Energy-Intelligent Forecasting for Taiwanese Office Buildings: Developing a BIM-Derived Dataset and Integrating Advanced AI Models

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Abstract

Reliable and rapid energy forecasting is essential for early-stage decision-making in office building design, yet data-driven modeling in Taiwan is hindered by the lack of region-specific datasets that reflect local building typologies and climates. This study addresses this gap by introducing TOBE (Taiwanese Office Building Energy), a BIM-derived dataset developed for Taiwanese office buildings and designed to reflect regional characteristics. 1,006 simulated office-building cases were created to provide three energy targets: annual electricity (AE), energy use intensity (EUI), and lifecycle electricity (LE). To enable high-accuracy prediction without manual hyperparameter tuning, four machine learning learners (RBFNN, LSSVR, AdaBoost, and XGBoost) were hybridized with the Forensic-Based Investigation (FBI) metaheuristic optimizer and evaluated using 10-fold cross-validation. Results show that boosting-based learners consistently outperform NN- and SVM-based baselines. The best models achieved strong generalization, including AE with FBI_AdaBoost (MAPE = 3.45%; R^2 = 0.944), EUI with FBI_XGB (MAPE = 1.86%; R^2 = 0.954), and LE with FBI_AdaBoost (MAPE = 3.51%; R^2 = 0.945). The proposed BIM-to-AI pipeline offers a practical route to scalable, data-driven energy assessment tailored to Taiwanese office buildings.

Keywords –

BIM-derived dataset; Taiwanese office buildings; building energy prediction; boosting algorithm; Forensic-Based Investigation (FBI).

1 Introduction

Building energy consumption accounts for approximately 17.5% of global greenhouse gas emissions and around 30% of annual carbon emissions from the construction sector [1]. Worldwide, building energy utilization is projected to increase by 1.3% annually between 2018 and 2050, indicating a long term upward trend that challenges global decarbonization efforts [2]. In Taiwan, service and residential buildings consumed roughly 15% of the nation's total energy demand in 2020, with office buildings contributing significantly due to intensive cooling and electrical loads [2]. These figures highlight the pressing need for accurate and scalable prediction tools that can support energy efficient office building design and long-term sustainability planning in Taiwan's dense urban environments.

Traditional simulation based tools such as EnergyPlus and TRNSYS provide detailed insights into building energy performance, yet they require extensive input specifications and long computation times that limit their practicality during early design stages [3-5]. A single detailed simulation may require hours to complete, making these tools unsuitable for evaluating large numbers of design alternatives. Machine learning (ML) methods address these limitations by rapidly modeling nonlinear interactions among building features, and studies have shown that ML informed design decisions can yield potential energy savings of up to 30% [6]. However, the development of robust ML models in Taiwan remains constrained by the lack of large scale, high resolution, and region-specific datasets that accurately represent local office building characteristics.

Understanding the physical and operational characteristics of Taiwanese office buildings is essential for developing reliable datasets. Typical buildings in Taiwan feature rectangular or square floor plans, range from 9 to 26 stories, and incorporate façade systems such as glass curtain walls, aluminium panels, and brick that reflect contemporary architectural practice and green building requirements [7, 8]. Climatic variations across northern, central, and southern Taiwan further influence cooling loads, underscoring the importance of incorporating geographic diversity into dataset construction [9]. Building Information Modeling (BIM) offers an effective solution by enabling detailed 3D representations of building geometry, materials, and operational parameters. Leveraging BIM alongside cloud-based simulation tools makes it possible to generate thousands of consistent models, ensuring comprehensive coverage of design variables relevant to energy analysis [10-12].

Recent advances in building energy prediction have shown that ensemble learning models consistently outperform single model approaches. For example, XGBoost has achieved mean absolute percentage errors as low as 1.92% for electricity consumption prediction, while Random Forest models have reached classification accuracies near 78.7% for Energy Use Intensity (EUI) analysis [13, 14]. Achieving optimal performance nevertheless depends on effective hyperparameter tuning, which often involves searching for large and complex parameter spaces. Metaheuristic optimization algorithms have been employed to address this challenge, and the Forensic Based Investigation (FBI) algorithm has demonstrated strong stability and fast convergence without requiring algorithm specific tuning parameters [15, 16]. These characteristics make FBI a promising optimization strategy for developing hybrid ML models aimed at building energy prediction.

Despite these advancements, no existing study has proposed a Taiwanese office buildings dataset to support ML based energy prediction. To address this research gap, this study introduces a comprehensive TOBE (Taiwanese Office Building Energy) dataset, generated from detailed BIM models that capture geometric, material, and environmental attributes of real-world office buildings in Taiwan. Using this dataset, hybrid machine learning models optimized with the FBI algorithm are developed to predict the three key energy indicators for Taiwanese office buildings, including annual electric (AE), EUI, and lifecycle electric (LE). The proposed framework provides a scalable and data driven approach that strengthens early-stage decision making and supports long term energy planning for Taiwan's commercial building sector, contributing a region specific and comprehensive foundation for advancing sustainable office building design.

2 Research Methodology

This research was guided by two primary objectives. The first objective was to leverage BIM techniques to create a novel and robust dataset of energy consumption patterns for typical office structures in Taiwan - the TOBE dataset. The second objective was to develop and train AI models to predict related energy consumption patterns in order to provide accurate and early-stage insights into energy consumption to minimize future building energy demand. This approach contributes to a more comprehensive and sustainable framework for construction. The entire research process is presented in **Fig. 1**.

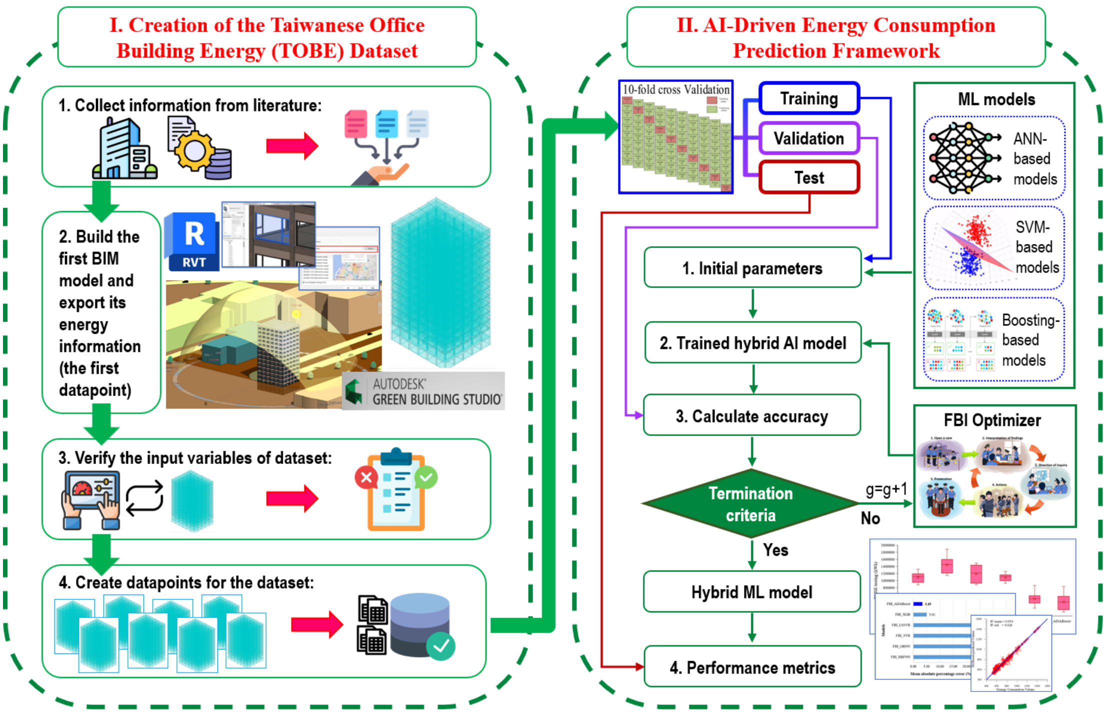

Fig. 1. Research process

2.1 TOBE Dataset Development

The TOBE dataset was established to represent the characteristics of contemporary office buildings in Taiwan systematically and to support machine learning based energy prediction. To identify the building attributes most relevant to energy consumption, a comprehensive review of previous studies and design guidelines, together with field surveys, was conducted for Taiwanese office buildings. Insights from literature, representative built examples, and field surveys highlighted consistent patterns in building geometry, façade systems, glazing configurations, and region specific climatic considerations. **Figure 2** illustrates some typical office buildings in Taiwan, and **Table 1** lists the initial set of variables derived from this investigation along with the typical ranges observed in Taiwanese office buildings. These variables capture the physical diversity required to construct realistic simulation scenarios for dataset creation.

A typical office building was modeled in Autodesk Revit using the characteristics identified earlier. All the input information required for this process was considered as input variables for the dataset. This initial model incorporated sixteen candidate variables, including: Floor area, number of stories, floor height, basement number, beam size, column size, floor thickness, stairs, roof thickness, walls, window materials, window-to-wall ratio, ceiling material, location, orientation, and HVAC system. After the BIM model was completed, the model's energy-related information was extracted using cloud-based Green Building Studio (GBS) software. Each variable was then independently modified and re-simulated to evaluate its impact on energy use, allowing non influential factors such as structural thicknesses, ceiling type, and stair configurations to be excluded.

Through this sensitivity based screening process, nine variables were identified as significant contributors to energy performance. These include floor area, floor height, number of stories, number of basements, exterior wall type, window type, window to wall ratio, geographic location, and orientation, as summarized in **Table 2**. By sampling across the ranges of these validated variables, a total of 1006 BIM models were generated and simulated to produce the final energy dataset. The value ranges of the three energy outputs derived from this dataset are also summarized in **Table 2**. Notably, these 1,006 TOBE cases were not produced through full-factorial enumeration; instead, constrained random sampling was used to achieve broad yet practical coverage of the feasible design space without generating an excessive number of combinations. As a result, the resulting TOBE dataset captures diverse combinations of geometry, envelope systems, and climatic conditions, ensuring a realistic and consistent foundation for training machine learning models aimed at early-stage energy assessment.

Chia Hsin Office, Chiayi city *Office complex building, Taipei* *ITRI office building, Hsinchu city*

Fig. 2. Some typical office buildings in Taiwan

Table 1. Key factors influencing energy consumption in Taiwan office buildings.

No.	Name	Information	Reference
1	Floor area	$480m^2 \sim 1470m^2$	[7]
2	Height of floor	3.2m ~ 4m	[7, 9]
3	Number of stories	9FL-26FL	[7]

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<tr>
<td>4</td>
<td>External wall materials</td>
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<table>
<tr><th colspan="3">Typical design of external walls in Taiwan office buildings</th></tr>
<tr><th>Main material</th><th>Structure</th><th>U (W/m2 K)</th></tr>
<tr><td>Brick</td><td>Porcelain tiles: 10mm, Mortar: 15mm, Brick: 230mm, Mortar: 10mm</td><td>2.144</td></tr>
<tr><td>Aluminium plate</td><td>Aluminium plate: 6mm, Mineral wool panel: 20mm, Air layer, Calcium silicate: 25mm</td><td>1.251</td></tr>
<tr><td>Glass curtain</td><td>Toughened glass: 8mm, Air layer, Fiber surfboard: 4mm, Mineral wool insulation board: 32mm, Fiber surfboard: 4mm</td><td>0.981</td></tr>
<tr><td>Steel curtain</td><td>Enamel: 6mm, Steel plate: 3mm, Mineral wool panel: 20mm, Air layer, Fiber surfboard: 4mm, Mineral wool insulation: 32mm, Fiber surfboard: 4mm</td><td>0.711</td></tr>
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<td>Window materials</td>
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<tr><th colspan="4">Typical structure of glass windows in Taiwan office buildings</th></tr>
<tr><th>Glass type</th><th>Thermal transmittance (W/m^2.K)</th><th>Shading coefficient (SC)</th><th>Visible light transmittance (VT)</th></tr>
<tr><td>Reflective glass: 10mm green-colored glass</td><td>5.67</td><td>0.57</td><td>0.21</td></tr>
<tr><td>Single layer low E glass: 6mm clear glass + G insulation paper</td><td>5.77</td><td>0.60</td><td>0.69</td></tr>
<tr><td>Two-layer low E glass: 6mm green glass + low E coating + 6mm clear glass</td><td>1.72</td><td>0.35</td><td>0.52</td></tr>
<tr><td>Three-layer low E glass: 6mm green glass + 9AS+ PET low E film + 9AS + 6mm clear glass</td><td>1.47</td><td>0.33</td><td>0.52</td></tr>
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<td>[18]</td>
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<tr><td>6</td><td>WWR</td><td>(Window-to-wall ratio) 20% ~ 76%</td><td>[7]</td></tr>
<tr><td>7</td><td>Location</td><td>Taipei, Hsinchu, Taichung, Tainan, Kaohsiung, Taitung, Hualien</td><td>[9]</td></tr>
<tr><td>8</td><td>Orientation</td><td>North, Northeast, East, South, Southeast, Southwest, West, Northwest</td><td></td></tr>
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Table 2. Input and output variables of TOBE dataset.

No.	**Variable name**	**Value range**	**Note**
Input 1	Floor area	480 ~ 1470	Unit: m^2
Input 2	Floor height	3.2 ~ 4	Unit: m
Input 3	Number of stories	9 ~ 26	Natural number
Input 4	Basement number	0 ~ 3	Natural number
Input 5	External walls	1, 2, 3, 4	1 to 4 corresponding to brick, aluminium plate, glass curtain, and steel curtain, as presented in **Table 1**
Input 6	Windows	1, 2, 3, 4	1 to 4 corresponding to reflective glass, single-layer low E glass, double-layer low E glass, and three-layer low E glass, respectively, as presented in **Table 1**
Input 7	WWR	20% ~ 76%	If the type of external wall is a glass curtain, the WWR is equal to 0. For the others, WWR range is 20% ~ 76%
Input 8	Location	1, 2, 3, 4, 5, 6, 7	1 to 7 corresponding to Taipei, Hsinchu, Taichung, Tainan, Kaohsiung, Taitung, and Hualien, respectively
Input 9	Orientation	1, 2, 3, 4, 5, 6, 7, 8	1 to 7 corresponding to North, Northeast, East, South, Southeast, Southwest, West, and Northwest, respectively
Output 1	AE	713651 ~ 10842300	Unit: kWh
Output 2	EUI	518 ~ 1443	Unit: MJ/m²/year
Output 3	LE	21409.5 ~ 235.27	Unit: MW

2.2 AI-Based Energy Prediction

To develop an effective energy forecasting tool for Taiwanese office buildings using the TOBE dataset, four machine learning techniques were employed: Radial basis function neural network (RBFNN) representing neural network (NN)-based models, least squares support vector regression (LSSVR) representing support vector machine (SVM)-based models, and two boosting algorithms (AdaBoost, XGBoost). These models were selected based on prior literature indicating their high performance in energy prediction tasks. Boosting methods are especially suitable here because the TOBE dataset is structured tabular data with a moderate sample size (1,006 cases), where tree-based ensembles often generalize well with minimal preprocessing and can efficiently capture nonlinear interactions among BIM-derived geometric, material, and climatic variables. Meanwhile, the NN- and SVM-based models were retained as reference learners to ensure a balanced comparison.

To improve predictive accuracy, the hyperparameters of each model were optimized using the FBI algorithm, a parameter free metaheuristic designed to iteratively refine candidate configurations through an adaptive search strategy. The FBI optimizer evaluates each candidate model using validation data and updates the hyperparameters until convergence or until a stopping criterion is met. This automated tuning process eliminates the need for manual adjustments and enhances the robustness of model calibration.

Model training followed a 10 fold cross validation procedure to minimize sampling bias, prevent overfitting and improve generalizability. Throughout the optimization and training process, model performance was assessed using standard regression metrics, including mean square error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2). These metrics provide complementary insights into prediction accuracy, relative error magnitude, and model explanatory power, ensuring a comprehensive evaluation of each algorithm.

3 Results and Discussion

3.1 Annual Electric

AE is one of the important outputs in TOBE dataset. It defined as the total annual electricity consumption of a building. Offering insights into electricity consumption over a year, this metric helps determine building operational costs and environmental impact.

Table 3. Performance of the four hybrid models.

Method		Testing data			
		RMSE	MAPE	MAE	R^2
FBI_ RBFNN	Mean	1091754	28.80%	777582	0.700
	Std.	142479	3.49%	82746	0.063
FBI_ LSSVR	Mean	1082352	22.60%	632261	0.701
	Std.	108131	3.57%	62177	0.070
FBI_XGB	Mean	489026	5.01%	145527	0.933
	Std.	172772	1.51%	43359	0.048
FBI_ AdaBoost	**Mean**	**396941**	**3.45%**	**98827**	**0.944**
	Std.	**235577**	**1.78%**	**43953**	**0.067**

Table 3 presents the performances of the four hybrid models. The results reveal that boosting algorithm-based models (FBI_XGB and FBI_AdaBoost) outperformed both NN-based and SVM-based models in all metrics. FBI_AdaBoost achieved the highest accuracy, with the lowest testing RMSE (396,941 kWh), MAPE (3.45%), and the highest R^2 (0.944). FBI_XGB followed closely, maintaining high predictive reliability and narrow error distribution. In contrast, NN-based models, particularly FBI_RBFNN, recorded the highest MAPE and lowest R^2, indicating limited suitability for this dataset.

Performance comparisons are illustrated in **Figs. 3-5**. MAPE and R^2 plots (**Figs. 3-4**) highlight the superior consistency of the BA-based models. Boxplots of MAE (**Fig. 5**) show tighter distributions and lower medians for FBI_AdaBoost and FBI_XGB, confirming their robustness and reduced estimation bias.

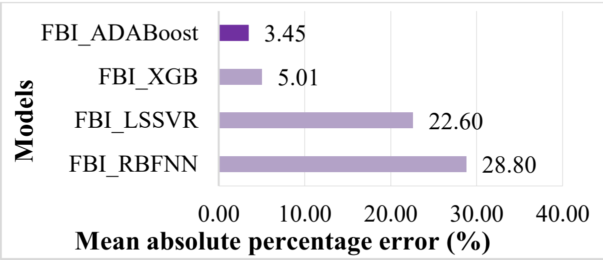

Fig. 3. Average MAPEs of hybrid models

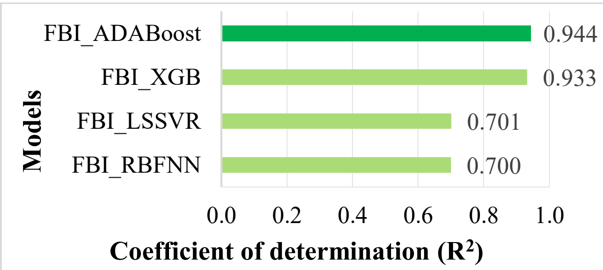

Fig. 4. Average R^2 of hybrid models

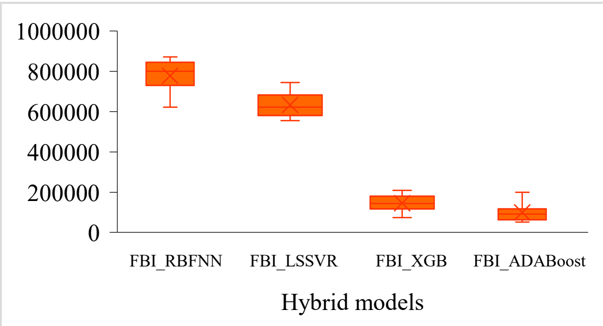

Fig. 5. MAE boxplot of hybrid models

These findings emphasize the critical role of model selection in energy prediction tasks. The BA-based models' strong generalization, high accuracy, and low variance make them well-suited for complex energy forecasting problems, particularly in data-rich environments like the TOBE dataset. Among them, FBI_AdaBoost emerges as the most effective model, offering practical utility for early-stage energy planning and decision-making in Taiwan's office building sector.

3.2 Energy Use Intensity

EUI is a straightforward but powerful measure of how efficiently a building uses energy. It is calculated by dividing the total energy consumed by a building in 1 year by its total floor area. Accurate EUI prediction models are essential for effective energy management, optimisation, and sustainability and can achieve potential energy savings of up to 30%. EUI is one of the energy performance indicators that can be extracted from GBS.

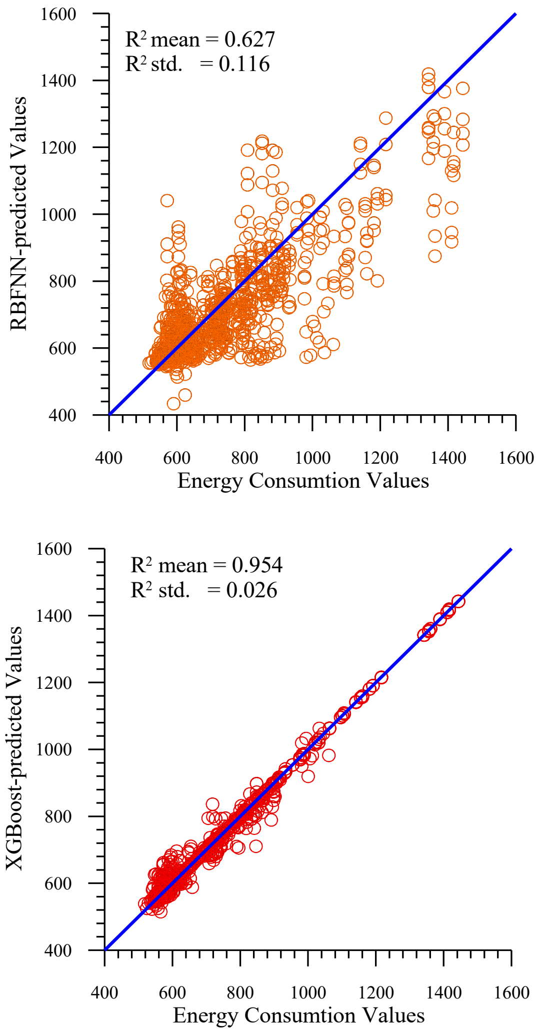

Fig. 6. Scatter plot of the EUI models

Table 4. Performance of the four hybrid models.

Method		Testing data			
		RMSE	MAPE	MAE	R^2
FBI_ RBFNN	Mean	113.22	9.66%	75.69	0.627
	Std.	14.85	1.23%	9.48	0.116
FBI_ LSSVR	Mean	92.65	8.67%	62.55	0.746
	Std.	17.14	1.14%	9.48	0.107
FBI_XGB	**Mean**	**37.98**	**1.86%**	**12.60**	**0.954**
	Std.	**11.81**	**0.50%**	**3.23**	**0.026**
FBI_ AdaBoost	Mean	46.09	2.85%	19.49	0.932
	Std.	12.91	0.79%	5.32	0.031

As seen in **Table 4**, the RBFNN and LSSVR models performed relatively poorly across all metrics. RBFNN gave the weakest results, with the highest RMSE (113.22 ± 14.85 MJ/m²/year) and MAPE (9.66% ± 1.23%) on the test set. In contrast, XGBoost achieved the best overall performance, with the lowest RMSE (37.98 ± 11.81 MJ/m²/year), lowest MAPE (1.86% ± 0.50%), and highest R2 (0.954 ± 0.026), demonstrating strong predictive accuracy and generalization. FBI_AdaBoost ranked second, showing that boosting-based methods outperformed the NN- and SVM-based models.

Figure 6 further illustrates the contrast between RBFNN, the weakest model, and XGBoost, the best-performing model, through predicted-versus-simulated energy consumption plots. RBFNN shows wide dispersion around the 45° reference line, indicating larger prediction errors and only moderate explanatory power, whereas XGBoost predictions cluster closely around the line with only minor deviations. This confirms that XGBoost provides substantially more accurate and robust energy consumption predictions than RBFNN.

3.3 Lifecycle Electric

In Autodesk GBS, the LE indicator quantifies the total electricity consumption of a building over a specified analysis period, typically aligned with its expected service life. It aggregates annual electric use from all major end uses, such as lighting, plug loads, HVAC systems, and auxiliary equipment, and projects this consumption forward using consistent operating assumptions. This indicator is often coupled with utility rate information to estimate long-term operating costs. As a result, LE provides a useful basis for evaluating the economic and environmental benefits of energy efficiency strategies across the whole building life cycle.

Based on the two preceding results, boosting-based models provide the strongest predictive performance on the TOBE dataset. Accordingly, this section employs FBI_AdaBoost and FBI_XGB to develop prediction models for lifecycle electricity in Taiwanese office buildings. **Table 5** summarizes the 10-fold cross-validation performance of both models. For visualization,

Figs. 7 and 8 compare the fold-wise test MAPE and R^2 values across the 10 folds, respectively.

Across the 10-fold cross-validation, both boosting models demonstrate strong predictive capability for LE in Taiwanese office buildings. FBI_AdaBoost achieves the best average performance, yielding lower mean errors (RMSE = 10,664; MAE = 2,891) than FBI_XGB (RMSE = 13,932; MAE = 4,146), together with a higher mean coefficient of determination (R^2 = 0.945 vs. 0.931). The low mean MAPE values (3.51% for FBI_AdaBoost and 5.02% for FBI_XGB) further indicate good relative accuracy, supporting the suitability of boosting-based learners for this dataset.

Table 5. 10-fold performances of boosting models.

FBI_XGB (testing performance)				
Fold	**RMSE (KW)**	**MAPE (%)**	**MAE (KW)**	**R2**
1	18,156.5	6.14	4,911.3	0.929
2	9,583.5	7.58	4,959.1	0.977
3	17,235.9	4.30	3,275.6	0.920
4	5,375.0	2.57	2,027.0	0.994
5	10,931.0	4.31	3,613.4	0.942
6	22,697.5	7.48	6,041.2	0.849
7	7,504.9	4.51	3,013.6	0.985
8	10,974.1	3.67	3,543.9	0.951
9	12,978.4	3.71	4,000.9	0.958
10	23,877.9	5.89	6,069.4	0.808
Mean	**13,931.5**	**5.02**	**4,145.5**	**0.931**
Std.	**6,294.8**	**1.68**	**1,322.3**	**0.060**

FBI_AdaBoost (testing performance)				
Fold	**RMSE (KW)**	**MAPE (%)**	**MAE (KW)**	**R2**
1	15,842.1	5.01	3,714.9	0.946
2	5,737.8	4.11	1,952.4	0.992
3	17,689.7	4.22	3,316.0	0.916
4	5,992.8	1.98	1,611.8	0.993
5	7,406.1	2.93	2,375.7	0.973
6	6,107.6	2.94	2,688.0	0.989
7	3,341.9	2.60	1,402.2	0.997
8	7,598.2	2.93	2,511.1	0.976
9	5,698.4	2.22	1,765.2	0.992
10	31,229.0	6.16	7,572.6	0.671
Mean	**10,664.4**	**3.51**	**2,891.0**	**0.945**
Std.	**8,590.8**	**1.33**	**1,802.1**	**0.099**

Nevertheless, robustness differs across folds. FBI_XGB exhibits more stable explanatory power (std. R^2 = 0.060) and does not show extreme deterioration, although weaker generalization is observed in a small number of splits. A brief diagnostic comparison of **Table 5** shows that Fold 10 is the most difficult test partition for both boosting models: FBI_XGB records its lowest R^2 (0.808) and highest RMSE (23,877.9) in this fold, while FBI_AdaBoost shows an even larger drop (R^2=0.671; RMSE = 31,229.0; MAE = 7,572.6). This concurrent degradation suggests that Fold 10 likely contains harder-to-predict or more extreme cases than the remaining folds. Therefore, the Fold 10 result is interpreted as evidence of a challenging partition, while the larger decline of FBI_AdaBoost indicates that it is more sensitive than FBI_XGB to such cases, despite achieving better average LE prediction performance overall.

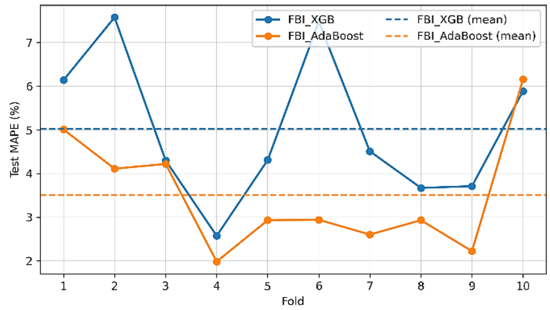

Fig. 7. MAPE comparison across 10 folds

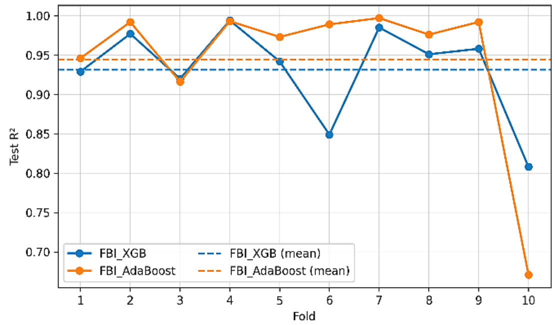

Fig. 8. R^2 comparison across 10 folds

4 Conclusions

This study aims to (i) establish a region-specific, simulation-consistent dataset for Taiwanese office buildings and (ii) develop a high-accuracy prediction framework suitable for early design without labor-intensive manual calibration. The proposed TOBE dataset was generated via a BIM-to-simulation workflow, in which representative office-building geometries were modelled in Autodesk Revit and evaluated using Green Building Studio. A sensitivity-based screening procedure reduced the input space to nine influential variables that are physically meaningful and readily extractable from standard BIM deliverables. The final dataset comprises 1,006 cases and includes three electricity-related targets: annual electricity, energy use intensity, and lifecycle electricity.

Four learning algorithms (RBFNN, LSSVR, AdaBoost, and XGBoost) were then optimized using the FBI metaheuristic and assessed through 10-fold cross-validation, with results indicating that boosting-based models are consistently the most effective for TOBE. From a feasibility and application standpoint, the proposed pipeline is designed for real-world deployment in early-stage decision-making. The nine retained inputs can be obtained directly from BIM or basic design documentation, enabling rapid estimation of AE, EUI, and LE without repeatedly running computationally expensive simulations.

Overall, the combination of TOBE and the FBI-optimized boosting models provides a scalable foundation for data-driven electricity forecasting to support energy-efficient design and planning in Taiwanese office buildings. Because the inputs were pre-screened through BIM-based sensitivity analysis, the framework already focuses on energy-relevant variables. Nevertheless, enhancing model interpretability remains an important next step. Future research should quantify the relative influence of these variables using feature-importance techniques such as XGBoost gain and SHAP values, thereby enabling the predictive framework to provide more explicit and actionable support for design decision-making. In addition, the framework should be further validated using measured operational data, when available, to assess its real-world applicability and transferability.

Acknowledgments

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