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IMAGE-BASED AUTOMATIC MODELING AND PERFORMANCE EVALUATION FOR HOUSE PLANS IN THE EARLY DESIGN STAGE

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Abstract

The performance evaluation is crucial in comparing multiple house plans during the early stages. However, simulation-based methods often face challenges such as time consumption and complex modeling processes. Therefore, this paper extracted the features from house plans and proposed an image-based algorithm for automatic geometric simulation modeling. The algorithm successfully modeled 16,000 house plans and obtained simulation results for their energy consumption, indoor thermal comfort, and daylighting. This paper further compares the MARS-based and XGBoost-based surrogate models for performance evaluation using the house plan dataset. The results indicate that XGBoost performed better on all metrics.

Introduction

As the global population continues to grow and building facilities improve, people are spending significantly more time indoors, making living conditions increasingly important (Andersen et al. 2016). Key performance indicators related to living conditions include energy consumption, indoor thermal comfort, daylighting, etc. In the early design stage, building performance evaluation is also crucial for architects, as it serves as an important standard to compare building parameters and develop more sustainable design solutions (Chen et al. 2024). Without performance evaluation during the design stage, the impacts of high energy consumption, poor daylighting, and inadequate indoor comfort may persist for decades.

Building performance evaluation is typically conducted through physical modeling and simulation using tools such as Radiance and Energy Plus. However, these tools have limitations, including high computational demands and long modeling times (Lu et al. 2024), which hinder their ability to respond quickly to evaluate and adjust numerous design parameters during the design stage. This has become a significant technical barrier to performance optimization in the early design stages (Attia et al. 2012). Before simulation can take place, we need to convert models in formats like CAD and Revit into geometric simulation models (GSMs), which are compatible with simulation tools like Radiance and Energy Plus. Additionally, when designing house plans, designers often select a reference scheme from existing house plan datasets. For a large number of design options available in these datasets, it is essential to quickly obtain large-scale performance evaluation results. Jones and Reinhart (Jones and Reinhart 2019) conducted a design experiment comparing two simulation tools with varying response times, revealing that faster feedback can enhance design exploration, boost design confidence, and improve overall building performance. To address the time-consuming challenges, some researchers have proposed simplifying the modeling process to reduce time consumption (Li et al. 2023; D. Yan et al. 2022). Although these methods can accurately describe physical rules, they still fall short of providing instant feedback within seconds.

Moreover, with the rapid development of generative design, images have become a key input and output type for many generative models. A significant challenge lies in how to quickly conduct performance simulations and label performance metrics for image-format house plan datasets. Existing research approaches, which rely on pre-defined baseline models, are not applicable in this context.

To address this, this paper extracted the features from house plans and developed an image-based GSM automatic modeling algorithm (GSM algorithm) to convert the house plan from image format to GSM model. This algorithm has been applied to a dataset containing 16,000 house plans. Performance labels of energy consumption, indoor thermal comfort, and daylighting are assigned to each datum, thereby enhancing the semantic information of the house plan dataset. Finally, Multivariate Adaptive Regression Splines (MARS) and eXtreme Gradient Boosting (XGBoost) models were trained on this dataset to construct a performance evaluation surrogate model at the house level.

Literature review

To predict and optimize energy consumption, indoor thermal comfort, and daylighting, it is essential to conduct performance evaluations while adjusting the design parameters of the house plan. When using traditional performance simulation tools, the modeling process for GSM is cumbersome. Developing a surrogate model also requires a dataset prepared through GSM modeling and simulation for training purposes. Yan et al. (D. Yan et al. 2022) accelerated the modeling process in DeST 3.0 by providing 15 prototype buildings. Li et al. (Li et al. 2023) developed a fully automated simulation platform, Venis, based on a sensitivity analysis-based multi-criteria decision algorithm, Rhino, and Grasshopper. This platform performed 3,471 iterations with an average time spent of 5.78 minutes. Additionally, for image formats, He et al. (He et al. 2021) achieved the image-to-GSM process by automatically extracting an ordered list of room vertices.

As design tasks increase, using surrogate models as a replacement for physical simulation tools has become a more efficient solution. Relevant studies can be categorized based on the scope of the research objects into three levels: 1) site level, 2) building level, and 3) floor and house level. At the site level, Wang et al. (Wang et al. 2021) developed an ANN-based surrogate model for a site containing 12 buildings, focusing on daylight, sunlight hours, sky view, and outdoor thermal comfort. By repeatedly adjusting the positions of each building, they constructed a comprehensive dataset to explore the impact of building layout on the environment. Hu et al. (Hu et al. 2023) focused on a residential area, simplifying buildings into boxes and similarly developing a surrogate model based on ANN. Their integrated surrogate model methodology improved design efficiency by 500 times. At the building level, Chen et al. (Chen et al. 2024) proposed a rapid approach to predict energy demand and thermal comfort based on multiple regression methods, using an air-conditioned office building as an example. Ciulla and D'Amico (Ciulla and D’Amico 2019) simulated 195 non-residential building scenarios across 5 climate zones,15 cities, and 13 combinations of shape factors and thermal parameters. They developed a multiple linear regression model to predict building energy consumption under these various scenarios. At the house level, Li et al. (Li et al. 2024) utilized the RPLAN dataset, considering the interior layouts, material properties, and weather features, to establish a daylight prediction model based on a multimodal Generative Adversarial Network (GAN). Lee et al. (Lee et al. 2020) took a rural house as an example, which included room types such as living room, bathroom, bedroom, and utility room. They used ANN to develop a metamodel for energy prediction, analyzing the impact of technical variables such as window glazing U-value and linear thermal transmittance on energy consumption.

Besides, defining the features that describe buildings and houses is also crucial, as these features serve as inputs to the surrogate model. These features can be primarily categorized into geometry features and technical specification-level features (Lee et al. 2020). Geometry features include orientation, building width, building height, etc. (Hu et al. 2023). Technical specification level features include U-values, Glass Solar Heat Gain Coefficient (SHGC), etc. (Chen et al. 2024). In addition to using features to describe buildings, Singaravel et al. (Singaravel et al. 2018) divided the whole building into several components, including walls, roof, ground floor, etc., establishing a component-based approach to reduce the machine learning model's reliance on specific datasets. This approach also enhances the reusability across different geometrical designs of buildings. Energy prediction results depend on the abstract representations of the various components of the building rather than specific design parameters. Moreover, algorithms such as Convolution Neural Network (CNN) (Singh and Smith 2023) and GAN (Lee et al. 2020) can automatically learn the data features, with inputs being 3D data or 2D images, reducing the need for additional feature inputs.

These studies have advanced the performance evaluation from the site to the house level during the early design stage, taking into account the impacts of building shape, materials, and human activities on performance. However, there are still several limitations:

(1) GSM modeling is one of the critical processes for performance evaluation. The modeling of house plans in image format, which has been widely adopted in recent years, is often handled simplistically in existing research. While simulation tools can outline the shapes of rooms, the walls are not addressed. Honeybee often misidentifies wall types due to unprocessed wall space. This oversight does not affect daylight simulation, but it significantly impacts energy consumption and indoor thermal comfort simulations. To address this issue, this paper develops a GSM algorithm that processes walls correctly, creating accurate and applicable GSMs.

(2) Many studies treat buildings as simple shoe boxes, considering only the basic external contours and neglecting interior layouts. However, interior layouts significantly influence the accuracy of performance predictions. Therefore, this paper focuses on house plans to thoroughly consider the geometric design of each room.

(3) There are few articles addressing house level, and their performance metrics mainly focus on daylight (He et al. 2021; Li et al. 2024). This paper aims to incorporate energy consumption, indoor thermal comfort, and daylight as predictive targets, providing a broader decision-making reference for the early design stage.

(4) Many studies concentrate on technical specification-level features, taking the geometric design of a building as an example (Wang et al. 2023). These approaches fail to meet the performance evaluation needs that arise from modifying building shapes or layouts during geometric design. Furthermore, as numerous studies treat buildings as boxes, the features they use are basic such as area and shape factor, which are more related to the envelop (Granadeiro et al. 2013) and do not account for the complexities of interior layouts. Compared with buildings viewed as boxes, houses have more varied concave and convex shapes on the 2D plane. Therefore, this paper focuses on the geometric design of house plans and

innovatively proposes a feature system that includes 14 features such as room convexity and elongation to address the complex of room shapes. Then, MARS and XGBoost are trained to be a surrogate model using such features and the house plan dataset.

Methodology

Data preparation

The dataset used in this paper is based on the RPLAN dataset (Wu et al. 2019). This dataset contains over 80,000 real house plan images from Asia and is widely used in the field of generative design at the house level. Figure 1 shows some examples from the RPLAN dataset. It includes semantic information such as room types and house boundaries. Each data in the RPLAN dataset is a four-channel image. Figure 2 shows examples of three channels: the mask for the interior area, room numbers, and room types. In Figure 2 (f), "1" corresponds to the living room. The correspondence between numbers and room types is as follows: {"living room": 1, "kitchen": 2, "bedroom": 3, "bathroom": 4, "entrance": 6, "dining room": 7, "study room": 8, "storage": 10, "unknown": 16}. Before performing evaluations, the necessary information from the masks can be extracted into JSON format. For example, Figure 2 (c) shows the extraction results of room types and the coordinates of the two diagonal vertices of each room.

Figure 1: Examples from the RPLAN dataset

This paper randomly selected 1,000 house plans from the RPLAN dataset as the basic data. Considering that house plans undergo transformations such as rotation and flipping during the design process when applied to floor plans, the dataset will be expanded based on these transformations. The transformations in this paper include 8 rotational angles evenly divided over 360 degrees, as well as vertical flipping. In total, there are 16 variations. Therefore, the final house plan dataset used in this paper comprises 16,000 house plans.

Geometric Feature Extraction

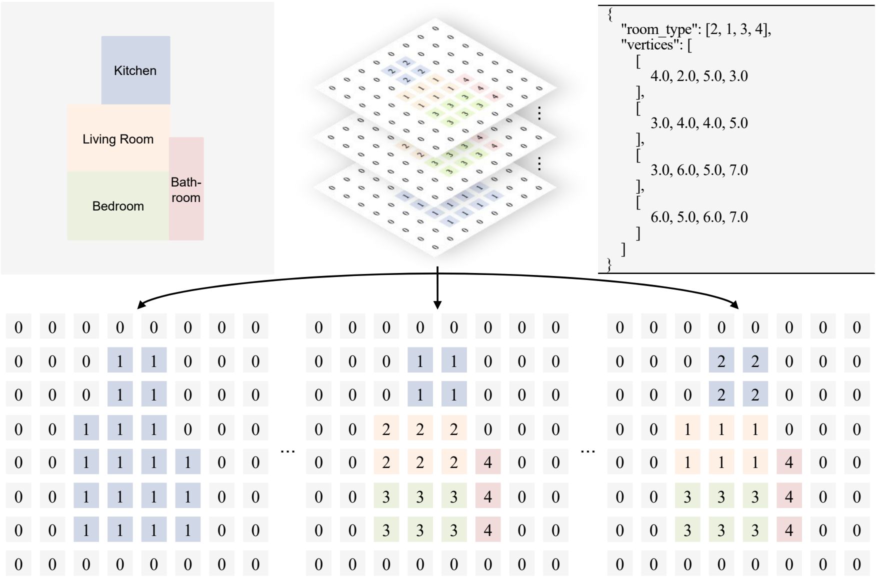
Existing research on the development of surrogate models at the house level is limited, resulting in a limited understanding of house plan features. Features such as orientation, length, width, and area are suitable for buildings viewed as shoeboxes. However, these features are insufficient when considering detailed interior layouts and the concave and convex shapes of rooms. This paper aims to improve the efficiency of comparing the performance of house plans with different geometric designs. Therefore, the focus is primarily on geometric features. The paper considers dimensions such as windows, walls, floors, and spaces within the house to ensure comprehensive feature identification. The final geometric feature system is shown in Table 1.

Table 1: House plan features as inputs for the surrogate model.

Feature	Equation
Window to room ratio	$\frac{\text{Window area}}{\text{Room area}}$
Window to total wall ratio	$\frac{\text{Window area}}{\text{Total wall area}}$
Window direction	$\{1,2,3,4\}$
Exterior wall ratio	$\frac{\text{Exterior wall area}}{\text{Total wall area}}$
Interior wall ratio	$\frac{\text{Interior wall area}}{\text{Total wall area}}$
Room convexity	$\frac{\text{Room area}}{\text{Area of the minimum bounding rectangle}}$
Elongation	$\frac{\text{Length of the minimum bounding rectangle}}{\text{Width of the minimum bounding rectangle}}$
Roundness	$\frac{(\text{Room perimeter})^2}{\text{Room area}}$
Shape factor	$\frac{\text{Envelope area}}{\text{Room volume}}$
Heat loss form factor	$\frac{\text{Envelope area}}{\text{Room area}}$
Relative compactness	$\frac{6 \times \sqrt[3]{(\text{Room volume})^2}}{\text{Surface area}}$
Room type	$\{1,2,3,4,6,7,8,10,16\}$
Rotation	$\{0, 45^\circ, 90^\circ, 135^\circ, 180^\circ, 225^\circ, 270^\circ, 315^\circ\}$
Flip	$\{\text{No flip}, \text{Vertical flip}\}$

GSM algorithm development and simulation data preparation

The house plan dataset serves as the foundational design data. In addition, performance evaluation values paired



(a) Image

(b) Mask

(c) Json

```
{
  "room_type": [2, 1, 3, 4],
  "vertices": [
    [
      4.0, 2.0, 5.0, 3.0
    ],
    [
      3.0, 4.0, 4.0, 5.0
    ],
    [
      3.0, 6.0, 5.0, 7.0
    ],
    [
      6.0, 5.0, 6.0, 7.0
    ]
  ]
}
```

(d) House Inside

0	0	0	0	0	0	0	0
0	0	0	1	1	0	0	0
0	0	0	1	1	0	0	0
0	0	1	1	1	0	0	0
0	0	1	1	1	1	0	0
0	0	1	1	1	1	0	0
0	0	1	1	1	1	0	0
0	0	0	0	0	0	0	0

(e) Room number

0	0	0	0	0	0	0	0
0	0	0	1	1	0	0	0
0	0	0	1	1	0	0	0
0	0	2	2	2	0	0	0
0	0	2	2	2	4	0	0
0	0	3	3	3	4	0	0
0	0	3	3	3	4	0	0
0	0	0	0	0	0	0	0

(f) Room type

0	0	0	0	0	0	0	0
0	0	0	2	2	0	0	0
0	0	0	2	2	0	0	0
0	0	1	1	1	0	0	0
0	0	1	1	1	4	0	0
0	0	3	3	3	4	0	0
0	0	3	3	3	4	0	0
0	0	0	0	0	0	0	0

In (f), Room type = { "living_room": 1, "kitchen": 2, "bedroom": 3, "bathroom": 4 }

Figure 2: Example of three channels from a house plan image

with each house plan are required as labels, which also serve as the ground truth for training the surrogate model. The performance evaluation in this paper includes energy consumption, indoor thermal comfort, and daylight. The performance values, considered as the true values, are obtained through physical simulations using software and plugins such as Rhino, Grasshopper, Ladybug, Radiance, and EnergyPlus. However, converting pixel-based house plan data into a GSM has a significant challenge. Therefore, this paper developed the GSM algorithm, which enables the batch and automatic processing of house plans, assigning performance labels to each one. The main challenge of this algorithm is that each house plan includes walls, which occupy part of the voxel space. In the GSMs, walls are merely facades and appear as lines in the top perspective. Therefore, the core of automatic modeling from image to GSM lies in handling the wall objects. The approach in this paper is to expand the adjacent rooms towards the walls, moving the room boundaries to the central axis of the walls. As shown in Figure 3, the GSM algorithm includes the following 6 steps.

(1) For each house plan from the RPLAN dataset, which contains multiple rooms, extract the vertex coordinates of each room from the image format. (2) Obtain the mask for the entire house from the room mask. (3) Assign all pixels within the house mask that do not belong to the room mask, that is, the interior walls, to the nearest room. (4) Expand all room masks outward to fill in the pixels that were not assigned due to the equidistance. (5) Set up windows. The window sizes are uniformly set according to the WWR of 0.2. (6) Extract all vertex information from the final room mask and window mask and save it as a JSON file. All the JSON files will be imported into Grasshopper to complete the simulation of energy consumption, indoor thermal comfort, and daylighting.

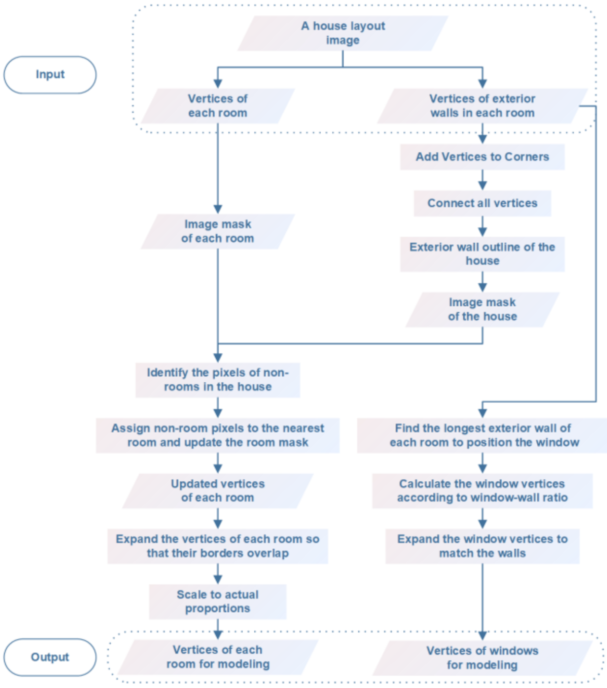


Figure 3: The logic of the GSM algorithm

For energy consumption, based on Energy Use Intensity (EUI), this paper uses cooling load to measure energy consumption (hereinafter referred to as EUI). Cooling energy consumption accounts for a significant proportion of Hong Kong's overall energy use and is a primary energy-saving target for the Hong Kong government (Anon n.d.). For indoor thermal comfort, based on the adjusted Predicted Mean Vote (PMV) (Ole Fanger and Toftum 2002). Absolute values below 0.5 are considered comfortable, and the proportion of comfortable hours throughout the year is used as the final metric for indoor thermal comfort in this paper (hereinafter referred to as

PMV). For daylighting, based on Useful Daylight Illuminance (UDI). UDI refers to the percentage of time throughout the year that natural light at a specific point in space meets the target illuminance range. The target range in this paper is 100 to 2,000 lux. The average UDI of all points within the target space is taken as the final metric for daylighting (hereinafter referred to as UDI). For the simulation component settings, weather data from Hong Kong was used as an example. The construction set for Hong Kong was referenced from mid-rise residential buildings in Climate Zone 2 according to the ASHRAE 90.1 Standard. The floor height was set to 2.75 meters. Windows positioned 1.5 meters above the ground. The window was set to 1 meter. Other settings, such as the schedule and cooling setpoint, were referred to (Wu et al. 2025).

Surrogate model based on MARS and XGBoost

MARS and XGBoost models are proven in many studies that they are outstanding in the tasks of building performance evaluation (García Nieto et al. 2023; Ali et al. 2023). So, this paper is based on these two models to develop the surrogate model, accelerating the efficiency of performance evaluation.

(1) MARS model. It is a non-parametric regression method that captures complex nonlinear relationships by segmenting the data and fitting linear models within each segment. The MARS model can automatically select important features and has excellent interpretability (García Nieto et al. 2023).

$$y = \beta_0 + \sum_{j=1}^{n} \beta_j B_j(x) + \epsilon \tag{1}$$

$$B_j(x) = \left(x - t_j\right)_+ or (t_j - x)_+ \tag{2}$$

Where y is the response variable, β_0 is the intercept term, $B_j(x)$ is the basis functions, ϵ is the error term, t_j is the split point, and $\left(x - t_j\right)_+$ represents the value when $x > t_j$; otherwise, it is zero.

(2) XGBoost model. It is based on an optimized gradient-boosting framework that supports user-defined objective functions. It is widely used in the analysis of energy-efficient building characteristics (Konhäuser and Werner 2024), as well as in the evaluation (Zaker Esteghamati and Flint 2021) and optimization (H. Yan et al. 2022) of building performance. The iterative goal of the XGBoost model is to minimize the loss function, that is, to minimize Equation (3).

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{3}$$

Where $l(y_i, \hat{y}_i)$ is the loss function to measure the error between y_i and $\hat{y}_i$, $\Omega(f_k)$ is the regularization term to control the complexity of the model.

(3) Model evaluation. To evaluate the predictive performance of the MARS and XGBoost surrogate model, this paper utilizes widely recognized metrics for assessing the accuracy of machine learning models, including R-squared (R^2), MSE, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Variation (CV) of RMSE. The calculation are as shown in Equation (4)-(8).

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{4}$$

$$MSE = \frac{1}{N}\sum_{k}^{N}(y_k - \hat{y}_k)^2 \tag{5}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{k}^{N}(y_k - \hat{y}_k)^2} \tag{6}$$

$$MAE = \frac{1}{N}\sum_{k}^{N}|y_k - \hat{y}_k| \tag{7}$$

$$CV(RMSE) = \frac{RMSE}{\frac{1}{N}\sum_{k}^{N}\hat{y}_k} \tag{8}$$

Where y_k is the predicted value for the k-th room, $\hat{y}_k$ is the true value for the k-th room, SS_{res} is the residual sum of squares of y and $\hat{y}$, and SS_{tot} is the total sum of squares of y and $\hat{y}$.

Experiment and Discussion

Data preprocessing result

To eliminate the effects of dimensionality and data distribution on model development, it is essential to standardize and normalize all data first. After comparing various standardization methods, including log transformation and z-score normalization, this paper ultimately adopts the Yeo-Johnson method for partial features. Not all features need to be transformed. For example, the classification feature of room type adopts one-hot encoding, so transformation is not required. The initial distribution of the data features is as shown in Figure 4 and the data distribution after transformation is as shown in Figure 5. The data distribution has effectively become more uniform. It helps to improve the model's ability to learn data features and improve the accuracy of prediction.

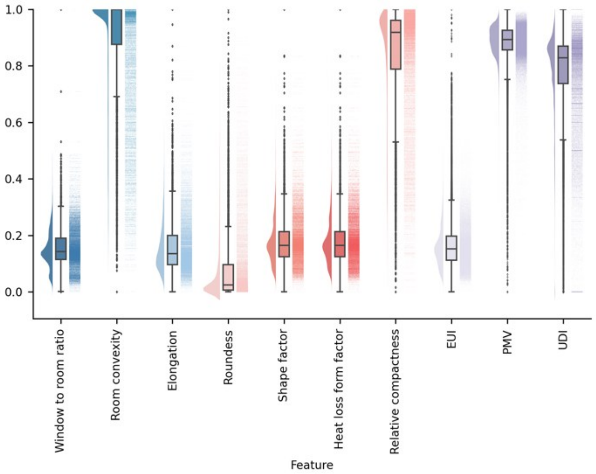


Figure 4: Initial data distribution of partial features

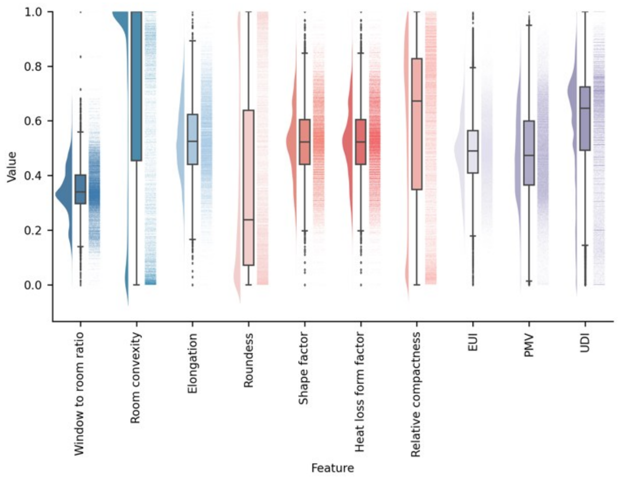


Figure 5: Data distribution of partial features after Yeo-Johnson transformation

The comparison of MARS and XGBoost model

MARS and XGBoost are trained as a surrogate model for predicting house performance separately using the house plan dataset in this paper. Since the XGBoost model can only process a data label in each training process, the three performance indicators, energy consumption, indoor thermal comfort, and daylighting, are predicted in three separate XGBoost models. The hyperparameter fine-tuning range of the two models is shown in Table 2. The prediction accuracy of all models is evaluated in Table 3.

Table 2: The hyperparameter fine-tuning range of MARS and XGBoost models

Surrogate model	Hyperparameter	Range
MARS	Max terms	[3,40]
	Max degree	[1,6]
	Penalty	[-1,4]
XGBoost	Max depth	[9-13]
	Learning rate	[0.01, 0.40]
	Num boost round	200

Table 3: The prediction comparison of MARS and XGBoost

		R2↑	MSE↓	RMSE↓	MAE↓	CV(RMSE)↓
EUI	XGBoost	0.9977	1.5056	1.2270	0.8576	1.34%
	Mars	0.9781	14.1607	3.7631	2.7066	4.10%
PMV	XGBoost	0.8673	5.89E-05	0.0077	0.0042	1.04%
	Mars	0.4481	2.45E-04	0.0156	0.0114	2.11%
UDI	XGBoost	0.9744	0.0007	0.0269	0.0167	3.50%
	Mars	0.8269	0.0049	0.0698	0.0431	9.08%

From Table 3, the following conclusions can be drawn:
(1) XGBoost outperforms MARS across all performance indicators and model evaluation metrics.
(2) Overall, XGBoost shows the greatest accuracy improvement in PMV compared to MARS, with R^2 increasing by 93.6%, MSE by 76.0%, RMSE by 50.6%, MAE by 63.2%, and CV(RMSE) by 50.7%.
(3) However, among the three performance indicators, the prediction accuracy of the XGBoost model for PMV is the lowest. This suggests that expanding the dataset may be necessary. Additionally, it can be observed that XGBoost performs better than the MARS model when dealing with small and imbalanced datasets.

Conclusion

Based on the findings presented in this paper, it is evident that performance evaluation is essential in comparing various house plans during the early design stages. The proposed GSM algorithm for geometric simulation modeling effectively processed 16,000 house plans, accelerating the simulation for energy consumption, indoor thermal comfort, and daylighting. The comparative analysis of surrogate models revealed that XGBoost consistently outperformed MARS across all performance metrics. In particular, XGBoost demonstrated significant improvements in accuracy, particularly in PMV, with substantial enhancements in R^2, MSE, RMSE, MAE, and CV(RMSE). However, it is important to note that the prediction accuracy for PMV was the lowest among the performance indicators, indicating a potential need for a larger dataset to enhance model performance. Overall, these results show the advantages of using XGBoost, especially in scenarios involving small and imbalanced datasets, providing the way for more efficient performance evaluations in house plan design.

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