning system efficiency (kW/RT)
9.	LED	LED light usage (%)
10.	Rooms	Number of rooms (only for hotels)

After cleaning: Office – 290, Hotels – 203, and Retail - 125 samples

https://www.bca.gov.sg/BESS/BenchmarkingReport/BenchmarkingReport.aspx

Comparison of model performance

Baseline approach: Multiple Linear Regression (MLR)

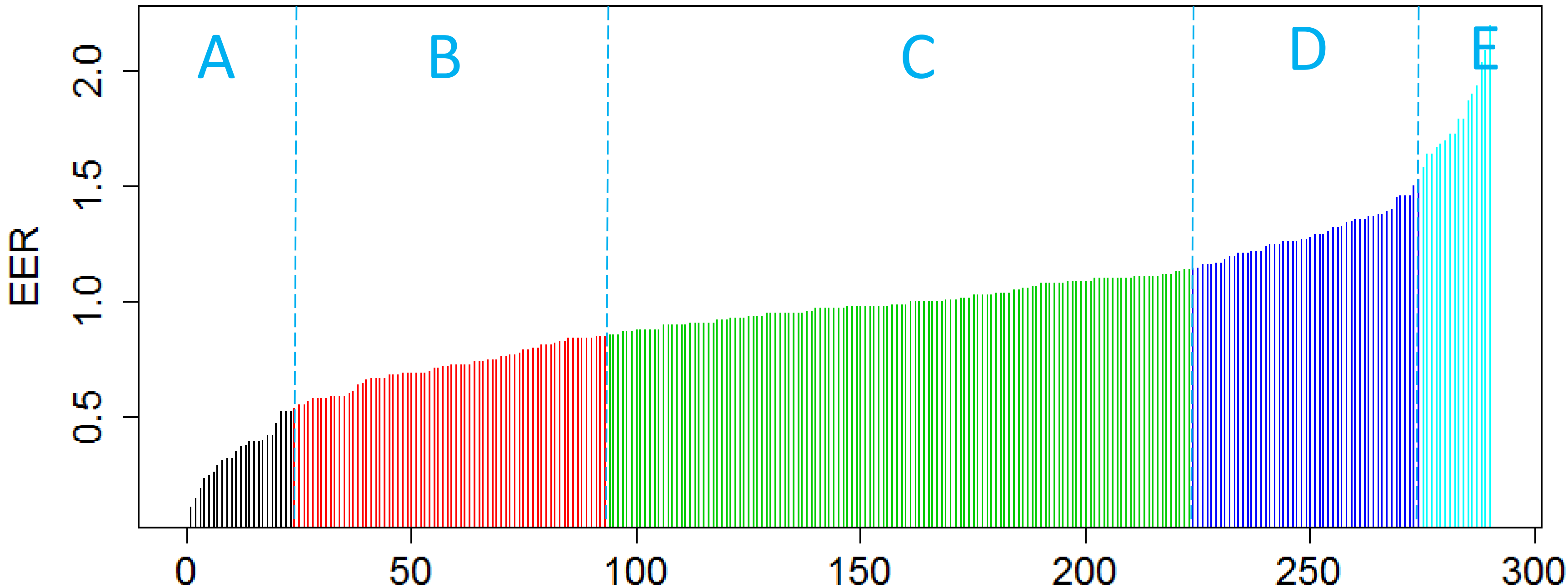
- Used in the Energy Star program in the USA
- Used in an earlier labelling program for Singapore [1]
- and many other studies

Building type	**R-squared (%)**		**NRMSE**	
	MLR	XGBoost	MLR	XGBoost
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 (12.1%)**		**-21.9 (52.5%)**	

[1] Siew Eang Lee and Priyadarsini Rajagopalan. 2008. Building energy efficiency labelling programme in Singapore. Energy Policy 36, 10 (2008), 3982–3992.

Grade distribution and Grade Lookup Table

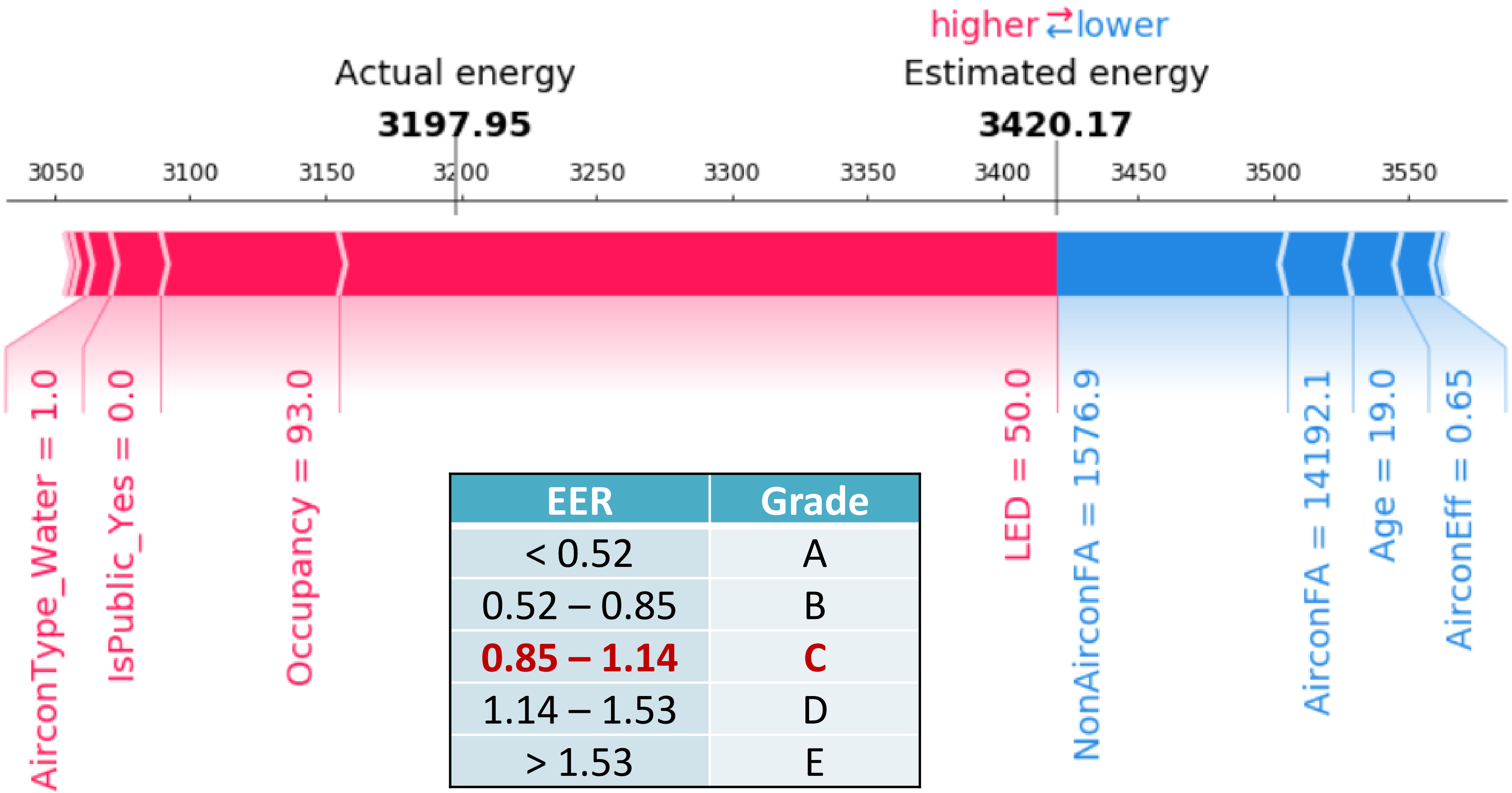
For office buildings in Singapore



EER	Grade
< 0.52	A
0.52 – 0.85	B
0.85 – 1.14	C
1.14 – 1.53	D
> 1.53	E

Model interpretation

Visual explanation of individual model prediction using SHAP force plot



EER	Grade
< 0.52	A
0.52 – 0.85	B
0.85 – 1.14	**C**
1.14 – 1.53	D
> 1.53	E

$$EER = \frac{Actual}{Estimated} = \frac{3197.95}{3420.17} = 0.94$$

Limitations and conclusion

Our proposed BEEM benchmarking approach

- Account for multiple factors (size, age, occupancy, Aircon type, etc.)
- Highly accurate – using nonlinear models (XGBoost algorithm)
- Explainable – local model interpretation (using SHAP values)
    - Which factors influence the energy usage in individual building?
- 5-point scale letter grade (for easy understanding)

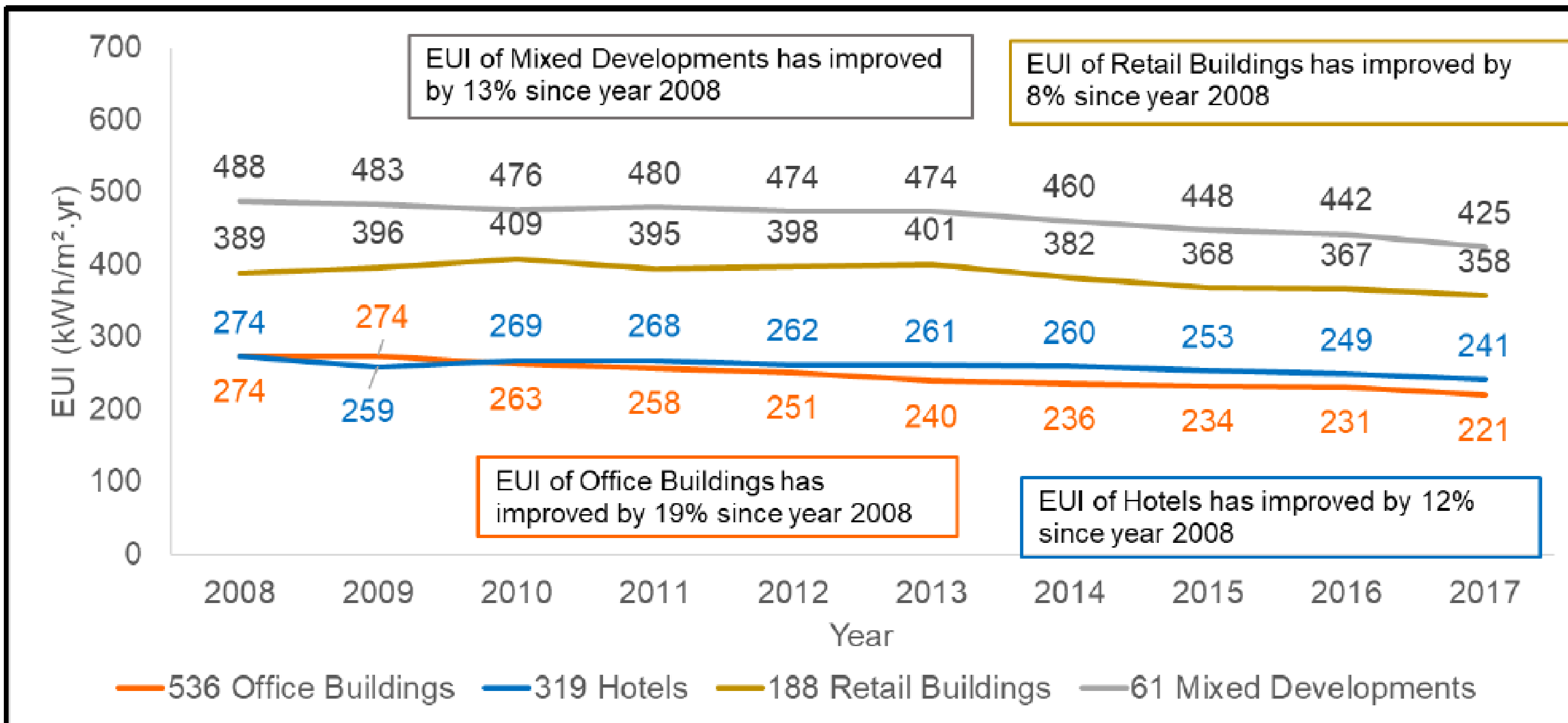
Limitations and future work

- Dataset - limited number of building attributes (10) and samples
- In-the-wild deployment and usability study
- Handling mixed-use buildings
- Targeted interventions and quantifying energy savings

Supplementary slides

BCA Building Energy Benchmarking Report 2018

Commercial buildings showed commendable improvement at 14% in EUI since 2008, with all categories achieving more than 8% of improvement.



Average EUI Trend by Commercial Building Types

GreenMark

40 points, out of a total of 165, are given to the building energy performance

Section 2 – BUILDING ENERGY PERFORMANCE		
2.1	Façade Performance	2
2.2	Air Conditioning System Operating Efficiency	16 for AC/ MV;
2.3	Natural / Mechanical Ventilation Performance	17 for NV
2.4	Lighting System Efficiency	6
2.5	Vertical Transportation System	1.5
2.6	Ventilation in Car Park	2
2.7	Ventilation in Common Areas	3
2.8	Energy Efficient Practices and Features	2
2.9	Renewable Energy	6.5
	Score for Section 2 – Building Energy Performance	**40**

https://www.bca.gov.sg/GreenMark/others/GM_ENRB_2017_simplified_criteria.pdf

Energy Star for office buildings

MLR model

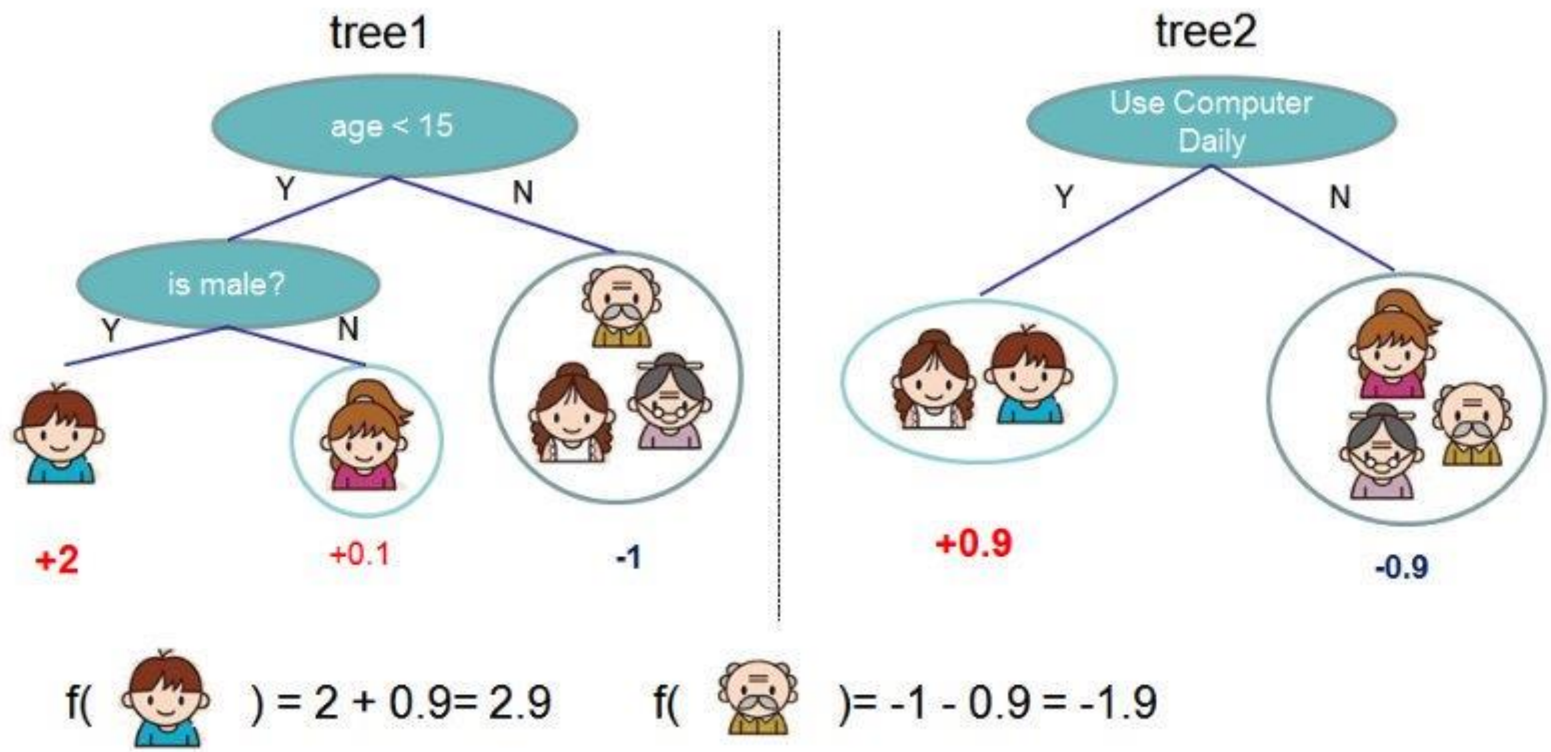
Summary				
Dependent Variable	Source Energy Intensity (kBtu/ft^2)			
Number of Observations in Analysis	886			
R^2 value	0.2200			
Adjusted R^2 value	0.2147			
F Statistic	41.32			
Significance (p-level)	< 0.0001			
	Unstandardized Coefficients	**Standard Error**	**T value**	**Significance (p-level)**
Constant	143.1	3.546	40.37	<0.0001
C_Square Footage *(max value of 100,000)*	0.0006768	0.0001698	3.985	<0.0001
C_Weekly Operating Hours	0.6130	0.1314	4.667	<0.0001
C_Number of Workers per 1,000 ft^2	15.90	3.794	4.190	<0.0001
C_Number of Computers per 1,000 ft^2	10.13	2.433	4.161	<0.0001
C_Percent Cooled x Ln (Cooling Degree Days)	4.529	1.992	2.274	0.0232
Small Bank	82.87	10.03	8.260	<0.0001

List of attributes used in the Energy Star system

List of variables	Hotel	K-12 School	Multifamily	Office	Retail	Worship
Number of guest rooms per 1,000 square feet	✓					
Number of workers per 1,000 square feet	✓	✓		✓	✓	
Number of refrigeration/freezer units per 1,000 square feet	✓				✓	
Heating Degree Days x percent of the building that is heated	✓	✓			✓*	✓
Cooling Degree Days x percent of the building that is cooled	✓	✓		✓*	✓*	✓
Presence of a commercial/large kitchen (yes/no)	✓					
Whether there is energy used for cooking (yes/no)		✓				
Whether the school is open on weekends (yes/no)		✓				
Whether the school is a high school (yes/no)		✓				
Number of units per 1,000 square feet			✓			
Number of bedrooms per unit			✓			
Total Heating Degree Days			✓			
Total Cooling Degree Days			✓			
Low-Rise building (yes/no)			✓			
Square footage				✓		
Weekly operating hours				✓	✓	✓
Number of computers per 1,000 square feet				✓		
Whether or not the building is a bank branch (yes/no)				✓		
Whether the building is a supermarket (yes/no)					✓	
Adj. for no. of workers per 1,000 square feet for supermarket					✓	
Percent cold storage						
Number of religious worship seats per 1,000 square feet						✓
Percent of square footage used for food preparation						✓
Total number of variables	6	6	5	7	7	5

*Using natural log of Cooling/Heating Degree Days

XGBoost algorithm



Here is an example of a tree ensemble of two trees. The prediction scores of each individual tree are summed up to get the final score. If you look at the example, an important fact is that the two trees try to *complement* each other. Mathematically, we can write our model in the form

$$\hat{y}_i = \sum^{K} f_k(x_i), f_k \in \mathcal{F}$$

SHAP values

SHAP values - unified measure of additive feature attributions, $\varphi_i \in \mathbb{R}$:

$$\varphi_i = \boxed{\sum_{S \in F \setminus \{i\}} \frac{|S|!\,(M - |S| - 1)!}{M!}} \, [\underbrace{f_{S \cup \{i\}}(x_{S \cup \{i\}})}_{\text{output with } i^{\text{th}} \text{ feature}} - \underbrace{f_S(x_s)}_{\text{output without } i^{\text{th}} \text{ feature}}]$$

weighted average of all possible subsets of S in F

where

F = {all input features}

S = {subset of input features}

M = |F| = number of input features

SHAP values

SHAP value
attributions,

Computing SHAP values:

- $f_{S\cup\{i\}}$ is trained with the i^{th} feature present
- f_S is trained without the i^{th} feature
- compute difference $f_{S\cup\{i\}}(x_{S\cup\{i\}}) - f_S(x_s)$ for the current input
- retrain the model on all feature subsets $S \in F\setminus\{i\}$
- take weighted average of all possible differences

$\varphi_i = \sum_S$ ... $(x_s)]$

without
ature

where

F = {all input fe

S = {subset of i

M = |F| = numbe

average of all
possible subsets of S in F

Model interpretation

Feature importance using SHAP summary plot