XENIA: eXplainable ENergy Informatics and Attributes for building energy benchmarking

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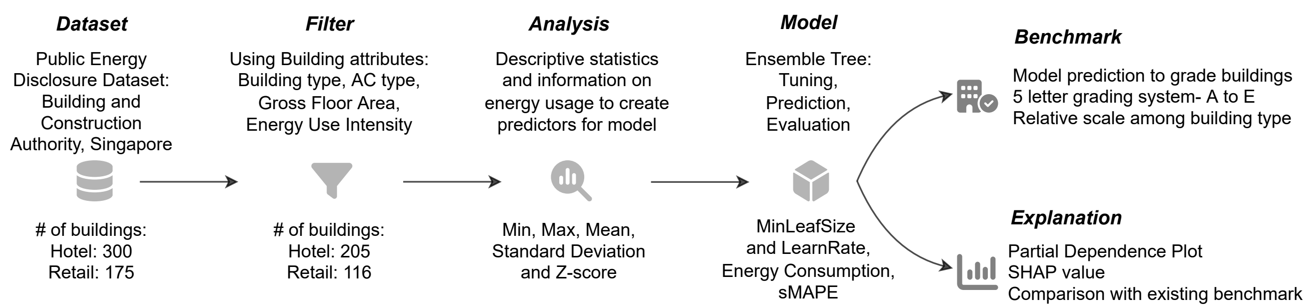

Figure 1: XENIA workflow from the original dataset to benchmarking and model explanation

ABSTRACT

Benchmarking energy usage help identify operational and strategic best practices suitable for an establishment while creating awareness of energy consumption. Therefore in this work, we present XENIA, a data-driven energy benchmarking methodology for buildings in Singapore using a public dataset of building attributes. We develop an ensemble tree model to predict energy consumption using the building attributes as predictors. Symmetric mean absolute percentage error of these models for hotel and retail buildings is 5.15% and 5.02%, respectively. A benchmark grade is then assigned to each building using the actual and predicted energy consumption. To interpret the model, we provide a global explanation using the partial dependence function to show the effect of building attributes on energy consumption. For local explanation, i.e., for a specific building, we use the SHAP value to show the influence of each building attribute in the prediction model. The results for hotels and retail buildings show that change in AC and non-AC floor has the highest positive impact on energy consumption.

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CCS CONCEPTS

• **Information systems** → **Data analytics**; • **General and reference** → Metrics; • **Computing methodologies** → Model verification and validation.

KEYWORDS

Explainable AI, Machine Learning, Energy Benchmarking, Shapley value, Partial Dependence, Ensemble Model

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1 INTRODUCTION

The energy consumption of buildings was 36% of the global energy demand in 2020 while accounting for 37% of CO_2 emissions [14]. This share of global demand shows that the building sector is among the largest energy consumers, and with rapid urbanization, energy demand is rising. Therefore, buildings are among the prime avenues to exercise measures such as energy efficiency, automation, shaping energy consumption behavior, and promoting user awareness. These measures collectively influence the energy performance of a building, and thus the evolution of energy benchmarking schemes is vital from planning, policy, and stakeholder perspectives.

Table 1: Descriptive statistics of the selected and derived building attributes after filtering/cleaning the dataset

		Hotel				Retail			
Attribute	Description	Min	Max	μ	σ	Min	Max	μ	σ
build_age	Building age (years)	1	93	20.33	19.17	1	49	19.20	12.64
ac_fa	AC floor area (m^2)	60	51103	6179.91	9904.38	20	49572	14442.90	13036.97
nac_fa	Non AC floor area (m^2)	0	16327	1233.31	2628.19	0	36479	3985.68	6006.76
per_led	LED coverage (%)	0	100	41.17	41.50	0	100	34.12	35.94
avg_occupy	Average occupancy (%)	1	100	73.24	16.51	27	100	90.06	14.90
num_room	Number of rooms	1	591	130.97	146.67	-	-	-	-
energy_con	Energy Consumption (kWh)	6083	2.17×10^7	2.04×10^6	3.33×10^6	1.39×10^5	2.65×10^7	7.04×10^6	6.60×10^6
is_public	Is it a public building?	Categorical: *'Yes'* if it is a public building or *'No'* otherwise (only for Retail buildings)							
ac_type	Type of AC	Categorical: *'Water Cooled'*, *'Air Cooled'* or *'Others (Split, Unitary)'* type of AC							

Benchmarking energy usage is a systematic process of assigning a competitive rank by comparing the energy performance of a building with other buildings of a similar class or group. In particular, data-driven energy benchmarking evaluates the energy performance of a building with respect to either historical energy consumption [6], a comparison with simulated building stock [7], industry baseline [15], or a group of peers for the building [8]. Therefore data-driven benchmarking process offers a solution to include energy consumption, building attributes, and the activity within a building. However, this approach relies on the quantity and quality of data available for the buildings.

The dataset from the Buildings and Construction Authority, Singapore, employs Energy Usage Intensity (EUI) as a metric to segregate buildings into different classes. However, EUI as a metric can be inefficient since the energy consumption depends on the activity inside the building and its built characteristics. Therefore, capturing the effects of building attributes is the prime motivation for data-driven energy benchmarking. Since most data-driven models rely on a black-box model to predict energy consumption, the explanation and interpretation of such models are vital. Previous studies employ LIME [5, 9] and SHAP values [1, 10, 13] for local interpretation of energy benchmarking. Therefore, the main contributions of this work is:

- Data-driven model based on building attributes for prediction of building energy consumption
- Assignment of energy benchmarking grade by comparing the buildings in the peer group
- Explanation of model behaviour for energy benchmarking through partial dependance and SHAP value
- Comparison with existing benchmark and certification

In addition, we release the source code of XENIA implementation and interactive results in a public repository[1].

2 METHODOLOGY

The data-based methodology for benchmarking the buildings follows the outline in Figure 1. An ensemble tree model based on Least Square Boost (LSBoost) [12] is developed to accurately predict the building energy consumption. Partial Dependence and SHAP value are calculated respectively for global and local interpretation of building attributes. The following sections provide the description of data, prediction model, benchmarking, and model explanation.

2.1 Data: Energy and building attributes

The Building and Construction Authority (BCA), Singapore, releases the yearly energy disclosure data submitted by building owners under the Building Control Act [3]. We first use the dataset for the year 2017 to separate two different building types- hotel and retail buildings. Further, we derive energy consumption, Air-conditioned (AC) floor area, and Non-AC floor area of a building from the available values of gross floor area, percentage of AC floor area, percentage of Non-AC floor area, and EUI. We also use the data on the Certificate of Statutory Completion to calculate the age of the building. We then filter the data according to current practices and literature [2], and remove the rows with missing data within each building type. The final dataset thus has 205 hotels and 116 retail buildings. A description of seven building attributes used as predictors is provided in Table 1, along with the descriptive statistics. Building attributes such as AC efficiency is removed due to high percentage of missing values.

2.2 Model development: XENIA

This step involves the development of a model for predicting energy consumption for hotel and retail buildings. It is essential to capture building characteristics on energy consumption; hence, we use the building attributes as predictors for the model. Since the assignment of benchmark grade uses predicted energy consumption, it is essential to develop an accurate model to enable a fair comparison of buildings within the particular type.

For regression and classification tasks, decision trees find wide acceptance as interpretable models. But they are prone to overfitting and optimizing at the local node as per the splitting criteria. On the other hand, ensemble tree based methods use several decision trees to overcome these limitations. An ensemble tree model combines weak learners to form an ensemble of decision trees- creating a strong learner to improve the accuracy of a prediction or classification task. Therefore, here we use ensemble tree based regression model with LSBoost to fit regression ensembles to predict energy consumption. The piecewise-constant nature of approximation in LSBoost provides an advantage of few large errors or very small errors while providing robustness from the effects of outliers in the

[1] https://github.com/kevinjoshi9888/xenia-benchsys22

predictors [4]. The LSBoost approach fits a new learner at every step based on the difference in the observed response and aggregated prediction of all learners from the previous steps as shown in eq. 1.

$$\min_{\forall x_n \in X} y_n - \eta f(x_n) \quad (1)$$

where, y_n is the dependent variable, $f(x_n)$ is the aggregate prediction of all the learners till the observation and η is the learning rate. The model uses `LearnRate` parameter ranging from 0 to 1 for the decision to fit a new learner. Combining all the weak learners collectively forms an ensemble that minimizes the mean-squared error of the model fit. The model is tuned to minimize the error in prediction, and we use the scale-independent metric symmetric Mean Absolute Percentage Error (sMAPE) to evaluate the model performance. The developed model has an sMAPE of 5.15% and 5.02% for hotel and retail buildings respectively. In comparison, the previous work using CatBoost shows an sMAPE of 7.21% and 4.93% for models of hotel and retail buildings [2].

2.3 Benchmarking: Metric and Grading

This step involves deriving a metric to compare the energy performance of a building with other buildings of the same class. We use the Energy Efficiency Ratio (EER) to compare the energy consumption of buildings on a relative scale. EER is calculated as shown in eq. 2, using the building's actual and predicted energy consumption.

$$EER = \frac{energy\_con}{pred\_energy\_con} \quad (2)$$

The value of `energy_con` is derived from the original dataset, whereas the `pred_energy_con` is the predicted energy consumption of the building as per the model derived for its class. Since EER is a ratio, `energy_con > 0`, and `pred_energy_con > 0` for a building- there are 3 distinct possibilities for the value of EER.

- if $EER < 1$ the building energy consumption is less than the peer group energy consumption of its class
- if $EER > 1$ the building energy consumption is more than the peer group energy consumption of its class
- if $EER = 1$ the building energy consumption is equal to the peer group energy consumption of its class

EER is calculated for each building and is further used to assign a 5-letter energy benchmarking grade. Since $EER = 1$ represents an energy performance similar to the peer group, a margin of ± 0.05 is used to assign C grade for buildings within the range: $0.95 \leq EER \leq 1.05$. On either side of this margin, the building energy performance is better ($EER > 1.05$) or worse ($EER < 0.95$) than the peer group. Therefore, the next grade is assigned as B and D for the ranges: $0.75 \leq EER < 0.95$ and $1.05 < EER < 1.25$, respectively. The final assignment is for grades A and E, where $EER < 0.75$ and $EER \geq 1.25$ respectively. The benchmarking thus has a grading from A to E where A represents the best relative energy performance. Figure 2 shows all the buildings in the hotel and retail class, their grading and the distribution of number of buildings in each grade.

3 EVALUATION

In a linear model, the coefficients provide a means to explain the model decision and the influence of features on the predicted value. However, such a straightforward interpretation does not exist for

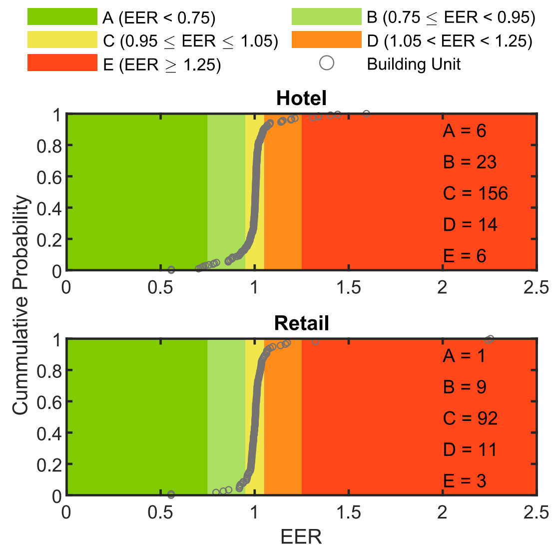

Figure 2: Energy Efficiency Ratio and benchmarking of buildings, legends show the range of EER for each grade.

complex machine learning-based models. Therefore, we use the partial dependence plot to explain the overall effect of features and SHAP value to determine the local effect for a particular building.

3.1 Global Explanation: Partial Dependence

The partial dependence plot (PDP) function determines the average marginal effect of a feature on prediction [4]. We use PDP to show relationships the model has learned between the features (building attributes) and prediction (energy consumption). Figure 3 shows the PDP of all the features. For hotels,

- `ac_fa` → most significant effect on variation in energy consumption
- `nac_fa`, `avg_occupy`, and `num_room` → less significant effect on variation in energy consumption
- `build_age`, `per_led`, and `ac_type` → least effect on energy consumption

For retail buildings,

- `ac_fa` and `nac_fa` → effect similar to hotels
- `per_led`, `build_age` and `avg_occupy` → less significant effect on variation in energy consumption
- `is_public` and `ac_type` → least significant effect on variation in energy consumption

3.1.1 Hotel buildings. As the `ac_fa` increases, the energy consumption increases after the mean `ac_fa` ($6180m^2$). Until the mean `ac_fa`, the energy consumption decreases slightly with a reduction in `ac_fa`. However, there is a sharp increase at approximately 2.75σ, and the energy consumption remains nearly constant beyond 3σ. This shows that for any further increase in `ac_fa`, the model does not predict significant variation in energy consumption. The relationship is similar for `nac_fa` as the energy consumption increases with an increase in non-AC floor area, but the variation is less significant than `ac_fa`. Such an effect of `ac_fa` and `nac_fa` can be justified as the energy consumption increases with an increase in a building's AC and non-AC floor area. Secondly, the `avg_occupy` shows a minimal effect on energy consumption variation till 1.5σ, but increases as the `avg_occupy` reach near the total capacity. The smaller values for `num_room` negatively impact energy consumption, while hotels with more rooms see an increase in energy consumption. These results show that the peer group performs similarly with respect to average occupancy, but the number of rooms increases the energy consumption. The `build_age` has a small and non-uniform effect on energy consumption. This effect is mainly due to the newer building designs and the use of energy-efficient lighting and AC. In contrast, older buildings turn to retrofit for better energy savings considering that higher `per_led` use lowers the energy consumption. The `ac_type` shows that using air-cooled AC lowers energy consumption, while the split and unitary or water-cooled AC systems increase energy consumption.

3.1.2 Retail buildings. The increase in `ac_fa` and `nac_fa` positively affect the energy consumption of a retail building. This observation is similar to hotels; however, the relationship is more linear for AC floor area, and the non-AC floor area contribution saturates after 1σ. The retail buildings see a reduction in energy consumption for lower values of `avg_occupy`. Such an effect can be due to prudent utilization of AC when the occupancy is less and natural lighting during daytime. Moreover, the higher coverage of LED indicates a reduction in energy consumption. The effect of `per_led` in retail buildings is more significant than in hotels due to large common spaces utilizing LED lighting. Interestingly, the `build_age` feature is prominent for retail buildings since it shows that older buildings perform better than newer buildings. The effect of the building's status as public shows negative relation with energy consumption, indicating that the energy performance of public retail buildings is better than private retail buildings. The air-cooled and split or unitary `ac_type` reduces the energy consumption, while similar to hotels, the water-cooled AC systems increase energy consumption. Moreover, the effect of `ac_type` is more significant in retail buildings than in hotels.

3.2 Local Explanation: SHAP value

SHapley Additive exPlanation (SHAP) values proposed by [11] is an additive feature attribution method. SHAP values are model-agnostic and explain a model prediction for a particular query point as a contribution of each feature to the model output. The SHAP value of the feature indicates either a positive or negative influence of the feature on model prediction, i.e., a feature increases or decreases the prediction value. Therefore, the features with high absolute SHAP values significantly affect the model prediction. Table 2 gives the mean of absolute SHAP values for each feature to summarize the global importance. The `ac_fa` is the most significant feature affecting energy consumption for hotel and retail classes by an average of 0.6139σ and 0.7047σ, respectively. The next significant features for hotels are `nac_fa` and `num_room` while for retail buildings the `nac_fa` and `build_age` influence the energy consumption. To show the local interpretation, Figure 4 shows SHAP dependence plot for each building and the attribute's influence on a building's energy consumption. The blue/pink color shows the positive/negative contribution of the attribute to a building.

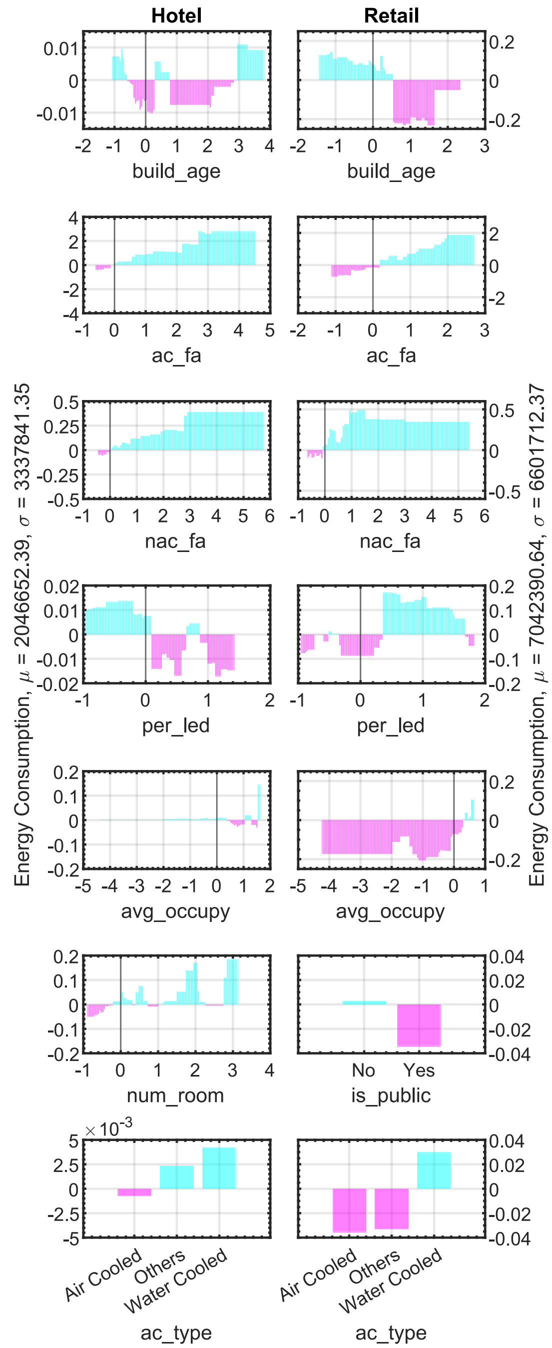

Figure 3: Partial Dependence of building attributes in XENIA (x-axis and y-axis are z-scores of predictors and target variable respectively)

3.2.1 Hotel buildings. SHAP dependence plot shows that `ac_fa` is the most significant feature influencing energy consumption. The SHAP value is negative, approximately below $5000m^2$ of `ac_fa`; beyond that, it is positive and increases with an increase in `ac_fa`. Therefore, the influence of `ac_fa` on energy consumption is linear.

Table 2: Mean absolute SHAP value of each predictor: the magnitude of average impact on XENIA model output

Hotel		Retail	
Predictor	$\mu(\lvert SHAP\rvert)$	Predictor	$\mu(\lvert SHAP\rvert)$
ac_fa	0.6139	ac_fa	0.7047
nac_fa	0.0727	nac_fa	0.1306
num_rooms	0.0477	build_age	0.1072
avg_occupy	0.0236	avg_occupy	0.0950
build_age	0.0145	per_led	0.0662
per_led	0.0143	ac_type	0.0098
ac_type	0.0015	is_public	0.0029

Similarly, the nac_fa influence the energy consumption linearly. However, the magnitude of influence is lower than ac_fa. Most hotels with nac_fa > $2000m^2$ show a positive influence on energy consumption. The next significant attribute for hotels is num_room in a building. Energy consumption increases with an increase in the number of rooms in a hotel. However, there are some instances where a higher value of num_room affects energy consumption negatively. This indicates that other features such as ac_type or avg_occupy also contributes to the energy consumption. For example, the avg_occupy of a building affects the energy consumption significantly, but only when the value is more than 75%. The influence of per_led is smaller, but the reduction in energy consumption is evident at higher percentages of LED. Moreover, the dispersion in SHAP value along the y-axis for per_led shows the presence of interacting features among the predictors. Among the ac_type, the water-cooled AC influences the energy consumption positively, while the split or unitary ACs had more influence in increasing energy consumption than the air-cooled AC. An example of a hotel building with grade A, $EER = 0.5566$, and $EUI = 207.05$ is highlighted in the plot; local interpretation for the building is,

- ac_fa of the hotel is $2124m^2$, which is lower than the mean ac_fa of the class → negative effect on energy consumption, $SHAP = -0.3613$, indicates that hotels with lower ac_fa can reduce energy consumption.
- nac_fa of the hotel is $7212m^2$, which is very high among the hotel class positive effect on energy consumption, $SHAP = 0.2121$. This indicates nac_fa also consumes energy in the form of lighting or plug level loads.
- num_room in this hotel is 107, which is near the average → positive effect on energy consumption, $SHAP = 0.0467$.
- avg_occupy is 70%, which is lower in the case of a hotel with fewer rooms → less significant but positive effect on energy consumption, $SHAP = 0.0090$. Such effect can also be due to the minimum base load consumption of the hotel, irrespective of the occupancy.
- build_age of the hotel is 13 years, indicates a relatively new building → less significant but positive effect on energy consumption, $SHAP = 0.0180$. It should be noted that the SHAP values show a dispersion along the y-axis for build_age, indicating interactions of other features.
- per_led coverage in the hotel is 30% → less significant but positive effect on energy consumption, $SHAP = 0.0109$. While the effect is smaller, a higher percentage of LEDs can help reduce energy consumption.
- ac_type in the hotel is 'split or unitary' configuration, typical for a small hotel → least significant effect in increasing energy consumption, $SHAP = 0.0035$.

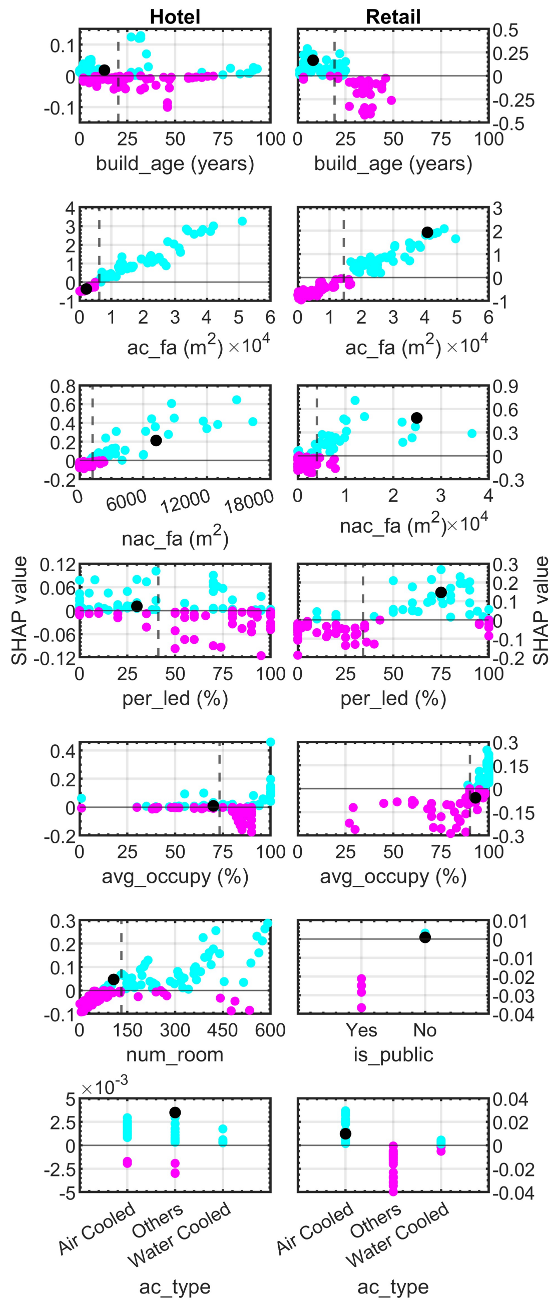

Figure 4: SHAP value plot of attributes for each building. Data points highlighted in black - example of grade A and grade C building in the hotel and retail class respectively; dashed line - mean value of feature across dataset.

Table 3: Comparison of XENIA benchmark with existing EUI based classification and Green Mark certification

		Hotel					Retail				
Attribute	Value	A	B	C	D	E	A	B	C	D	E
XENIA	# of buildings	6	23	156	14	6	1	9	92	11	3
Green Mark	Gold	1	2	1	2	0	0	2	15	2	0
	Gold Plus	0	1	5	0	0	0	0	5	0	0
	Platinum	1	5	6	1	0	0	0	9	1	0
EUI Quartile	Top	4	7	43	2	0	0	2	15	4	1
	2nd	1	5	42	5	2	0	1	32	4	0
	3rd	0	6	42	0	3	0	4	23	2	0
	Bottom	1	5	29	7	1	1	2	22	1	2

3.2.2 Retail buildings. SHAP dependence plot shows that `ac_fa` is the most significant feature influencing energy consumption. Like hotel buildings, an increase in `ac_fa` increases energy consumption. Above the value of $17500m^2$, the feature positively influences energy consumption. While the relation is not strictly linear for `nac_fa`, it is evident that an increase in non-AC floor area contributes positively to energy consumption. Interestingly, the `build_age` feature shows that newer buildings have higher energy consumption and the age of a building has a negative influence. This can be due to the larger floor area covered by AC or the building design necessities a sizeable thermal load. Such interaction is also seen with `per_led` feature. More extensive coverage of LED shows a positive influence on energy consumption. Since the total floor area of some buildings is higher, the energy consumption due to lighting load increases. The effect of `avg_occupy` on the energy consumption shows a negative effect at lower occupancy for some buildings. However, for some buildings, the influence is more significant and positive at occupancy levels of more than 80%. Some buildings show negative effects with an increase in occupancy; this suggests that other features, such as AC efficiency and AC type, influence energy consumption when the occupancy levels increase. The air-cooled `ac_type` shows only a positive influence on energy consumption, while unitary and split ACs show a negative effect. The retail building's status as `is_public` has the least significant influence. However, public buildings have a negative influence, and non-public buildings positively influence energy consumption. An example of a retail building with grade C, $EER = 1.0052$, and $EUI = 382.19$ is highlighted in the plot; the local interpretation for this building is,

- `ac_fa` of the building is $40727m^2$, which is considerably higher than the mean `ac_fa` of the class → positive and most significant effect on energy consumption, $SHAP = 1.9306$, indicates that building consumes more energy with higher `ac_fa`.
- `nac_fa` of the building is $24913m^2$, which is considerably higher than the mean `nac_fa` of the class → positive and significant effect on energy consumption, $SHAP = 0.4826$, indicates non-thermal loads like lighting and plug level loads for the building can increase energy consumption.
- `build_age` of the building is 8 years, indicates a relatively new building → significant but positive effect on energy consumption, $SHAP = 0.1662$. It should be noted that the SHAP values decrease with `build_age`, indicating high demand for thermal and lighting load in newer buildings.
- `avg_occupy` is 93%, which is higher → less significant and negative effect on energy consumption, $SHAP = -0.0582$. Such an effect can be due to diligent energy efficiency measures and awareness.
- `per_led` coverage in the building is 75% → significant and positive effect on energy consumption, $SHAP = 0.1466$. The effect is significant, and a higher percentage of LEDs can help reduce energy consumption, especially in a large building with a gross floor area of $65640m^2$.
- `ac_type` in the building is 'water-cooled' configuration → less significant effect, $SHAP = 0.0097$.
- `is_public` status of the building is non-public → least significant effect on energy consumption, $SHAP = 0.0008$.

3.3 Comparison with existing classification

The current benchmarking approach in Singapore is the Green Mark certification that assigns a Gold, Gold Plus, and Platinum rating. Table 3 shows the number of buildings in XENIA model with Green Mark certification. It should be noted that 175 buildings in the hotel and 76 in the retail class are not certified. But, among those certified, the benchmarking by XENIA segregates the buildings more granularly. Notably, for hotels and retail class, none of the certified buildings are among the E grade.

4 CONCLUSION

This work presents a data-driven energy benchmarking methodology and an accurate model for predicting the energy consumption of a building. The methodology uses a public dataset of buildings in Singapore that provides the energy consumption and building attributes for hotel and retail classes of buildings. The explanation of the model uses partial dependence- to show the global influence of building attributes on energy consumption and SHAP values- to show the influence of each feature of a building in predicting its energy consumption. The relationship between the features and energy consumption is evident in the strong influence of some prominent features like the floor area of the building, the number of rooms in the hotel, and average occupancy. However, the interaction between building attributes and their influence on energy consumption needs further investigation.

REFERENCES

[1] Pandarasamy Arjunan, Kameshwar Poolla, and Clayton Miller. 2020. EnergyStar++: Towards more accurate and explanatory building energy benchmarking. *Applied Energy* 276 (2020), 115413. https://doi.org/10.1016/j.apenergy.2020.115413

[2] Pandarasamy Arjunan, Kameshwar Poolla, and Clayton Miller. 2022. BEEM: Data-driven building energy benchmarking for Singapore. *Energy and Buildings* 260 (2022), 111869. https://doi.org/10.1016/j.enbuild.2022.111869

[3] Building and Construction Authority. Singapore. 2018. *BESS (Building Energy Submission System)*. Retrieved August 9, 2022 from https://www.bca.gov.sg/BESS/BenchmarkingReport/BenchmarkingReport.aspx

[4] Jerome H. Friedman. 2001. Greedy Function Approximation: A Gradient Boosting Machine. *The Annals of Statistics* 29, 5 (2001), 1189–1232. http://www.jstor.org/stable/2699986

[5] Antonio Galli, Marco Savino Piscitelli, Vincenzo Moscato, and Alfonso Capozzoli. 2022. Bridging the gap between complexity and interpretability of a data analytics-based process for benchmarking energy performance of buildings. *Expert Systems with Applications* 206 (2022), 117649. https://doi.org/10.1016/j.eswa.2022.117649

[6] Matheus Soares Geraldi and Enedir Ghisi. 2022. Data-driven framework towards realistic bottom-up energy benchmarking using an Artificial Neural Network. *Applied Energy* 306 (2022), 117960. https://doi.org/10.1016/j.apenergy.2021.117960

[7] Matheus Soares Geraldi, Veronica Martins Gnecco, Antonio Barzan Neto, Bárbara Augusta de Mafra Martins, Enedir Ghisi, Michele Fossati, Ana Paula Melo, and Roberto Lamberts. 2021. Evaluating the impact of the shape of school reference buildings on bottom-up energy benchmarking. *Journal of Building Engineering* 43 (2021), 103142. https://doi.org/10.1016/j.jobe.2021.103142

[8] Veronica Martins Gnecco, Matheus Soares Geraldi, Michele Fossati, and Maria Andrea Triana. 2022. Comparison between national and local benchmarking models: The case of public nursery schools in Southern Brazil. *Sustainable Cities and Society* 78 (2022), 103639. https://doi.org/10.1016/j.scs.2021.103639

[9] Xiaoyu Jin, Fu Xiao, Chong Zhang, and Ao Li. 2022. GEIN: An interpretable benchmarking framework towards all building types based on machine learning. *Energy and Buildings* 260 (2022), 111909. https://doi.org/10.1016/j.enbuild.2022.111909

[10] Xue Liu, Hao Tang, Yong Ding, and Da Yan. 2022. Investigating the performance of machine learning models combined with different feature selection methods to estimate the energy consumption of buildings. *Energy and Buildings* 273 (2022), 112408. https://doi.org/10.1016/j.enbuild.2022.112408

[11] Scott M. Lundberg and Su-In Lee. 2017. A Unified Approach to Interpreting Model Predictions. In *Proceedings of the 31st International Conference on Neural Information Processing Systems* (Long Beach, California, USA) *(NIPS'17)*. Curran Associates Inc., Red Hook, NY, USA, 4768–4777. https://dl.acm.org/doi/10.5555/3295222.3295230

[12] MATHWORKS. 2022. *Ensemble Algorithms*. Retrieved July 7, 2022 from https://in.mathworks.com/help/stats/ensemble-algorithms.html

[13] Sokratis Papadopoulos and Constantine E. Kontokosta. 2019. Grading buildings on energy performance using city benchmarking data. *Applied Energy* 233-234 (2019), 244–253. https://doi.org/10.1016/j.apenergy.2018.10.053

[14] United Nations Environment Programme. 2021. *2021 Global Status Report for Buildings and Construction: Towards a Zero-emission, Efficient and Resilient Buildings and Construction Sector*. Nairobi. https://globalabc.org/sites/default/files/2021-10/GABC_Buildings-GSR-2021_BOOK.pdf

[15] Irfan Qaisar and Qianchuan Zhao. 2022. Energy baseline prediction for buildings: A review. *Results in Control and Optimization* 7 (2022), 100129. https://doi.org/10.1016/j.rico.2022.100129