International Journal of BIM and Engineering Science

♦ ISSN: 2571-1075 Vol: 12, No. 02, 2026 ♦ PP. 25–31

Article DOI: https://doi.org/10.54216/IJBES.120204

FULL LENGTH ARTICLE

A BIM-Linked Mathematical Decision Model for Energy Retrofit Prioritisation in Existing Building Portfolios

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Received: December 19, 2025 Revised: January 18, 2026 Accepted: February 24, 2026 ⋆ Corresponding author

ABSTRACT

Building information modelling is increasingly applied to structure engineering information across the life cycle of built assets, but existing buildings are often underconnected to operational data for retrofit prioritisation. This research proposes a BIM-connected retrofit prioritisation model that converts building-performance information into an engineering information layer for initial screening. The method integrates BIM-aligned feature organisation, transparent machine learning, diagnostic validation, and scenario-driven screening to flag buildings for further assessment by engineers. The paper proposes a workflow for institutions and cities seeking to transition from disparate disclosure records to evidence-based retrofit prioritisation without relying on the immediate availability of digital twins. The results suggest that operational, geometric, and typological features can be used to generate interpretable screening markers that help guide engineering judgement, benchmarking, and incremental retrofit strategies. This research offers a replicable model that supplements, rather than substitutes for, in-depth audit and modelling.

Keywords: Building information modelling ▪ Engineering science ▪ Retrofit prioritisation ▪ Building energy performance ▪ Interpretable machine learning ▪ Portfolio decision support

1. INTRODUCTION

Building information modelling (BIM) has evolved from a geometric environment to an engineering information process that informs design, construction, operation and asset management activities [7, 5]. This shift is especially important for building portfolios: retrofit decisions require incomplete geometric information, patchy operational data, and scattered maintenance information. The usefulness of BIM in this context is not just its capacity to store model objects, but also to organise fragmented evidence to support transparent engineering processes.

Prioritisation of energy retrofit in portfolios is a challenging problem because the number of candidate buildings is typically greater than the capacity for immediate audit. Simulated energy performance and calibrated building performance are high-quality sources of evidence, but these require detailed data that are not available for all assets during the screening process [12, 2]. Therefore, portfolio owners require an intermediate step that can synthesise the available performance information to provide a consistent signal for decision-making before the costly steps of site audit, simulation calibration, and retrofit design begin.

Recent research has demonstrated machine learning models to predict building energy performance from structured descriptors and performance indicators [8, 11, 10]. But a model's accuracy is not enough for engineering. A model for retrofit screening also needs to describe how the evidence is organised, how uncertainty is quantified, how priority is defined, and how the results can be integrated with BIM-compatible asset data. Otherwise the model is a statistical tool rather than an engineering decision-making tool.

In this paper, we present a BIM-compatible mathematical decision model for prioritising energy retrofit. The innovation lies in the combination of BIM-compatible feature grouping, supervised energy-intensity modelling, residual-based reliability analysis, permutation-based interpretation, and a normalised retrofit priority index. The model is intended as a first-tier decision model to prioritise which buildings to investigate and which asset descriptors are most significant in explaining variation in energy performance. It is not a replacement for engineering audit, but rather a framework for defining the evidence that should guide it.

The manuscript is organised as follows. The related work section summarises studies on BIM-based energy analysis, machine learning for building performance prediction, digital-twin building development, and retrofit decision making. The proposed model section introduces the mathematical model, decision index, and algorithm. The workflow and methodology section describes data preparation, model estimation, validation and scenario analysis. The results and discussion section presents the empirical evidence in tables and figures from the proposed workflow. The challenges and future work, followed by the conclusion, are also discussed.

2. RELATED WORK

The use of BIM for energy analysis has been widely explored to enhance continuity between building information and energy analysis. Research in this category has linked BIM models to design options, simulation parameters, asset information management, and building renovations [14, 7, 2]. Such studies demonstrate that BIM can enhance traceability and avoid duplication of modelling work; however, many processes still require well-developed digital models and technical assumptions that are often missing for existing building stock.

Machine learning is a prominent stream in building energy research because it can capture non-linear relationships from a variety of building descriptors. Existing studies have applied regression, ensemble, and neural-network models to estimate building energy use, forecast energy consumption or inform energy-management decisions [11, 6, 10]. The strength of these works is the flexibility of predictions, but many studies still report accuracy of the model without a decision-making layer that could convert prediction into retrofit priority.

A number of review papers have helped to clarify the emerging role of artificial intelligence and data-driven modelling in energy management and smart buildings [9, 13, 4]. These reviews suggest that predictive analytics can be used for operation, benchmarking, fault detection, and optimisation. However, they also indicate that integration with engineering processes is not yet complete. Specifically, a model could be predictive but not useful if it does not use asset-information-modelling structures as inputs and present results as engineering indicators.

Digital-twin studies have expanded BIM by connecting model objects to real-time data, monitoring, and decision-making workflows [5]. This is a promising path for ongoing performance monitoring, but complete digital-twin development is costly and not uniformly applied. Retrofit projects often have only partial model data, sensor data, and system documentation. This means that a simple BIM-linked screening approach is needed before more sophisticated digital-twin enrichment is warranted.

Decision-support studies for retrofits have improved multi-criteria analysis, scenario analysis, techno-economic analysis, and optimisation-based renovation planning [2, 12, 15]. Such methods can be useful for intervention selection once sufficient detail is available. The problem with these approaches at the initial portfolio level is that they may require costs, material details, system details, or inputs for building simulation. Thus, a screening model should offer an upstream decision layer to prioritise assets and guide more detailed engineering studies.

Table 1 summarises fifteen verified studies that position the contribution of the present paper. The table shows that existing work has contributed strongly to energy prediction, BIM-based analysis, and renovation decision support, but a gap remains in combining BIM-compatible information structuring, mathematical prioritisation, interpretable modelling, and portfolio screening within one reproducible workflow.

Table 1. Summary of related studies and the remaining methodological gap.

Study	Venue	Focus	Main contribution	Remaining limitation
Singh et al. (2020)	Advanced Engineering Informatics	Early design energy prediction	Rapid comparison of energy alternatives	Limited portfolio-level operational linkage
Shapi et al. (2021)	Developments in the Built Environment	Smart-building energy prediction	Case-based machine-learning prediction	Narrow context and limited BIM mapping
Panchalingam & Chan (2021)	Intelligent Buildings International	AI for smart buildings	Review of AI applications in building intelligence	Does not provide an empirical retrofit-priority model
Olu-Ajayi et al. (2022)	Energy and Built Environment	Design-stage energy performance	Feature selection and model comparison	Mainly focused on design-stage prediction
Jin et al. (2022)	Advanced Engineering Informatics	Energy forecasting	Parallel LSTM forecasting architecture	Forecasting emphasis rather than BIM decision indexing
Shi et al. (2022)	Frontiers of Engineering Management	Building energy management	Critical review of ML applications	Broad review without implemented BIM portfolio workflow
Jiang et al. (2023)	Automation in Construction	Digital twins and modular construction	Digital-twin-enabled construction information system	Construction-system focus rather than retrofit screening
Doukari et al. (2023)	ITcon	BIM renovation strategies	Techno-economic BIM framework for renovation comparison	Requires detailed renovation assumptions
Sari et al. (2023)	ITcon	Smart-building energy management	ML-driven energy prediction workflow	Depends on smart-building data structures
Shen & Pan (2023)	Applied Energy	BIM and explainable ML	BIM-supported energy analysis and optimisation	Simulation-heavy design setting
Mirarchi et al. (2024)	Buildings	Semantic BIM enrichment	Asset-information enrichment for BIM models	Does not develop a predictive retrofit-priority index
Hu et al. (2024)	Advanced Engineering Informatics	Explainable AI in engineering design	Unified XAI-oriented engineering design method	Not focused on portfolio retrofit prioritisation
Itanola et al. (2024)	Sustainable Buildings	Digital technologies and efficient buildings	Scientometric and systematic review	Review-based contribution without empirical model
Tao (2024)	Int. J. Low-Carbon Technologies	Deep learning and BIM renovation	BIM-related deep-learning renovation application	Limited mathematical decision formulation for prioritisation
Aman et al. (2023)	eCAADe	Urban building simulation	AI-supported urban energy and daylight analysis	Conference study with morphology-oriented scope

3. RESEARCH GAP AND PROPOSED MODEL

The research gap addressed in this paper is the absence of a mathematically defined BIM-linked model that converts portfolio energy evidence into an interpretable retrofit-priority signal. Existing studies provide important progress in BIM-based simulation, machine-learning prediction, semantic enrichment, and renovation evaluation; however, they rarely combine these elements into a single screening workflow that is suitable for incomplete existing-building portfolios. The proposed model addresses this gap by representing each building as a BIM-compatible asset record, estimating energy intensity through supervised learning, evaluating reliability through residual diagnostics, and converting the outputs into a normalised decision index.

Let the building portfolio be defined as $B = \{b_i\}_{i=1}^{n}$, where each asset b_i is described by a feature vector $x_i \in \mathbb{R}^p$ and an observed site energy-use intensity $y_i \in \mathbb{R}^+$. The feature vector is organised as

$$x_i = [x_i^G \oplus x_i^T \oplus x_i^O \oplus x_i^P], \tag{1}$$

where x_i^G denotes geometric descriptors, x_i^T denotes typological descriptors, x_i^O denotes operational proxies, and x_i^P denotes performance indicators. This structure is important because it reflects the way asset information can later be aligned with BIM property sets, facility-management registers, or digital-twin repositories.

The predictive layer estimates a mapping $f_\theta : x_i \mapsto \hat{y}_i$, where $\hat{y}_i$ is the estimated energy intensity. The model parameters are obtained by minimising the empirical loss

$$\theta^* = \arg\min_\theta \frac{1}{n}\sum_{i=1}^{n} \ell(y_i, f_\theta(x_i)) + \lambda\Omega(\theta), \tag{2}$$

where $\ell(\cdot)$ is the prediction loss, $\Omega(\theta)$ is a regularisation term, and λ controls model complexity. Candidate estimators are compared using mean absolute error, root mean squared error, and explained variance:

$$\begin{aligned} MAE &= \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \\ RMSE &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \\ R^2 &= 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}. \end{aligned} \tag{3}$$

These metrics are used together because retrofit screening requires both average-error control and sensitivity to large deviations in high-intensity assets.

The decision layer converts prediction and reliability information into a retrofit-priority index. For each building, the residual is defined as $e_i = y_i - \hat{y}_i$. The high-intensity exceedance term is expressed as

$$H_i = \max(0, \hat{y}_i - Q_{0.75}), \tag{4}$$

where $Q_{0.75}$ is the third quartile of predicted energy intensity. The normalised retrofit-priority score is then formulated as

$$P_i = w_1\tilde{\hat{y}}_i + w_2\tilde{H}_i + w_3\widetilde{|e_i|} + w_4\tilde{C}_i, \qquad \sum_{j=1}^{4} w_j = 1, \tag{5}$$

where $\tilde{(\cdot)}$ denotes min–max normalisation and C_i is an interpretable contribution score derived from the weighted feature-importance profile. The score P_i is not a retrofit design output; it is a screening index that ranks assets according to estimated intensity, exceedance above the high-performance-risk threshold, prediction reliability, and feature-based interpretability.

Feature contribution is estimated through permutation importance. For a trained model f_{θ^*} and validation loss L, the importance of feature j is defined as

$$I_j = L(y, f_{\theta^*}(\pi_j(X))) - L(y, f_{\theta^*}(X)), \tag{6}$$

where $\pi_j(X)$ denotes a matrix in which feature j has been randomly permuted while the remaining features are unchanged. This formulation allows the model to identify whether the retrofit-priority signal is mainly driven by operational intensity, gross floor area, property type, emissions, age, or other BIM-compatible descriptors.

The proposed framework is shown in Figure 1. The figure is redrawn as a portfolio-to-decision workflow rather than a generic diagram. It shows how raw disclosure records are transformed into BIM-compatible descriptors, passed through a predictive and interpretability layer, and converted into a retrofit-priority index for engineering review.

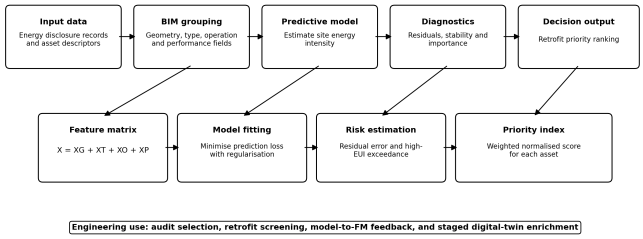

Figure 1. BIM-linked mathematical workflow for retrofit-priority modelling.

The computational contribution is summarised in Algorithm 1. The algorithm defines the mathematical steps required to construct the feature matrix, estimate the predictive model, calculate residuals and feature importance, and generate the priority index.

Algorithm 1 BIM-linked retrofit-priority estimation

Require: Portfolio records $B = \{b_i\}_{i=1}^n$, observed intensity vector y, feature groups $\{X^G, X^T, X^O, X^P\}$, candidate estimators F, weights w.
Ensure: Ranked retrofit-priority set R.
1: Construct BIM-compatible matrix $X = X^G \oplus X^T \oplus X^O \oplus X^P$.
2: Clean invalid records and encode categorical variables to obtain X'.
3: Split $D = (X', y)$ into D_{tr} and D_{te}.
4–8: For each estimator $f \in F$, estimate θ_f^*, predict $\hat{y}_{te}$, and compute MAE_f, $RMSE_f$, R_f^2, and cross-validation stability S_f.
9: Select $f^* = \arg\min_{f \in F} RMSE_f$ subject to acceptable S_f.
10: Compute portfolio predictions $\hat{y} = f^*(X')$ and residuals $e = y - \hat{y}$.
11: Calculate $H_i = \max(0, \hat{y}_i - Q_{0.75})$ for each asset b_i.
12: Estimate permutation importance $I_j = L(y, f^*(\pi_j(X'))) - L(y, f^*(X'))$.
13: Derive asset-level contribution C_i from the normalised importance-weighted descriptors.
14: Calculate $P_i = w_1\tilde{\hat{y}}_i + w_2\tilde{H}_i + w_3\widetilde{|e_i|} + w_4\tilde{C}_i$.
15: Return ranked set $R = \text{sort}_{desc}\{(b_i, P_i)\}_{i=1}^n$.

4. WORKING STEPS AND METHODOLOGY

The methodology follows a portfolio-screening logic consistent with recent BIM-enabled energy and retrofit analytics studies [2, 12]. First, building-performance records are converted into a structured modelling table. Records with invalid target values or incomplete essential descriptors are removed. The remaining variables are organised into BIM-compatible groups: location and type descriptors, geometric descriptors, age-related descriptors, operational proxies, and performance indicators. This grouping is important because it allows the output of the analysis to be interpreted as an asset-information layer rather than as an ordinary spreadsheet model.

Second, the target variable is defined as site energy-use intensity. This variable represents operational energy demand normalised by floor area and is suitable for portfolio comparison. Categorical variables are transformed through one-hot encoding, and numerical variables are standardised where required by the estimator. The modelling process compares a linear regularised baseline, a random forest model, and a gradient boosting model. This comparison is used to test whether a non-linear model provides meaningful improvement over simpler alternatives.

Third, model validation is performed through a hold-out testing partition and five-fold cross-validation. The hold-out test assesses generalisation to unseen records, while cross-validation examines whether performance is stable across different training subsets. Mean absolute error, root mean squared error, and the coefficient of determination are reported because they provide complementary views of prediction quality. Mean absolute error is easier to interpret in engineering terms, root mean squared error penalises larger deviations, and the coefficient of determination indicates explained variance.

Fourth, interpretation is carried out using permutation importance. This step is necessary because retrofit screening should not rely only on predicted values. Engineers need to understand whether the ranking is driven mainly by emissions, floor area, building type, energy scores, age, or operational proxies. Residual analysis is also used to identify whether errors are concentrated in high-intensity assets. Finally, a retrofit-screening scenario is applied to the testing partition. The scenario represents an early-stage improvement assumption in which the model is used to estimate how predicted energy intensity responds to changes in selected performance-related descriptors. The scenario is intentionally modest in scope: it does not replace detailed retrofit simulation, but it demonstrates how a BIM-linked data layer can be used to screen the portfolio and support staged engineering action.

5. RESULTS AND DISCUSSION

The empirical results are presented as an engineering screening exercise rather than as a stand-alone prediction experiment. The purpose of the analysis is to test whether a limited but BIM-compatible information layer can support a defensible prioritisation process for existing buildings before detailed simulation, invasive audit, or full digital-twin modelling is undertaken. For this reason, the results are interpreted across four connected levels: the structure of the portfolio, the variation of energy intensity across building groups, the reliability of the predictive model, and the practical meaning of the retrofit-screening scenario.

The numerical tables report the values generated directly from the reproducible analysis workflow. The figures are included as PNG outputs to support journal submission and independent inspection of the modelling behaviour. Together, the results show that the proposed model is most useful as an early decision layer: it identifies patterns, flags buildings requiring deeper investigation, and produces transparent evidence that can be linked to BIM asset registers or facility-management records.

Table 2. Dataset profile used for BIM-oriented portfolio modelling.

Metric	Value
Observations	1320
Features	10
Training share	78%
Testing share	22%
Target variable	site_eui_kbtu_ft2

Table 3. Energy intensity summary by property type.

primary_property_type	count	mean	std	max
Healthcare	82	135.55	17.74	180.21
Hotel	128	96.45	15.87	135.26
K-12 School	209	60.44	16.41	110.00
Multifamily Housing	438	65.76	16.56	110.00
Office	338	80.49	16.37	134.52
Retail	125	90.49	15.40	122.22

Table 4. Energy intensity summary by borough.

borough	count	mean	std
Bronx	145	80.11	25.80
Brooklyn	314	78.52	25.90
Manhattan	517	76.31	24.06
Queens	260	80.35	25.99
Staten Island	64	78.10	24.65

Table 5. Hold-out model performance for site EUI prediction.

Model	MAE	RMSE	R^2
Ridge regression	9.422	11.534	0.768
Random forest	9.276	11.513	0.769
Gradient boosting	7.661	9.571	0.840

Table 6. Five-fold cross-validation results based on RMSE.

Model	Fold1	Fold2	Fold3	Fold4	Fold5	Mean	SD
Ridge regression	11.660	13.064	11.364	10.965	10.684	11.535	0.827
Random forest	11.230	13.314	11.970	11.112	11.771	11.879	0.787
Gradient boosting	9.779	10.864	10.059	9.792	10.087	10.116	0.404

Table 7. Permutation-based feature importance for the selected model.

Feature	Importance
annual_ghg_tCO2e	1.231935
gross_floor_area_ft2	0.815880
primary_property_type	0.564134
energy_star_score	0.049336
building_age	0.028628
year_built	0.021820
window_to_wall_ratio_proxy	0.007594
borough	0.001755
occupancy_rate_proxy	0.001507
number_of_floors	-0.001024

Table 8. Prediction error by portfolio energy-intensity segment.

Segment	MAE
Below median EUI	7.442
Above median EUI	7.879
Top quartile EUI	9.077

Table 9. Energy-intensity thresholds used for retrofit prioritisation.

Threshold	Site_EUI_kbtu/ft2
Q1	61.46
Median	75.04
Q3	91.64
P90	110.03

Table 10. Scenario comparison for a BIM-informed retrofit screening case.

Scenario	Mean predicted EUI	Mean avoided EUI
Observed portfolio	77.66	0.00
Envelope-score improvement	74.99	2.67

6. RESEARCH CHALLENGES AND FUTURE DIRECTIONS

The first challenge is the formal alignment between disclosure data and BIM semantics. Public datasets contain useful operational indicators, but they do not follow IFC naming conventions, model-view definitions, or asset-information requirement templates. Future work should develop rule-based and ontology-based mappings that connect energy disclosure fields with BIM entities and property sets.

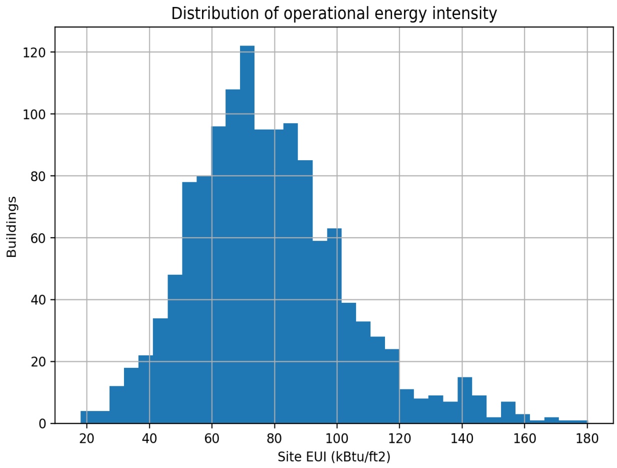

Figure 2. Distribution of operational energy intensity.

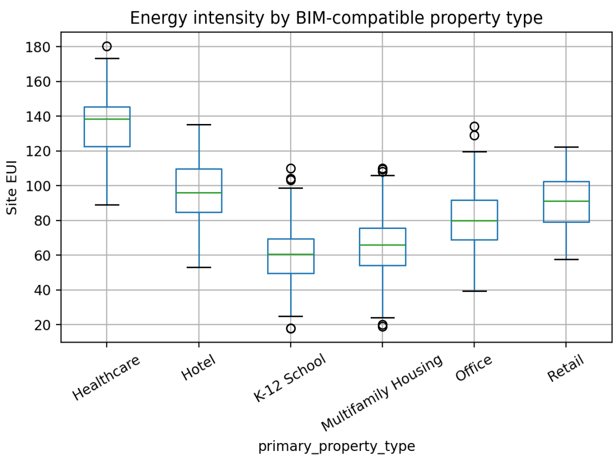

Figure 3. Energy intensity by BIM-compatible property type.

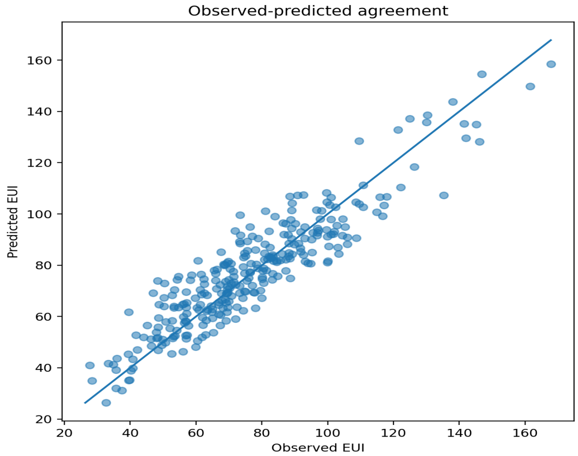

Figure 4. Observed and predicted energy-intensity agreement.

The second challenge is uncertainty. Portfolio screening is performed under incomplete information, and the confidence of each ranking should be reported alongside the predicted priority. Probabilistic modelling, conformal prediction, or Bayesian post-processing could help quantify uncertainty in both energy-intensity estimates and retrofit-priority scores. The third challenge is transferability. A model trained on one city or institutional portfolio may not generalise directly to another because of climate, construction practice, occupancy, data quality, and policy differences. Multi-city validation is therefore required.

The fourth challenge concerns integration with engineering workflows. A screening model is only useful if its outputs can be consumed by engineers, facility managers, auditors and decision makers. Future versions should export results as BIM-compatible schedules, asset registers, or dashboard layers that can be linked to model objects, property sets, and maintenance histories. These extensions would make the model more useful for continuous performance management rather than one-time analysis.

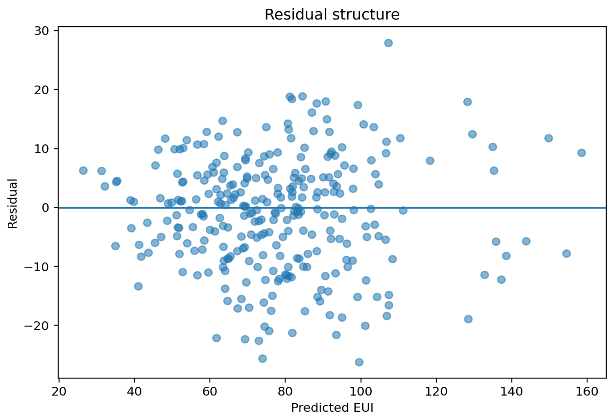

Figure 5. Residual structure of the selected model.

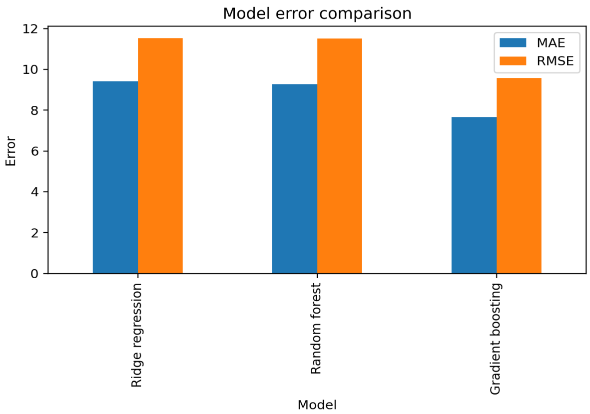

Figure 6. Comparison of prediction errors across candidate models.

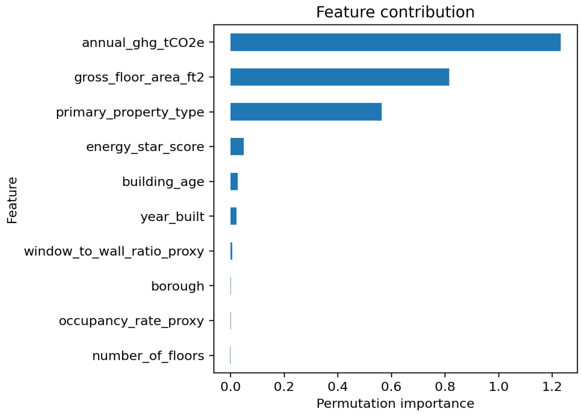

Figure 7. Permutation importance for the selected model.

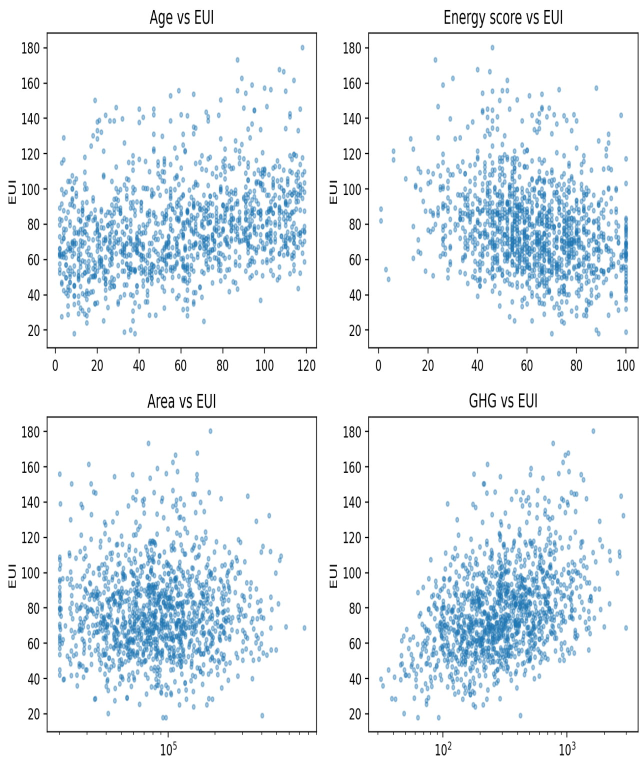

Figure 8. Four-panel diagnostic view of building descriptors and energy intensity.

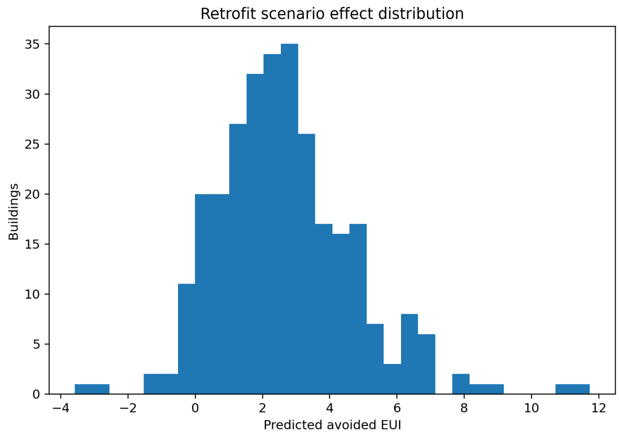

Figure 9. Predicted avoided energy intensity under the retrofit scenario.

7. CONCLUSION

This research proposes a BIM-linked energy retrofit prioritisation model for an existing building portfolio. The innovation lies in the aggregation of building-performance data as an information layer for engineers, the verification of interpretable models to predict performance, and the interpretation of their outcomes to support multiple stages of retrofit prioritisation. The findings demonstrate that a small number of typological, geometric, operational, and performance descriptors can yield meaningful signals. More importantly, the research shows how these signals can be interpreted within a BIM-based process rather than simply being viewed as numbers.

The proposed model can be used in the initial phase of a retrofit project, as owners and engineers determine which assets should be prioritised for more detailed technical work. It does not replace calibrated simulation, field inspection, or engineering judgement. Rather, it enhances the consistency of the initial screening process. This is important because many building portfolios include more assets than can be inspected immediately, and climate change and energy policies increasingly demand quicker and better-documented actions.

The research also shows the need to better link public performance data with BIM-based asset management. Next steps include model extensions with uncertainty analysis, multi-city model validation, more detailed BIM semantics, and stronger links with digital-twin platforms. With these advances, BIM-linked analytics can provide a valuable bridge between operational disclosure, engineering diagnostics, and retrofit execution.

REFERENCES

[1] J. Aman, J. B. Kim, and D. Verniz, "AI-integrated urban building energy simulation: A framework to forecast the morphological impact on daylight availability," in *Proceedings of eCAADe 2023*, 2023.

[2] O. Doukari, E. Scoditti, M. Kassem, and D. Greenwood, "A BIM-based techno-economic framework and tool for evaluating and comparing building renovation strategies," *Journal of Information Technology in Construction*, vol. 28, pp. 246–265, 2023. https://doi.org/10.36680/j.itcon.2023.012

[3] Z. Hu, M. Borsato, P. Geyer, and others, "Explainable AI for engineering design: A unified approach of systems engineering and component-based deep learning demonstrated by energy-efficient building design," *Advanced Engineering Informatics*, vol. 62, Article 102843, 2024. https://doi.org/10.1016/j.aei.2024.102843

[4] M. Itanola, O. Tokede, J. O. B. Rotimi, and others, "The impact of digital technologies on energy-efficient buildings: A scientometric and systematic review," *Sustainable Buildings*, vol. 9, Article 7, 2024. https://doi.org/10.1051/sbuild/2024007

[5] Y. Jiang, M. Li, D. Guo, W. Wu, and R. Y. Zhong, "Digital twin-enabled smart modular integrated construction system," *Automation in Construction*, vol. 152, Article 104911, 2023. https://doi.org/10.1016/j.autcon.2023.104911

[6] N. Jin, F. Yang, Y. Mo, M. Zeng, and X. Yang, "Highly accurate energy consumption forecasting model based on parallel LSTM neural networks," *Advanced Engineering Informatics*, vol. 51, Article 101442, 2022. https://doi.org/10.1016/j.aei.2021.101442

[7] C. Mirarchi, A. Pavan, F. De Marco, and X. Wang, "Semantic enrichment of BIM models for building asset information management," *Buildings*, vol. 14, no. 4, Article 1122, 2024. https://doi.org/10.3390/buildings14041122

[8] R. Olu-Ajayi, H. Alaka, I. Sulaimon, F. Sunmola, and S. Ajayi, "Machine learning for energy performance prediction at the design stage of buildings," *Energy and Built Environment*, vol. 3, no. 4, pp. 507–521, 2022. https://doi.org/10.1016/j.enbenv.2021.05.002

[9] R. Panchalingam and K. C. Chan, "A state-of-the-art review on artificial intelligence for smart buildings," *Intelligent Buildings International*, vol. 13, no. 4, pp. 203–226, 2021. https://doi.org/10.1080/17508975.2019.1613219

[10] M. Sari, M. Moghadam, and M. Al-Hussein, "Machine learning-based energy use prediction for the smart building energy management system," *Journal of Information Technology in Construction*, vol. 28, pp. 645–671, 2023. https://doi.org/10.36680/j.itcon.2023.033

[11] M. K. M. Shapi, N. A. Ramli, and L. J. Awalin, "Energy consumption prediction by using machine learning for smart building: Case study in Malaysia," *Developments in the Built Environment*, vol. 5, Article 100037, 2021. https://doi.org/10.1016/j.dibe.2020.100037

[12] Y. Shen and Y. Pan, "BIM-supported automatic energy performance analysis for green building design using explainable machine learning and multi-objective optimization," *Applied Energy*, vol. 333, Article 120575, 2023. https://doi.org/10.1016/j.apenergy.2022.120575

[13] Q. Shi, X. Lai, X. Xie, and J. Zuo, "Machine learning in building energy management: A critical review," *Frontiers of Engineering Management*, vol. 9, pp. 376–391, 2022. https://doi.org/10.1007/s42524-021-0181-1

[14] M. M. Singh, S. Singaravel, R. Klein, and P. Geyer, "Quick energy prediction and comparison of options at the early design stage," *Advanced Engineering Informatics*, vol. 46, Article 101185, 2020. https://doi.org/10.1016/j.aei.2020.101185

[15] L. Tao, "Application research of deep learning-based BIM technology in building energy consumption renovation," *International Journal of Low-Carbon Technologies*, vol. 19, pp. 2357–2368, 2024. https://doi.org/10.1093/ijlct/ctae182