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Implementation of BIM Energy Analysis and Monte Carlo Simulation for Estimating Building Energy Performance Based on Regression Approach: A Case Study

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Abstract: The energy performance prediction of buildings plays a significant role in the design phases. Theoretical analysis and statistical analysis are typically carried out to predict energy consumption. However, due to the complexity of the building characteristics, precise energy performance can hardly be predicted in the early design stage. This study considers both building information modeling (BIM) and statistical approaches, including several regression models for the prediction purpose. This paper also highlights a number of findings of energy modeling related to building energy performance simulation software, particularly Autodesk Green Building Studio. In this research, the geometric models were created using Autodesk Revit. Based on the energy simulation conducted by Autodesk Green Building Studio (GBS), the energy properties of five prototype and case study models were determined. The GBS simulation was carried out using DOE 2.2 engine. Eight parameters were used in BIM, including building type, location, building area, analysis year, floor-to-ceiling height, floor construction, wall construction, and ceiling construction. The Monte Carlo simulation method was performed to predict precise energy consumption. Among the regression models developed, the single variable linear regression models appear to have high accuracy. Although there exist some limitations in applying the equation in EUI prediction, the rough estimation of energy use was realized. Regression model validation was carried out using the model from the case study and Monte Carlo simulation results. A total of 35 runs of validation were performed, and most differences were maintained within 5%. The results show some limitations in the application of the linear regression model.

Keywords: Green Building; BIM; regression analysis; Monte Carlo simulation; building energy performance; DOE-2 simulation

Citation: Tahmasebinia, F.; Jiang, R.; Sepasgozar, S.; Wei, J.; Ding, Y.; Ma, H. Implementation of BIM Energy Analysis and Monte Carlo Simulation for Estimating Building Energy Performance Based on Regression Approach: A Case Study. *Buildings* **2022**, *12*, 449. https://doi.org/10.3390/buildings12040449

Academic Editors: Eusébio Z. E. Conceição and Hazim B. Awbi

Received: 28 February 2022
Accepted: 29 March 2022
Published: 5 April 2022

1. Introduction

The construction and operation of buildings contribute significantly to the consumption of resources and waste production [1]. More than 40% of energy consumption and correspondingly 30% of the CO_2 emissions are caused by buildings globally [2]. Since the energy consumption dominantly depends on the energy performance of the building, conducting energy simulation in the early design phase is essential. Since the beginning of the 21st century, the design of low-energy and zero-energy buildings has become an important topic. Academics and building designers have conducted several types of research related to building energy system design [3]. The Australian National Construction Code provides energy-saving rules and regulations that first-class buildings should comply with.

The energy performance prediction of buildings [4–6] plays a significant role in the design phases. Theoretical analysis and statistical analysis are typically carried out to predict energy consumption. However, due to the complexity of the building characteristics, precise energy performance can hardly be predicted. Recent studies have indicated that parametric analysis could improve the accuracy of energy performance prediction [7,8]. Nevertheless, the simulation process is relatively complicated, where various parameters need to be involved. The regression approach could further reduce the energy consumption intensity difference [9]. It is becoming desirable as a simplified approach. Therefore, the combination of parametric analysis [10] and regression approach [11–15] precision was adopted in the project. It is expected to improve the accuracy of the simulation. To realize building energy optimization in the early stage, analyzing the building envelope is considered an essential step [16–18]. Low-energy buildings [19,20] and zero-energy buildings can be designed after energy optimization in the early design phase.

Building energy performance measurement can be realized by utilizing the energy efficiency index [9,21] and energy simulation software such as EnergyPlus and DOE2.

Egan and Finn [22] stated data that can be gathered and provided for BEPS tools could be unlimited. However, the gathering of data can be expensive and time-consuming. The sensitivity of input parameters was analyzed quantitatively. By defining and modeling only based on the influential parameters with a high degree of accuracy, time spent on collecting and defining input parameter data and modeling can be significantly reduced [3].

As an innovative technique, BIM can assist with efficient building design by analyzing building massing and the form of building, then optimizing its envelope. Thermal and cooling loads can be managed by evaluating the heat transfer. Then, energy modeling can be performed to estimate the total energy cost of a building before construction [23]. The cost estimation can be performed in early-stage design [24]. Compared with EnergyPlus [25], the simulation can be performed in a more user-friendly way.

Significant time savings can be achieved by importing geometric models from the BIM software into the energy simulation tool without recreating the building geometry. Revit and Green Building Studio were chosen because both can communicate seamlessly via gbXML [26]. Building geometry can be exported from Revit to Green Building Studio for analysis of energy assessment.

Articles indicated that BIM simulation could provide the chance to explore alternative solutions in the early building design stage [23]. It could provide insight into the energy consumption of buildings based on alternatives selected. However, there exist some limitations, updates between models require additional operations, and real-time simulation and feedback are not available [26]. The accuracy of BEPS results can hardly be ensured in some cases. There is still a discrepancy between the actual data and the results calculated by BEPS. Recent studies have made contributions to improve simulation accuracy. The difference between the theoretical result and measured data is reduced to as low as 4% [27,28].

For the parametric analysis, the HVAC system, lighting system, façade [29], glazing system [30], and occupancy pattern [31] are considered to be key parameters. The Abercrombie Business School (ABS) was constructed in 2015. It is located on the Darlington campus at the University of Sydney (See Figure 1). There are numerous innovation and energy-efficiency designs in this building, which saves 50% annual carbon footprint compared with the benchmark.

Figure 1. Case study building: Abercrombie Business School.

2. Literature Review

This section compares research conducted on building energy performance. The review is as presented using the Aim–Method–Findings and Limitations form and is tabulated in the table below (Table 1).

Table 1. Summary of the review of selected articles.

Aim	Method	Findings and Limitations
Providing a more comprehensive approach to benchmarking building energy [32].	The clustering concept based on Fayyad's model (feature selection, clustering algorithm adaptation, results validation based on the data from the national database CBECS and local actual buildings, and interpretation).	Compared with the Energy Star approach, the clustering approach can incorporate all the statistically significant building characteristics affecting energy usage.
Developing a building energy performance analysis tool based on regression model for internal air temperature prediction [33].	Simulation modeling analysis based on the EnergyPlus software; multivariate regression model analysis based on the EnergyPlus software.	Utility of building energy performance analysis based on regression model can provide high accuracy results for internal air temperature prediction in the circumstances with numerous internal and external influential factors.
Offering a new simple estimating tool for building energy consumption-based linear regression model without an expert user [34].	Comprehensive analysis with TRNSYS software and the multiple linear regression method; sensitivity analysis using the Pearson coefficient.	The use of multiple linear regression can simply and immediately determine building energy balance for evaluation phases in energy planning.
Evaluating the impact on building energy analysis due to the variations of the thermo-physical property of building envelopes and occupancy [35,36].	Data analysis using gbXML-based on BIM; regression analysis.	The impact and the relative sensitivity of occupancy variations may become greater in the warmer location as the number of occupants increases. This research is still needed for the normalization of variables in further studies. In addition, the reference model is also required to use through various simulation engines to improve the accuracy comparison on the building energy performance.

Table 1. *Cont.*

Aim	Method	Findings and Limitations
Providing an optimizing measure for the building windows system through integration operational efficiency with comprehensive life cycle assessment (LCA) and life cycle costing (LCC) [35,36].	Life cycle assessment and life cycle costing analysis based on the FirstRate5 software; multiple linear regression analyses; Monte Carlo simulation; thermal energy simulation; simulation and modeling based on BIM.	1. The minimum opening of windows on the wall is an energy-saving option. 2. Comparing the windows' opening and solar aperture can determine that larger windows will cause excessive energy consumption in the cold-temperate zone. 3. Solar aperture on energy consumption is more significant than the U-value in the warm-temperate zone. 4. The major environmental impacts at various life cycle stages are usually identified by the LCA of different framed windows. 5. Optimum performance of windows varies with climate, longitude, latitude and solar radiation.
Evaluating the capacity of BIM technology design and address zero-net energy houses (ZEHs) [37].	Building information modeling analysis based on BIM and a simulation analysis based on BPS tools.	The interoperability of the BIM system with BPS tools shows that BIM plays a key role be in achieving net-zero levels for an existing residential house. However, BIM is still not good at determining the storage capacity of phase change materials (PCMs).
Presenting an efficient method integrated with building information modeling, energy simulation, and energy consumption prediction for building energy performance evaluation [38].	3D building energy modeling based on generic modeling (GM) approach; simulation analysis via the EnergyPlus software; Genetic Algorithm-Neural Network (GA-NN) for building energy consumption prediction model.	This building energy prediction method based on generating models and data depending on parametric modeling is more effective, user-friendly, and reliable for building projects. Limitations: (1) this approach still need to be improved for the design phase in complex building structures; (2) there is still a gap between the actual data and the result calculated by EnergyPlus.
Investigating the effects of roof shapes and buildings directly on the energy consumption of the residential buildings [39].	Modeling simulation analysis based on REVIT Autodesk Solar Analysis software.	Compared with flat roofs, gable and hip roofs are more stable regarding energy consumption in terms of orientation. Building orientation will provide a more significant impact on building energy performance than flat roof shape.
Investigating the availability of integrating the BIM and BEM methodologies for building energy performance analysis [40].	Experimental design via Autodesk Insight; modeling analysis based on AutoCAD and Autodesk REVIT	The energy performance can be effectively improved by the application of the linkage between the BIM and BEM methodologies in one environment: REVIT on Autodesk, Insight, and Green Building Studio. More information of the materials' thermal properties still needs to be added; the accuracy was not verified for the climatic conditions in the database of Autodesk REVIT.
A case study to assess the validity of BIM in the building design phase for sustainable buildings [41].	Building modeling by Revit Architecture 2018; simulation analysis based on the Green Building Studio.	BIM can effectively assist in evaluating the energy efficiency and cost of the building using Green Building Studio and Autodesk Revit 2018.

Table 1. *Cont.*

Aim	Method	Findings and Limitations
Developing life cycle BIM engaged framework for addressing the building energy performance gap (BEPG) [42].	Literature review; semi-structured interview; qualitative analysis based on Nvivo® software.	BIM can be used as a functional enabler to address the building energy performance gap (BEPG). However, the real BIM platform still needs to be developed and validated in actual projects in future studies.
To analyze the impact of the existing type of lighting (Ao) and glazing materials for the energy performance of commercial building [43].	Virtual modeling by the ArchiCAD software; manual observation; the energy evaluation via the ArchiCAD software.	BIM can effectively address various issues in the construction industry; the building energy consumption will be impacted by different types of frame materials; energy-efficient lighting such as LEDs can reduce building energy consumption.

As the attention of global warming has increased in recent years, building energy performance has become a topic of many researchers. In order to provide more accurate results from comparing the energy consumption, Gao and Malkawi [32] developed a new approach based on the clustering concept. This approach can compare buildings from a multi-dimensional domain of building features rather than the single dimension of the use type. Compared with the Energy Star approach, the clustering approach can offer the result by incorporating all major building characteristics which will affect the building energy consumption.

Bilous and Deshko [33] also analyzed the building energy performance through the regression model for internal air temperature prediction. The EnergyPlus software was utilized by them to create a room dynamic simulation model. After numerous simulations are carried out based on the model, it is proven that the regression model can be used on building energy performance analysis to provide high-accuracy results for internal air temperature prediction.

Except for the inner temperature prediction, Ciulla and D'Amico [34] devoted their effort to a new measure to evaluate the building energy needs based on the linear regression model. The authors of [34] operated comprehensive analyses by TRNSYS software and sensitivity analyses using the Pearson coefficient and found the use of multiple linear regression can simply determine building energy balance for evaluation phases in energy planning.

Build information modeling (BIM) has also attracted the attention of many researchers in building energy analysis. The authors of [35] implemented the data analysis and regression analysis using gbXML-based on BIM to evaluate the impact on building energy analysis due to the variations of the thermo-physical property of building envelopes and occupancy; they then found the number of occupants and the relative sensitivity of occupancy variations are positively correlated in a warmer location. BIM has also proven that it plays a key role be in achieving the net-zero level for existing residential houses in [37]. The author of [37] used building information modeling analysis based on BIM and a simulation analysis via building performance simulation (BPS) tools to address zero-net energy houses (ZEHs) in their research. The authors of [41] suggested that BIM can provide an effective contribution to support decision-making for sustainable buildings through a case study that examined an institute building located in the city of Alexandria (Egypt). In order to overcome the problem of building energy performance gap (BEPG), a life cycle framework was developed by A based on BIM. In the developing period, the Nvivo® software was used to develop the BIM-based framework via the qualitative analysis, and functions such as "information exchange", "design review", "energy-related quality control", "life cycle commissioning", and "real-time operation and maintenance management" were achieved.

As discussed above, many researchers indicate that BIM, indeed, can effectively improve the building energy performance analysis in the design phase. Nevertheless, the energy modeling simulation still needs to be implemented on other platforms. In order to solve this obstacle, [40] delivered new solutions via integration of the BIM and BEM. The BIM and BEM were combined within one environment through Insight and Green Building Studio, performing the energy model, and REVIT, performing the physical model, to reduce the energy consumption of the appliances via implementing the experimental design. In light of the result from the experimental design, authors of [40] believed that the energy performance could be effectively improved by the application of the linkage between the BIM and BEM methodologies in one environment.

3. Methodology

This section describes the modeling procedure of geometric modeling and energy modeling. The modeling procedure, building properties, and simulation outputs are explained.

Based on the energy simulation conducted by Autodesk Green Building Studio, the energy properties of seven prototype models and five case study models were determined. The impacts of individual design variables were implemented in the energy equations through DOE 2.2 engine.

The study was conducted in four phases: data collection, geometric and energy modeling, data analysis, and validation. Asadi and Amiri [27] proposed an effective method that analyzes seven outside perimeter shapes. Five of those shapes were matched in the ABS building. Respective geometric modeling and energy performance simulation were carried out.

Therefore, in this paper, a total of five prototype building shapes were studied, and related case studies were presented. BIM played a key role in the geometric modeling and energy performance simulation configuration. Five building shapes were studied, as shown in Figure 2 [27].

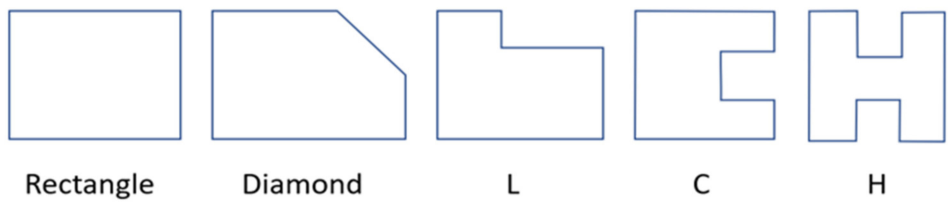

Figure 2. Sketch of five studied shapes.

3.1. BIM Modeling

At the beginning of the modeling phase, all five studied building shapes were modeled using Autodesk Revit. Idealized geometric models were created for each shape where building energy information was included. A Revit modeling workflow is shown in Figure 3.

In the Revit energy simulation, spatial and surface energy models were majorly considered. The spatial model presents the amount of discrete air (mass) subject to heat changes. At the same time, the surface energy model considers the heat transfer path through the analytical space boundaries. In the Revit modeling, the spatial model was used to create an analytical energy model. The analytical energy models for the respective shapes are shown in Figure 4 [27].

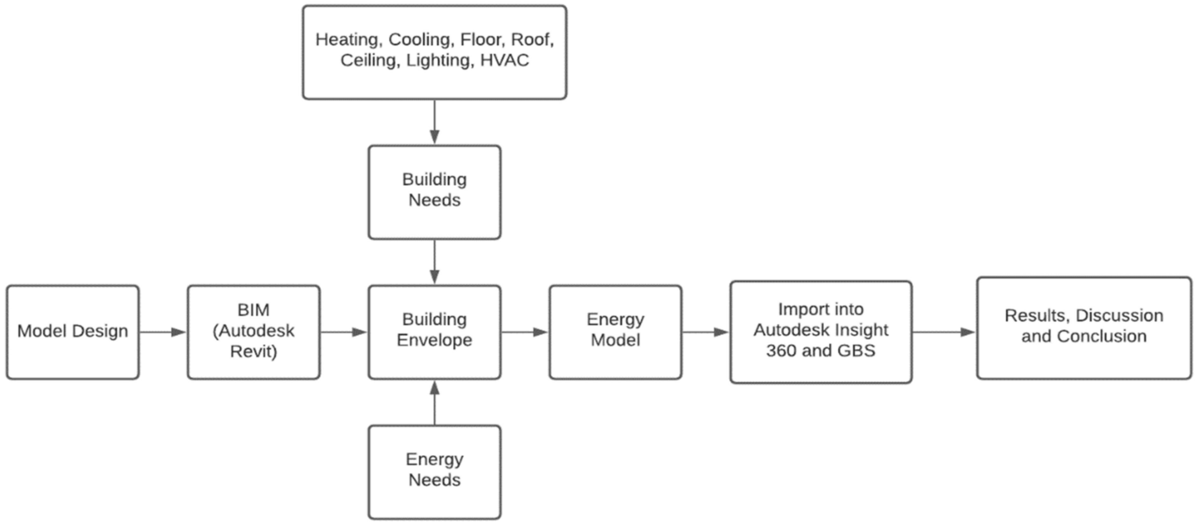

Figure 3. Revit modeling workflow.

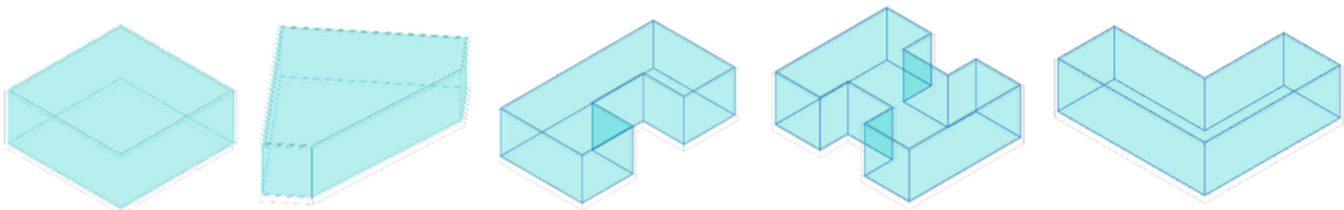

Figure 4. Revit analytical energy model.

The Appendix A contains BIM models of the five case study shapes (Figures A1–A5) and lists some related settings in Autodesk Revit (Figures A6–A9). The contents are supplemental to the main text.

3.2. Building Elements and Properties

In order to ensure the accuracy of the geometric model as well as the energy model, some constant variables were set in the modeling process of this research. Table 2 summarizes the constant parameters included in the geometric modeling. A 0.5% difference is allowed in the floor area.

Table 2. Summary of model constant parameters.

Constant Parameters	
Building type	School or University
Location	Sydney, NSW
Building area	100 m^2
Analysis year	2021
Floor-to-ceiling height	3 m
Floor construction	Floor-Grnd-Susp_65Scr-80Ins-100Blk-75PC
Wall construction	Basic wall (wall-Ext 102Bwk-75Ins-100BlK-12P)
Ceiling construction	Compound ceiling—Plain R2

The energy consumption of buildings is greatly influenced by the energy configurations. The energy settings could otherwise control the use of additional data defined in the Revit model, including material properties and thermal space properties. The specific energy settings of the models are tabulated in Table 3.

Table 3. Summary of building energy settings.

Energy Settings	
Energy analytical model mode	Use building elements
Building service	VAV-Single Duct
Building infiltration class	None
HVAC default system	Central VAV, HW Heat, Chiller 5.96 COP, Boiler 84.5 eff
Export Category	Rooms

The energy consumption of buildings is also related to the thermal properties of components such as walls, roof, ceiling, slabs, floor, and glass. The following table summarizes the thermal property of some significant building components (see Table 4).

Table 4. Summary of material thermal properties.

Material Thermal Properties	
Roofs	4 in lightweight concrete, U = 1.2750 W/(m^2·K)
Exterior Walls	8 in lightweight concrete block, U = 0.8108 W/(m^2·K)
Interior Walls	Frame partition with ¾ in gypsum board, U = 1.4733 W/(m^2·K)
Ceilings	8 in lightweight concrete ceiling, U = 1.3610 W/(m^2·K)
Floors	Passive floor, no insulation, tile or vinyl, U = 2.9582 W/(m^2·K)
Slabs	Un-insulated solid, U = 0.7059 W/(m^2·K)
Doors	Metal, U = 3.7021 W/(m^2·K)
Exterior Windows	Large, double-glazed windows (reflective coating)—industry, U = 2.9214 W/(m^2·K), SHGC = 0.13
Interior Windows	Large single-glazed windows, U = 3.6898 W/(m^2·K), SHGC = 0.86
Skylights	Large, double-glazed windows (reflective coating)—industry, U = 2.9214 W/(m^2·K), SHGC = 0.13

3.3. Energy Simulation in Green Building Studio

Green Building Studio uses the DOE-2.2 simulation engine to simulate the energy performance of the input energy model. After the energy options are configured in Revit, the cloud server automatically calculates the energy model. The results of the energy simulation are shown in GBS. For each building model, GBS automatically performs about 250 simulations. If the parameters change, the results obtained for each simulation are displayed in detail.

3.3.1. Energy Simulation Workflow

The following figure shows the workflow of GBS modeling (see Figure 5).

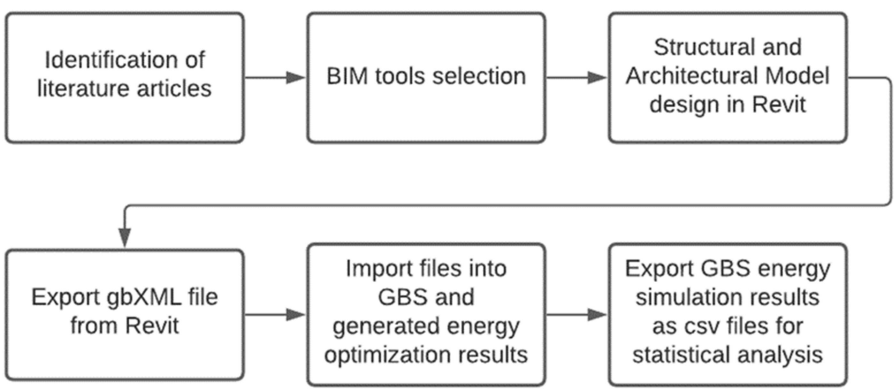

Figure 5. Green Building Studio modeling workflow.

As a plug-in for Revit, the GBS requires no additional information. On the one hand, gbXML input files contain relevant building energy data. On the other hand, most energy-related data reside in cloud-based servers and can be accessed instantly. Therefore, both conceptual and detailed information can be analyzed conveniently.

3.3.2. Energy Simulation Outputs

The following diagram shows the simulation results in the GBS simulation (see Figure 6). Those results were exported to RStudio for further statistical analysis.

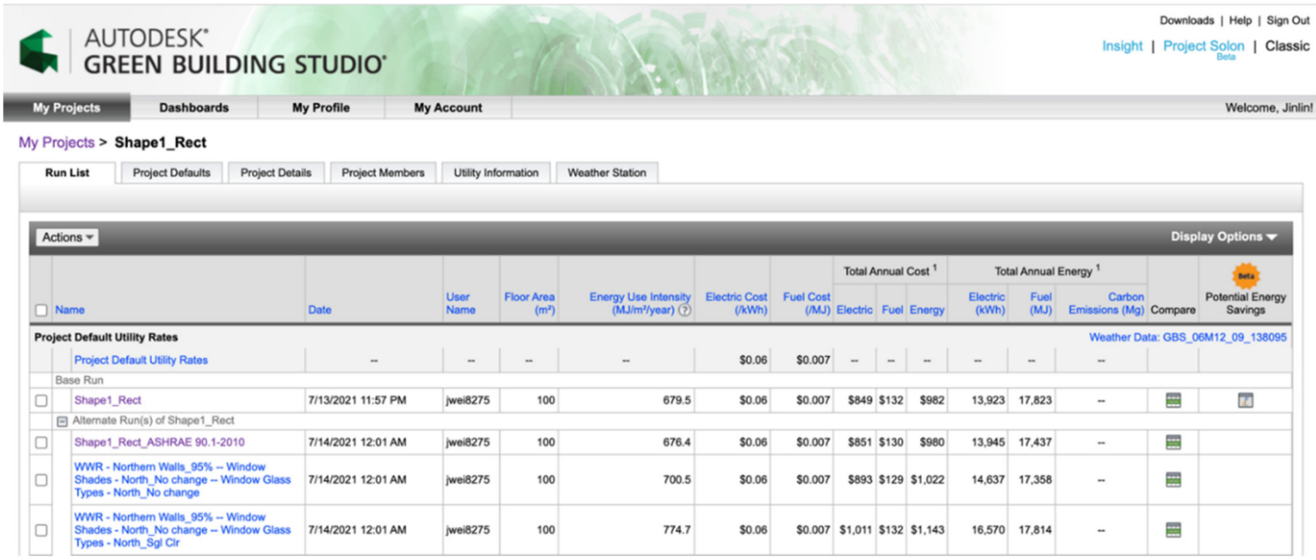

Figure 6. GBS simulation results.

The outputs of GBS energy simulation include:

- Customizable charts of heat or cooling loads;
- Energy use intensity (EUI);
- Electric cost and fuel cost;
- Customizable parametric studies;
- Annual carbon footprint;
- Building properties summary of construction areas, equipment capacities;
- Design review file.

3.3.3. Assumptions and Default Values in GBS

The Autodesk GBS could realize automatic energy analysis by reading the gbXML file. However, the default values are applied if the specific parameters were not specified in the gbXML file. The default values are different from those in Revit. These defaults were defined based on ASHRAE90.1, ASHRAE90.2, ASHRAE62.1, and CBECS data (see Table 5). Additionally, regional codes form the baseline for where ASHRAE does not apply.

Table 5. Summary of building energy settings.

Energy Settings	Baseline
Schedule	California Non-residential New Construction Baseline Study 1999
Thermal parameters of the envelope	ASHRAE 90.1 2007 and ASHRAE 90.2 2007
Equipment power density and DHW loads	California 2005 Title 24 Energy Code
The density of occupancy and ventilation	ASHRAE 62.1-2007
HVAC system	2003 Commercial Buildings Energy Consumption Survey

3.4. Case Study

In this study, five of the studied shapes were identified in the ABS building (see Figure 7). All shapes are highlighted in red. In the ABS building floor plan, the L shape (left top), U shape (left bottom), H shape (middle), diamond shape (right-top), and rectangular shape (right bottom) were modeled and simulated. The energy performance obtained from the simulation was used for validation.

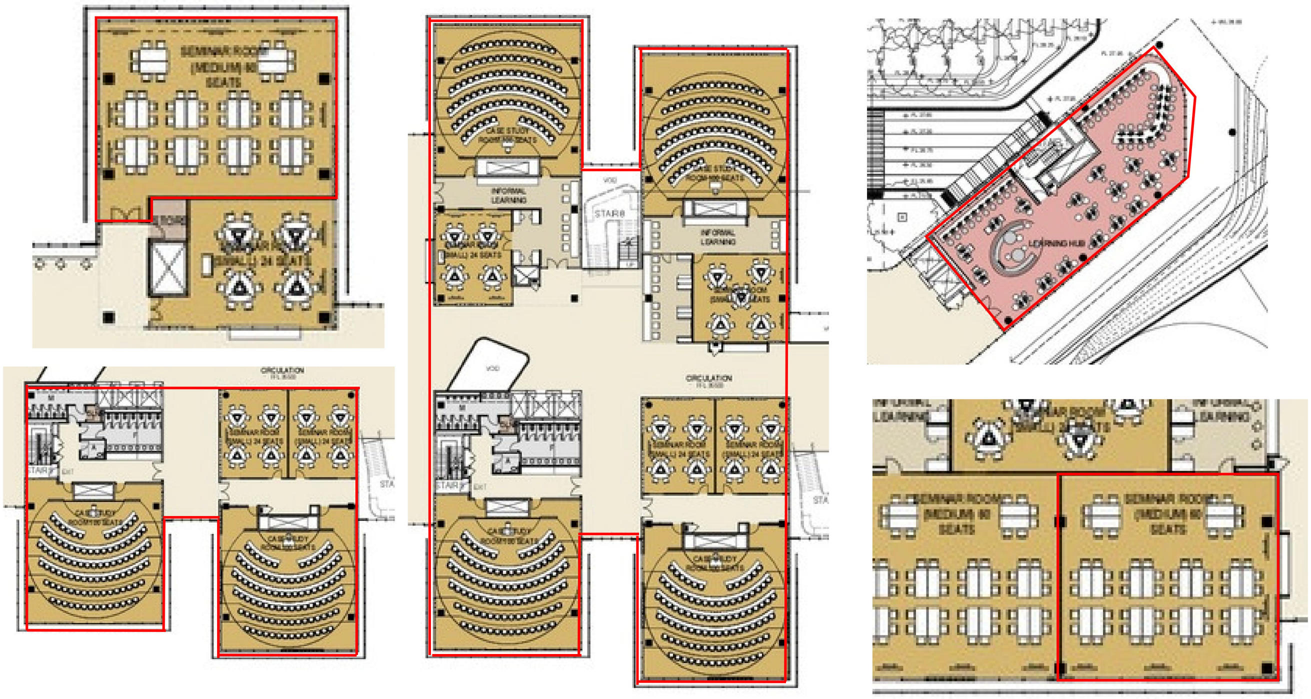

Figure 7. Five shapes (perimeter marked in red) identified in the ABS building.

All models are made to the original scale and area. The building structure, including the window area, was maintained with maximum effort. However, in the modeling process of the case study, some simplifications were made to the realistic model:

- The curved glass curtain walls are simplified to curtain walls with angles in the diamond shape model.
- Complex interior spaces in H shape and U shape were simplified to main walls only.
- The perimeter gaps of the H shape and U shape were filled with walls.

3.5. Design Variables

Design variables specify the range of variation in the properties and shape of the model and are crucial to energy design studies.

In this study, the variables were determined by Green Building Studio automatically. Parameters including wall construction, roof construction, infiltration, lighting efficiency, and plug load efficiency were considered most relevant to the building energy consumption in energy performance simulations. Moreover, the building material of the studied variables was strictly selected under ASHRAE90.1.

In the data analysis conducted in this study, the variables were divided into independent and dependent variables, following the principles of statistics. The variables related to building envelope, shape, and orientation were identified as independent variables. However, some design variables required additional processing or dummy code, including infiltration, lighting efficiency, and plug load efficiency.

The summary of design parameters and related analysis methods are tabulated in Table 6.

Table 6. Summary of Design Variables.

	Parameter	Analysis Methods
1	Wall Construction (U-Value)	Tried to carry out linear regression analysis with U-value and R-value. Analysis with U-value accepted.
2	Roof Construction (U-Value)	Tried to carry out linear regression analysis with U-value and R-value. Analysis with U-value accepted.
3	Infiltration (ACH)	ACH (air change per hour) was used in the regression analysisRanges from 0.17 to 2 L/s/m^3.
4	Lighting Efficiency	Lighting efficiency ranges from 0.3 to 1.9 w/sf, equivalent to 3.23 to 20.44 W/m^2.
5	Plug Load Efficiency	Ranges from 0.6 to 2.6 W/sf, equivalent to 6.46 to 27.98 W/m^2.

3.6. Monte Carlo Simulation

Monte Carlo simulation analyses the model statistically utilizing repeated random sampling. This technique is based on the principle of random in statistics. The probability distribution is used to determine the uncertainty of the model during the simulation. Moreover, it can be used to help explain the effects of uncertainty in forecasting and prediction models.

In this study, the Monte Carlo simulation method was performed to predict precise energy consumption. The simulation was applied to five ABS building models. To be specific, each design variable in each shape was simulated 4000 times. A total of 100,000 simulations was performed. Finally, complete simulation results (including EUI only) were provided for each design scenario.

3.7. Regression Analysis

In this study, regression analysis was performed to predict the relationship between five variables and energy use intensity (EUI). This technique incorporates single variable regression only for simplicity. The process thermal loading calculation is therefore shortened. Single variable regression focuses on the analysis of the association between a single dependent variable and its independent variables.

For the five prototype models and related case study ABS building models, 10,000 linear simulations were performed on each building model. The impact of the parameters on the annual energy use intensity was then analyzed. Approximately 40% of the data were used to test the developed case study models. The regression equation used for linear regression is shown as follows:

$$y = \alpha + \beta x \tag{1}$$

where y is the predicting EUI, α and β are the coefficients, and x is the variable.

3.8. Goodness of Fit

The coefficient of determination R^2 represents the goodness of fit of linear regression models. Chicco and Warrens [44] stated that R^2 is more informative in evaluating regression analysis compared with other frequently used statistical values, including MSE and RMSE. It visualizes the degree of similarity between the actual model and the regression model. Finally, the difference between observed and predicted values in the simulations could suggest if the regression models fit the data well. The equation for coefficient of determination is shown as follows:

$$R^2 = 1 - \frac{\sum_i (\hat{y}_i - \hat{y})^2}{\sum_i (y_i - \hat{y})^2} \tag{2}$$

y_i is the value of observation i;
$\hat{y}_i$ is the predicted value of y for observation i;
$\hat{y}$ is the mean of y value.

4. Results

This section shows the data analysis based on the building energy simulation, then presents regression models. The developed regression models were validated using several models of the ABS building. The lines of best fit are shown, and the accuracy of the regression model is discussed.

4.1. Linear Regression Models

Single variable linear regression models were established as the linear behavior was evident in the study of wall construction, plug load efficiency, infiltration, roof construction, and lighting efficiency. The results are tabulated in Tables 7–11.

Table 7. Summary of wall construction regression equations.

	Wall Construction: $y = \alpha + \beta x$				
	S1-Rec	**S2-L**	**S3-H**	**S4-DMD**	**S5-U**
α	668.36	667.86	668.59	662.01	665.27
β	14.62	21.31	25.87	15.27	26.20
R^2	0.896	0.881	0.875	0.893	0.875

Table 8. Summary of plug load efficiency regression equations.

	Plug Load Efficiency: $y = \alpha + \beta x$				
	S1-Rec	**S2-L**	**S3-H**	**S4-DMD**	**S5-U**
α	491.45	497.96	501.40	486.75	498.96
β	11.77	11.64	11.67	11.71	11.63
R^2	0.999	0.999	0.999	0.999	0.999

Table 9. Summary of infiltration regression equations.

	Infiltration: $y = \alpha + \beta x$				
	S1-Rec	**S2-L**	**S3-H**	**S4-DMD**	**S5-U**
α	668.98	672.33	675.86	662.72	672.70
β	21.97	26.35	28.00	23.70	28.74
R^2	0.853	0.907	0.919	0.871	0.920

Table 10. Summary of roof construction regression equations.

	Roof Construction: $y = \alpha + \beta x$				
	S1-Rec	**S2-L**	**S3-H**	**S4-DMD**	**S5-U**
α	646.74	649.29	652.85	640.60	649.82
β	25.33	25.40	25.10	24.91	24.72
R^2	0.998	0.999	0.999	0.998	0.998

Table 11. Summary of lighting efficiency regression equations.

	Lighting Efficiency: $y = \alpha + \beta x$				
	S1-Rec	**S2-L**	**S3-H**	**S4-DMD**	**S5-U**
α	528.71	534.52	538.343	523.53	535.74
β	11.87	11.67	11.67	11.71	11.64
R^2	0.999	0.999	0.999	0.999	0.999

Tables 7–11 show the summary of regression equations associated with each shape. The accuracy of the models is judged by the coefficient of determination (R^2). Regression

models for lighting efficiency, roof construction, and plug load efficiency have a high R^2 value, close to one. Nevertheless, regression models for wall construction and plug load efficiency have relatively lower R^2 values. The scattered data points are slightly dispersed around the line of best fit.

4.2. Regression Models Validation

4.2.1. ABS Case Study—Base Run Result

Figure 8 shows the comparison of EUI across five validated shapes for the original geometric model. A significant difference of EUI between the diamond shape and the other four shapes is observed.

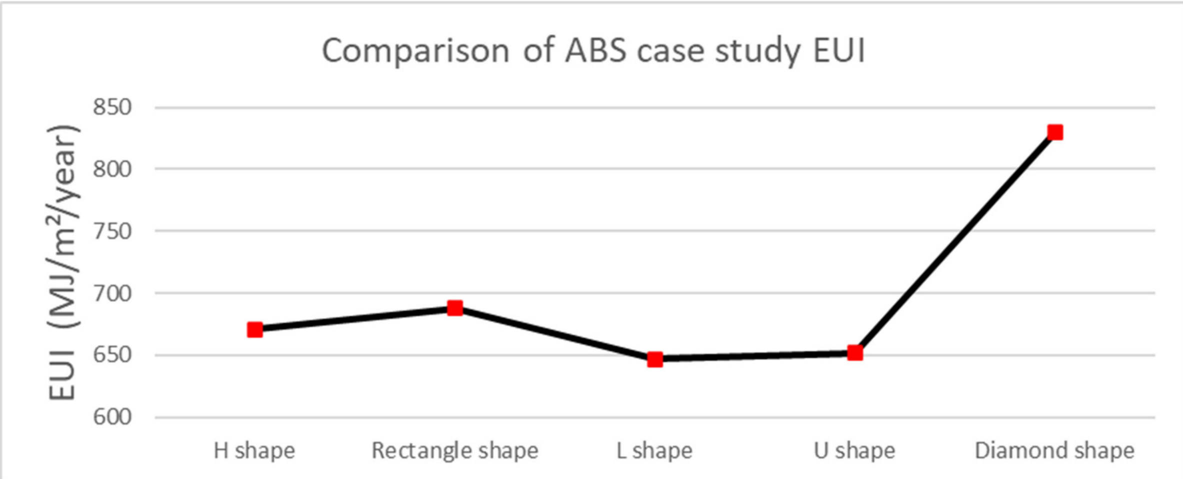

Figure 8. ABS Case study EUI comparison.

4.2.2. ABS Case Study—Validation

The following figures show the comparison between ABS case study models and the regression models. Errors are indicated as a percentage in absolute value (See Figures 9–13).

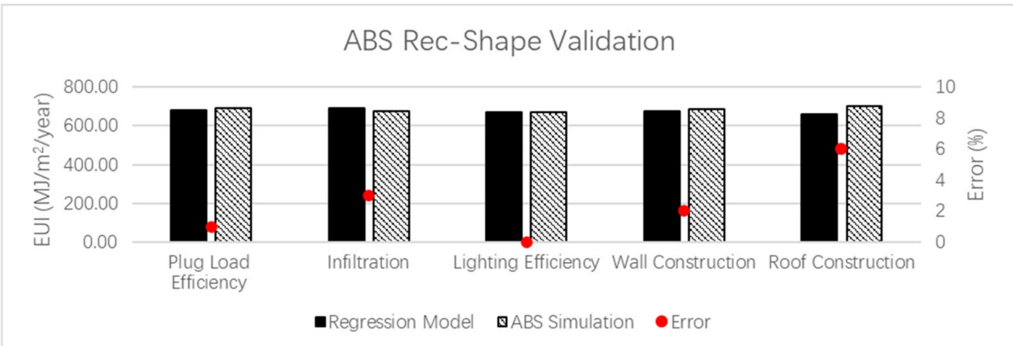

Figure 9. ABS Case study validation—Rectangle shape.

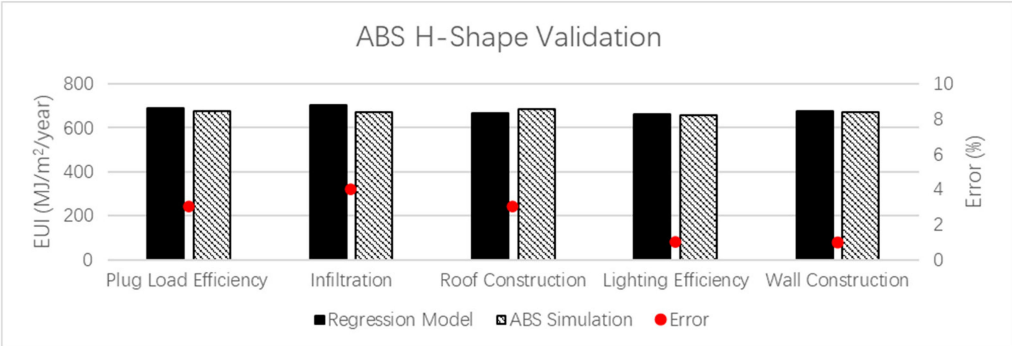

Figure 10. ABS Case study validation—H shape.

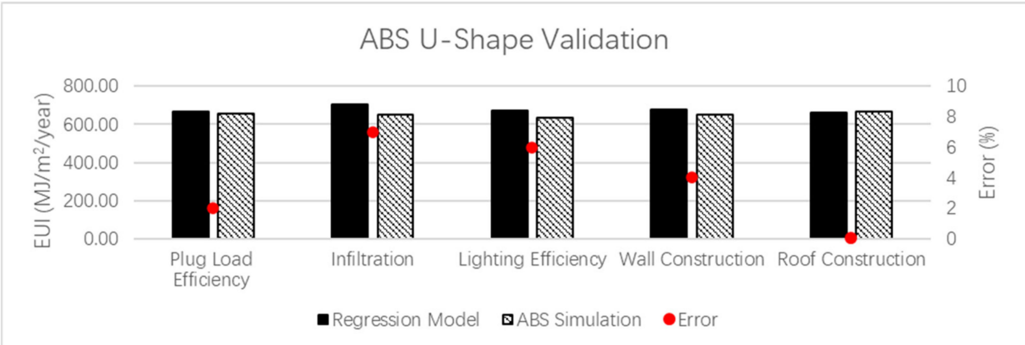

Figure 11. ABS Case study validation—U shape.

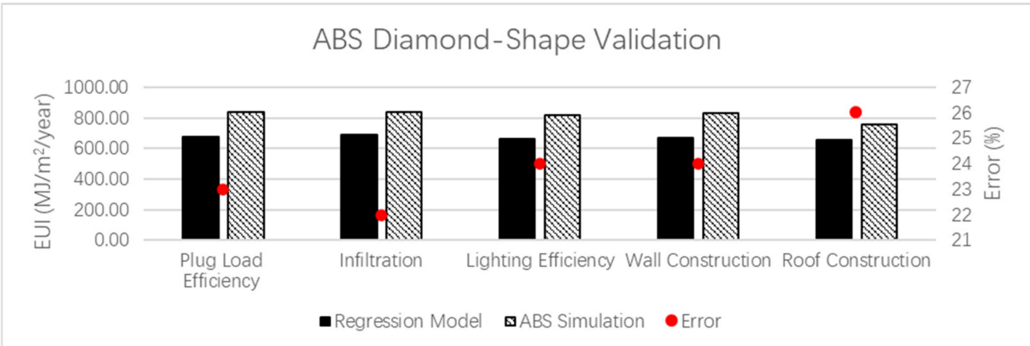

Figure 12. ABS Case study validation—Diamond shape.

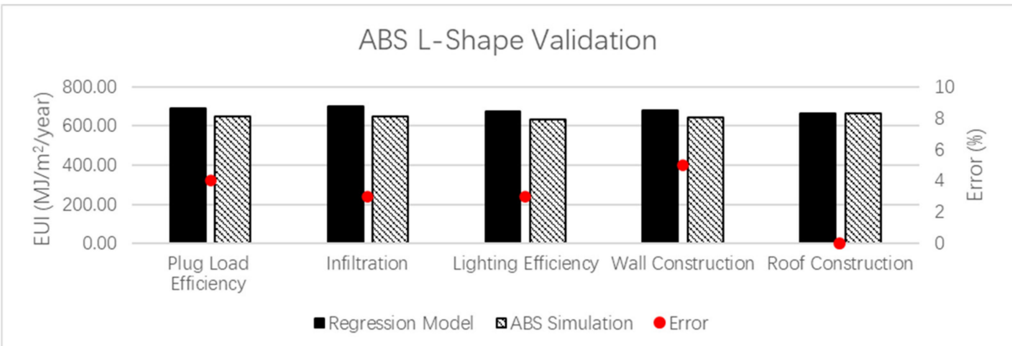

Figure 13. ABS Case study validation—L shape.

A total of 35 runs of validation were performed. The validation results indicate the accuracy and feasibility of regression equations. It can be observed from the H shape, Rectangle shape, L shape, and U shape validations that most errors values were maintained within 5%. The maximum difference was found at infiltration at the L building shape. At the same time, the lowest error tends to be zero.

Notably, the differences between ABS simulation results and a regression model are exceptionally high. The error ranges between 16% and 26%. The error range is not considered acceptable.

5. Discussion

Based on the results of the energy model simulations, the degree of influence of each design variable on the energy consumption was deduced. Regression model validation was carried out using the model from the case study and Monte Carlo simulation results. As a simplified solution, the accuracy is acceptable for most of the shapes.

The coefficient of determination demonstrates a good fit for single variable linear regression models. The regression equations for plug load efficiency and lighting efficiency both have an R^2 value close to one. No symmetric dispersion from the fitted line is observed in the figures (see Figures 14 and 15).

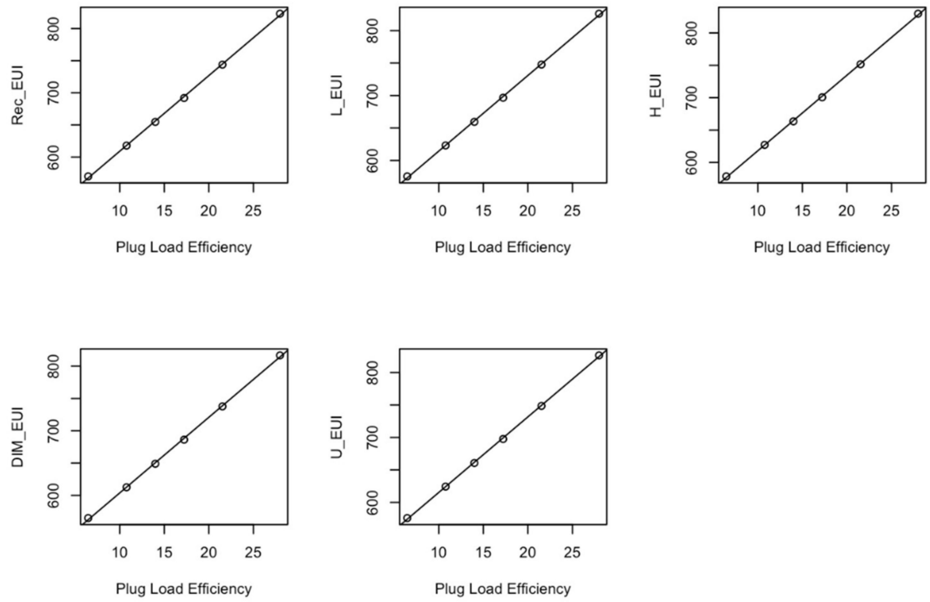

Figure 14. Plug load efficiency fitted line diagrams.

Therefore, it can be predicted from the accuracy of the regression model that simulation formulae for these two variables follow a perfect linear relationship.

The regression model for roof construction also has a high value of the coefficient of determination. The R^2 ranges from 0.998 to 0.999. However, there are several data points found in the graph that are symmetrical about the best-fit line. It can be judged that the values of the coefficients of determination are unreliable due to the nature of how they are calculated (see Figure 16). Therefore, there is a slight discrepancy between the regression model and the actual accuracy.

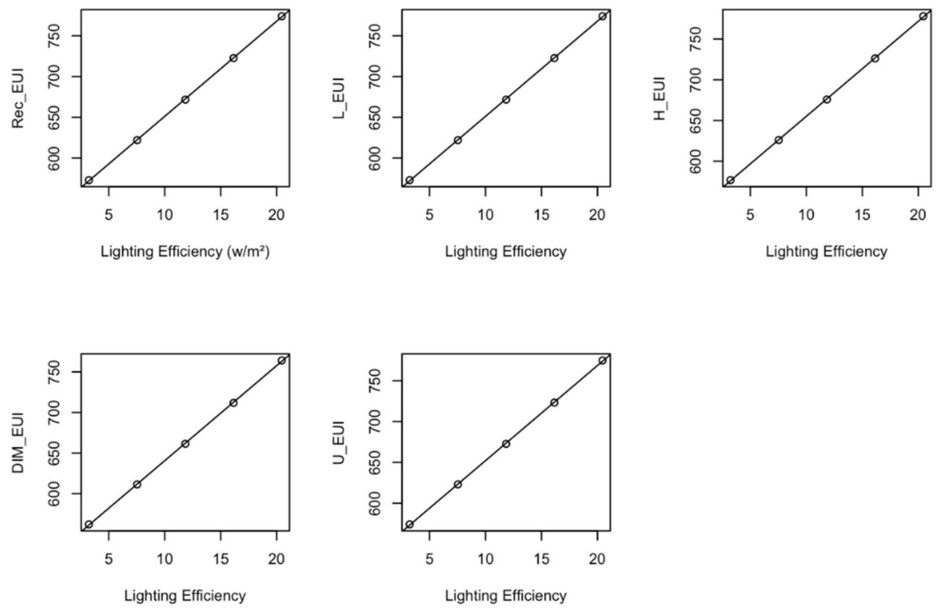

Figure 15. Lighting efficiency fitted line diagrams.

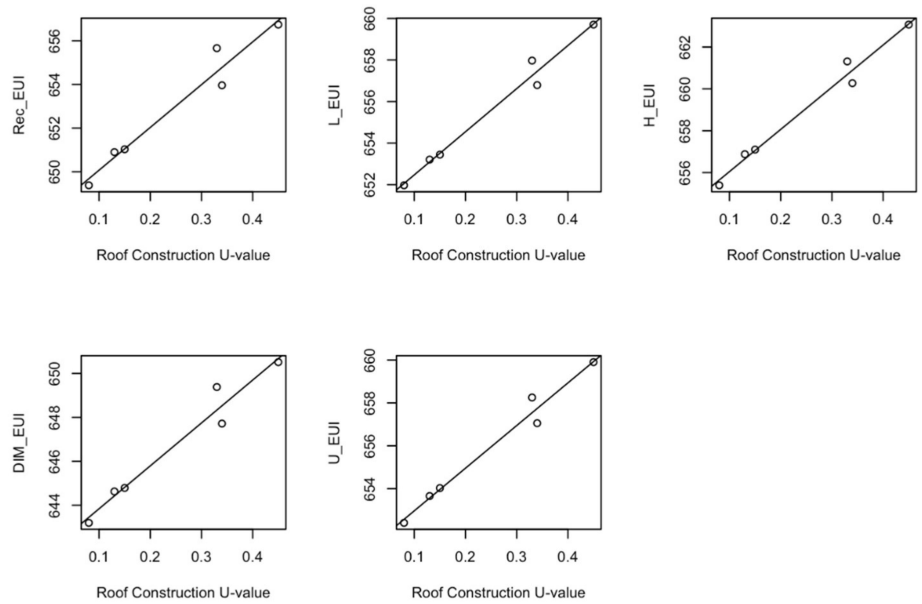

Figure 16. Roof construction fitted line diagrams.

The wall construction regression models have relatively lower R^2 values. The data points are scattered on both sides of the line of best fit but not too discrete, as shown in Figure 17. Overall, the fit of the regression model is good, and the accuracy is reliable.

Notably, the regression equation for infiltration has several data points below the best-fit line (see Figure 18). Even though the model is strongly linear in the interval of study, from the pattern of data point distribution, it can be expected that the entire equation is likely to be non-linear.

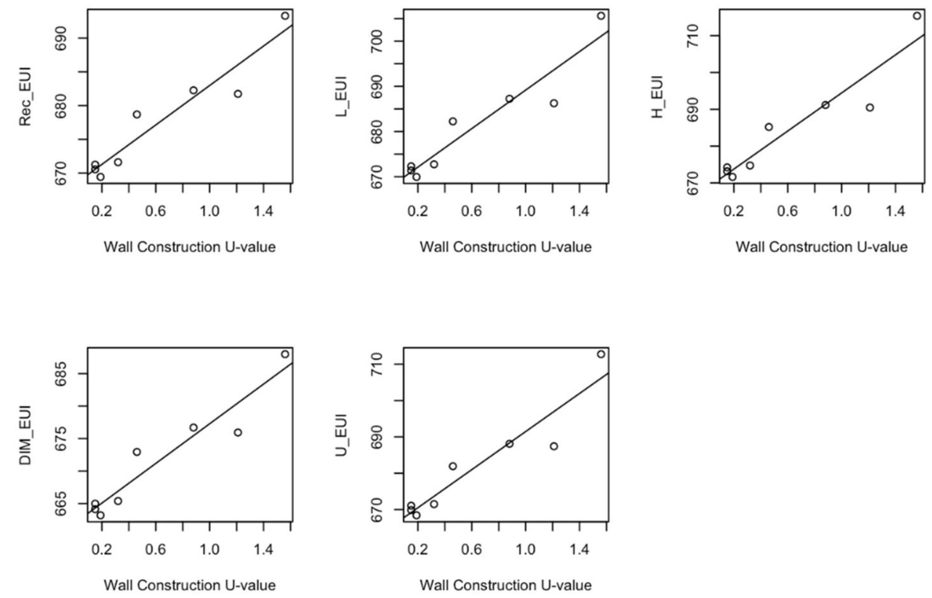

Figure 17. Wall construction fitted line diagrams.

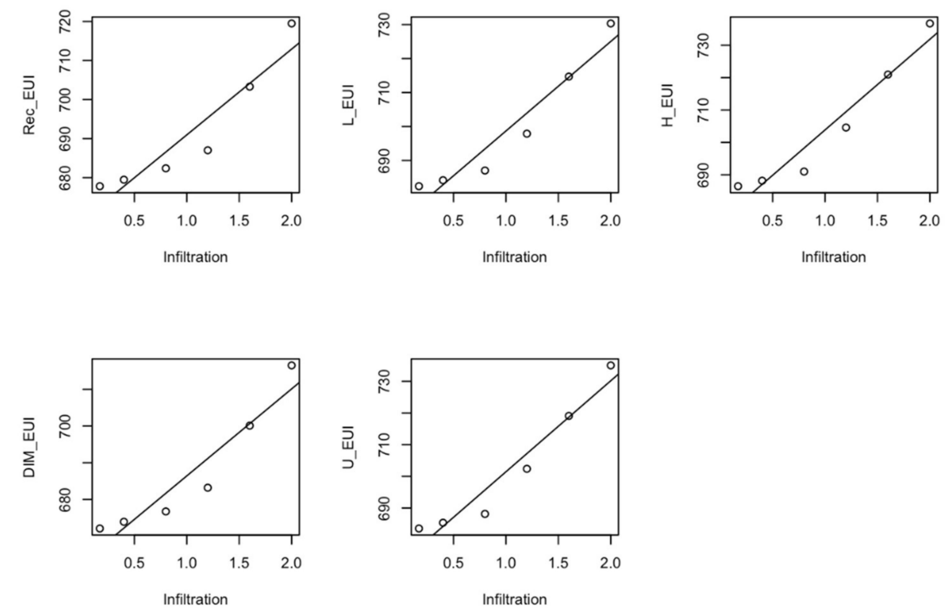

Figure 18. Infiltration fitted line diagrams.

In summary, the five univariate linear regression models developed were all highly accurate. A few characteristics of the data were found not reflected by the R^2 values. The accuracy of the regression model was therefore further validated by the observation of the respective best-fit lines.

Model validation generally meets objectives. Since Monte Carlo simulation was used to create new data sets, the accuracy of validation was ensured.

A significant error was observed in the validation of the diamond shape model. The error ranges between 16% and 25% (see Figure 19).

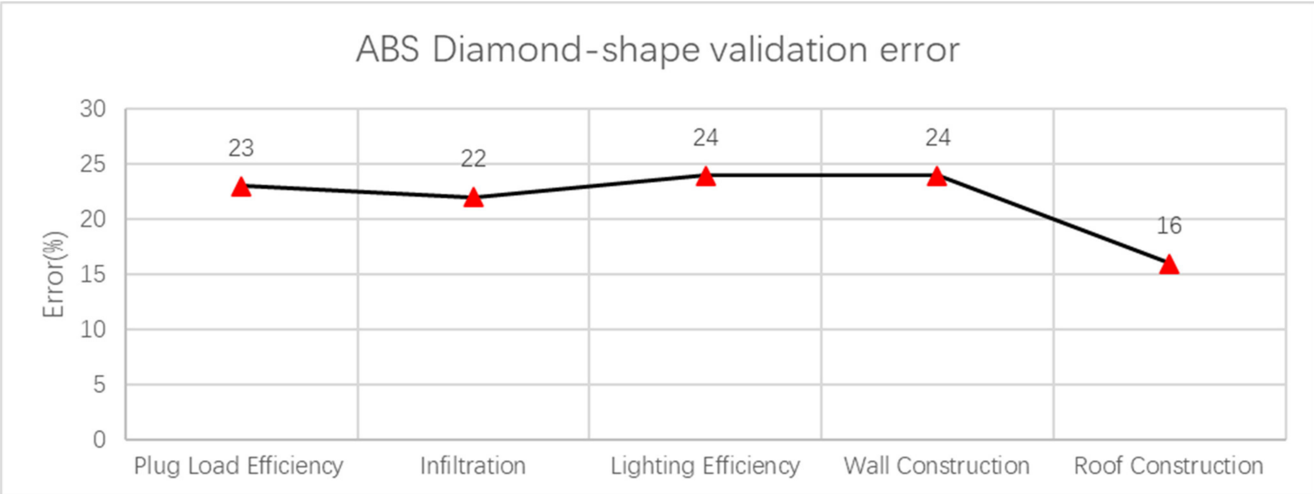

Figure 19. Case study ABS diamond shape error.

To further explore the causes, a series of reviews on the modeling process and data analysis were conducted. Finally, the cause of the error was determined to be the characteristics of the architectural model. The case study model and real building space for the diamond shape are shown in Figures 20 and 21.

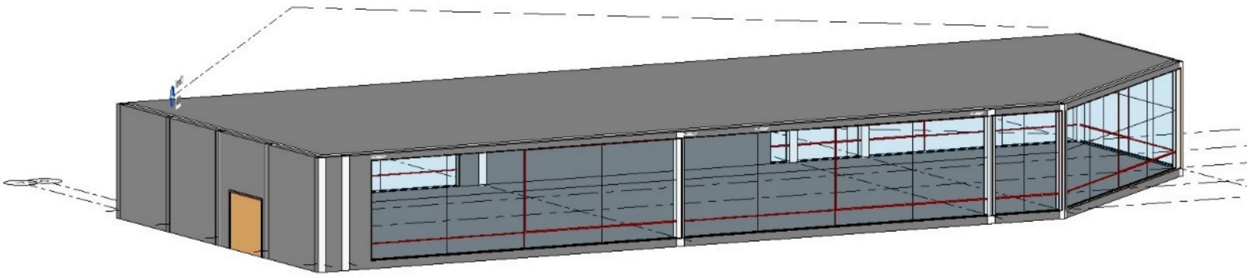

Figure 20. Case Study—ABS diamond shape BIM model.

Figure 21. Case Study—Photo of ABS diamond shape, ground level, learning hub.

The window–wall ratio for the modeled diamond shape is 71%, which is much higher than typical buildings. The large window area causes an increase in energy consumption. In addition, the floor-to-ceiling height is 1000 mm higher than the other shapes. As a result, the model has a large bias. Even though it is not apparent, a phenomenon similar to this is seen in other models. The WWR for the L shape is 26%, resulting in an error of up to 8%. The case study building data were tabulated in the Table 12.

Table 12. Summary of case study building data.

	Floor Area (m^2)	EUI (MJ/m^2/Year)	Floor-to-Ceiling Height (mm)
H shape	2824	671.0	3000
Rectangle shape	440	687.7	3000
L shape	342	646.7	3000
U shape	1119	651.8	3000
Diamond shape	604	829.7	4000

In the process of validating the model, it was confirmed that no significant correlation existed between energy consumption and floor layout. The difference of EUI between the other four validated shapes was not significant.

This section showed a series of simulations and data analyses for the idealized energy model. Limitations identified from the results were discussed, then regression models and equations were demonstrated. The case study model and validation results for the case study indicate the high accuracy of the regression model. An analysis of the errors that occurred in the simulation validation was carried out.

6. Conclusions

The study developed several regression models based on the results of building energy simulations. We highlighted a number of findings of energy modeling related to building energy performance simulation software, particularly Autodesk Green Building Studio. The strengths and limitations of employing BIM software in energy modeling were explored in the article. Based on the simulation results, the influence of design parameter change was confirmed.

The modeling and simulation process is relatively performable. A basic energy model can be built in half an hour. The energy model settings are simplified in Autodesk Revit. However, the running time is long, as simulations are run using a cloud-based service. For idealized conditions, Autodesk GBS conducts simulations based on either building element or conceptual massing element. Simulation results are acquirable, understandable, and workable.

Among the regression models developed, the single variable linear regression models appear to have high accuracy ($R^2 > 0.99$). Although there exist some limitations in applying the equation in EUI prediction, the rough estimation of energy use is realized. Most case study validations obtained error less than 5%, which further verified the feasibility of prediction.

Several issues were found as limitations of this study when carrying out a parametric analysis on building energy performance using the regression approach. Meanwhile, the existing simulation methods and the regression model building process were shown to have great potential for development.

The following suggestions can be made for future research:

- Due to the uncertainty and complexity of real-world models, models that include more significant parameters are recommended.
- The prototype model approach in this study has achieved success to some extent and can be used in future studies.
- Future modeling using BIM software could consider the energy setting and compare the influence of energy setting on the energy performance.
- Life cycle energy cost and other cost-related data generated by GBS can be further explored. A likewise regression analysis can be employed to develop equations.
- Cost-efficient alternatives need to be further identified based on the analysis of life cycle cost for the energy model.
- Due to the impact of COVID, measuring data comparison is not conducted. Acquiring the measured date is essential to improve the accuracy of the energy performance model.
- Further research could compare the current building design with BCA/Green Star regulations.

Author Contributions: Conceptualization, F.T., R.J., J.W. and Y.D.; methodology, F.T., R.J., J.W., Y.D. and S.S.; software, F.T., R.J., J.W. and Y.D.; validation, F.T., R.J., J.W., Y.D. and S.S.; writing—original draft preparation, F.T., R.J., J.W., Y.D. and S.S.; writing—review and editing, F.T., S.S. and H.M.; visualization, F.T., R.J., J.W., Y.D., S.S. and H.M.; supervision, F.T. and S.S.; project administration, F.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: We would like to deeply appreciate the university of Sydney and the University of New South Wales—Sydney to provide a convenient environment to undertake this research.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

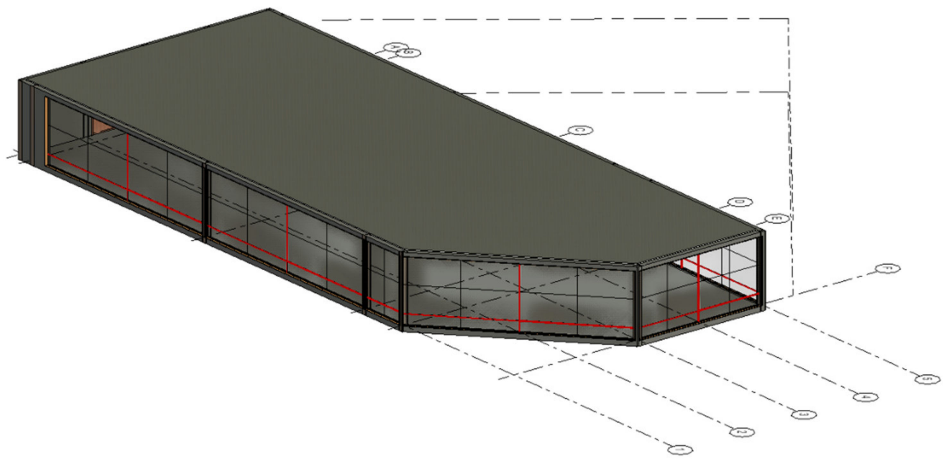

Figure A1. Case Study—Diamond shape BIM model.

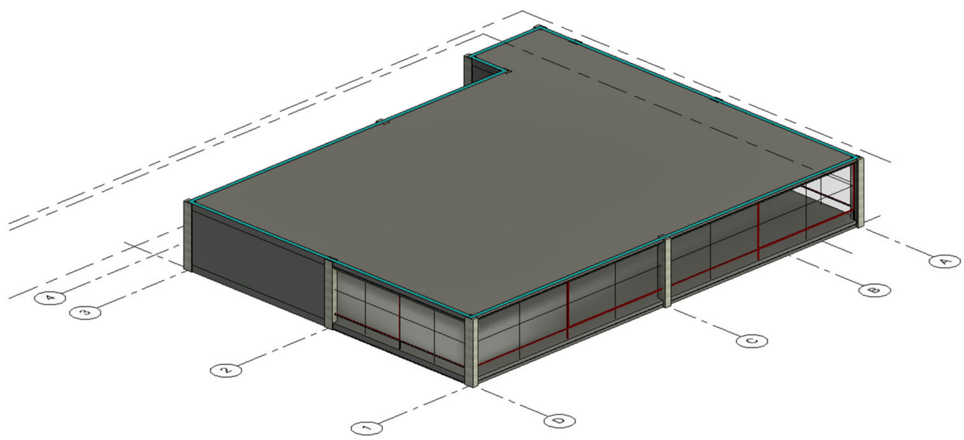

Figure A2. Case Study—L shape BIM model.

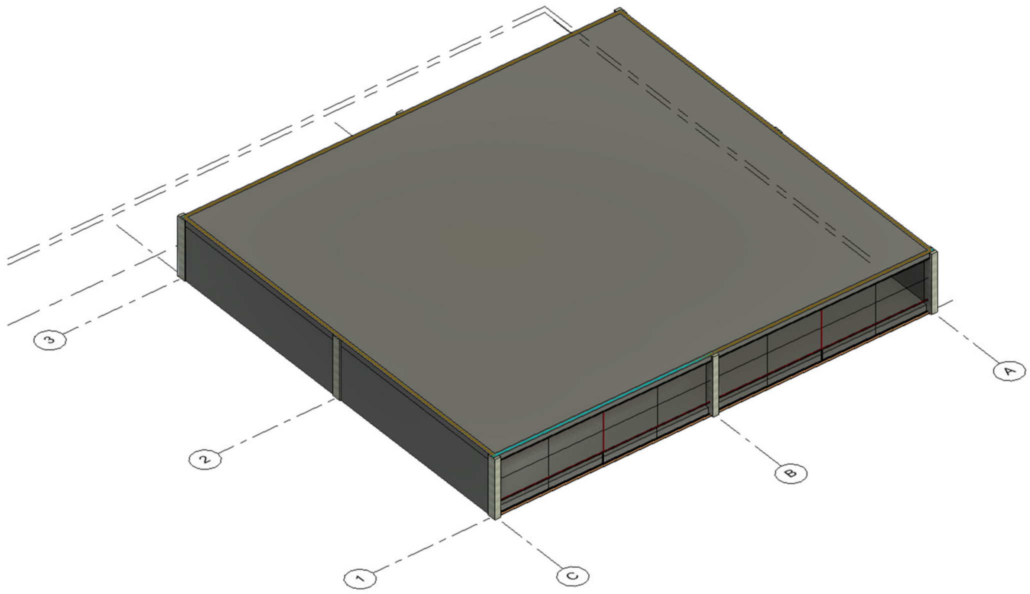

Figure A3. Case Study—Rectangle shape BIM model.

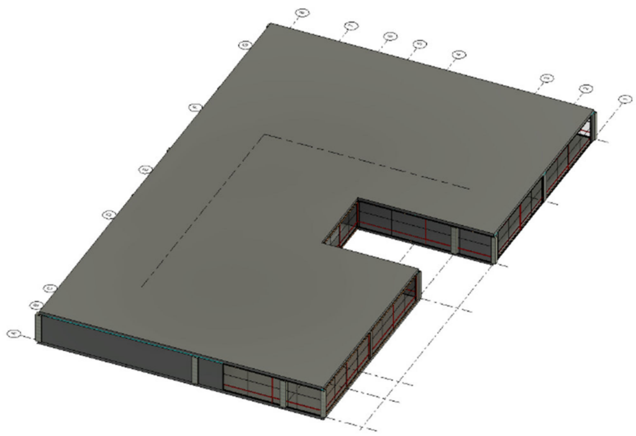

Figure A4. Case Study—U shape BIM model.

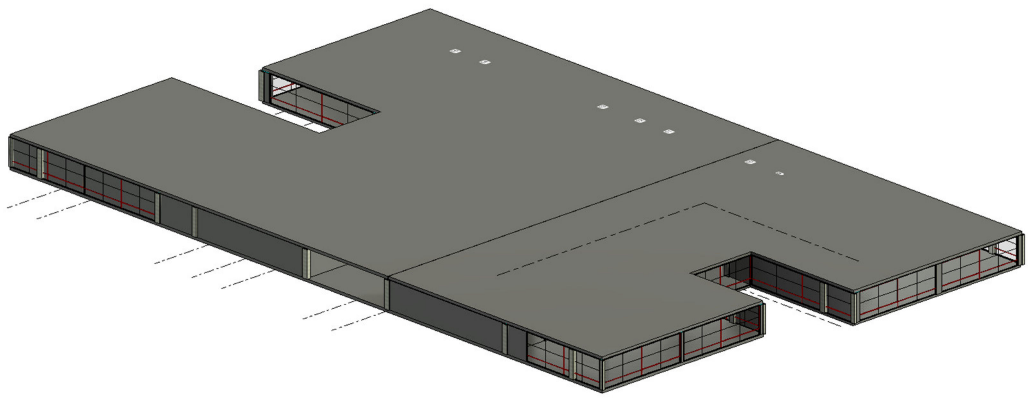

Figure A5. Case Study—H shape BIM model.

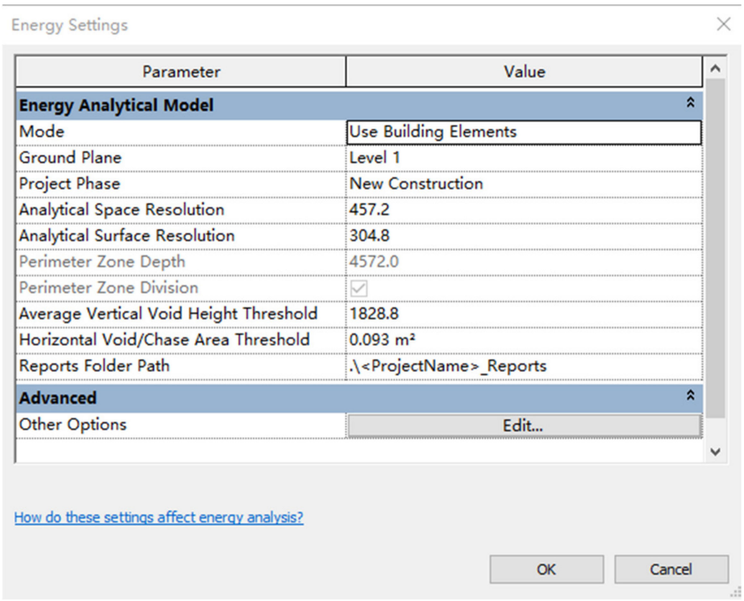

Figure A6. Case Study—Energy setting in BIM.

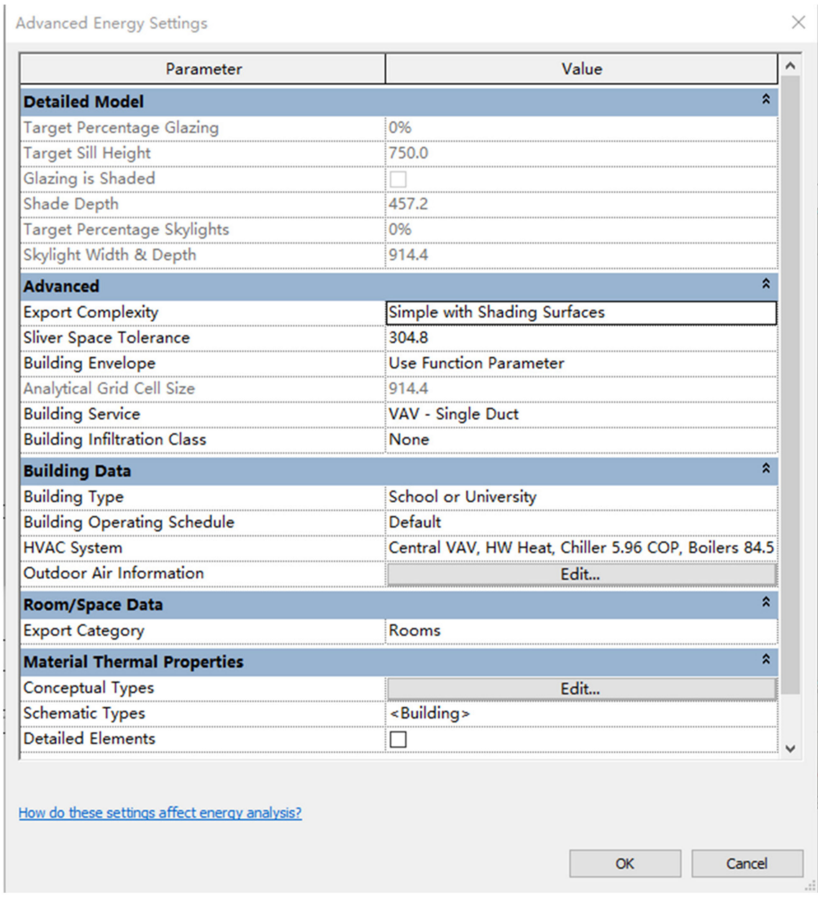

Figure A7. Case Study—Advanced Energy setting in BIM.

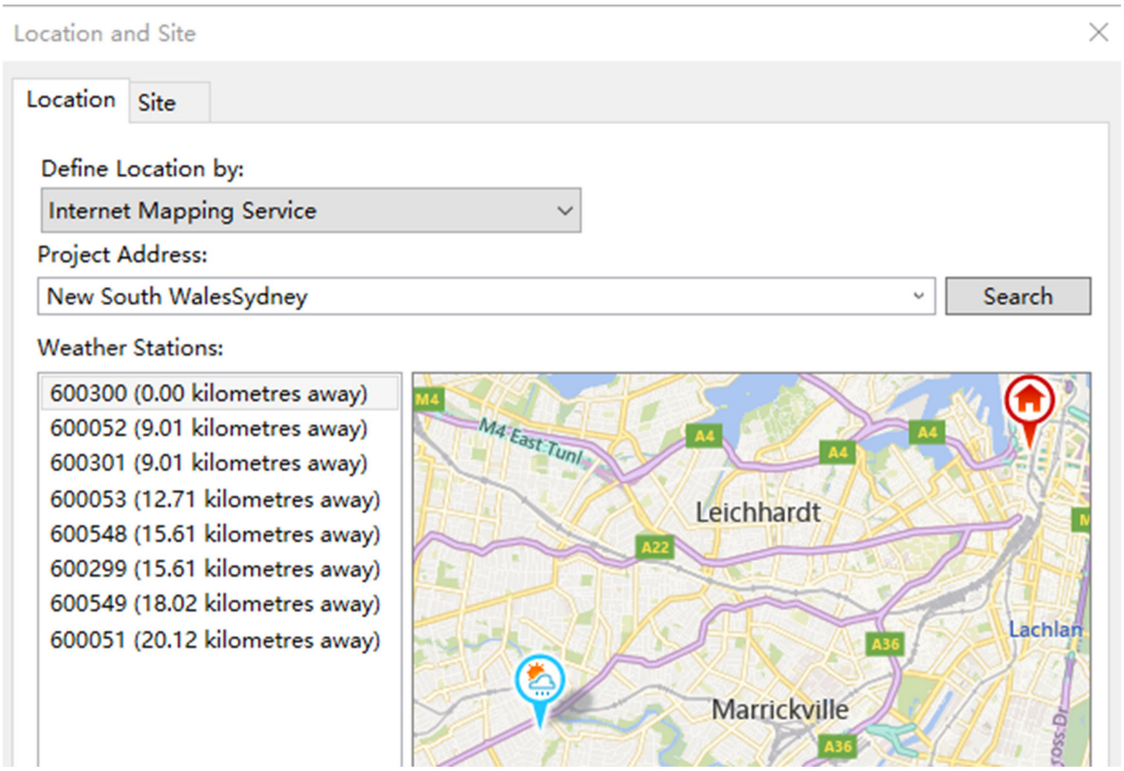

Figure A8. Case Study—Location setting in BIM.

Name	Floor Area (m²)	Energy Use Intensity (MJ/m²/year)	Electric Cost (/kWh)	Fuel Cost (/MJ)	Total Annual Cost[1] Electric	Total Annual Cost[1] Fuel	Total Annual Cost[1] Energy	Total Annual Energy[1] Electric (kWh)	Total Annual Energy[1] Fuel (MJ)	Carbon Emissions (Mg)	Compare	Potential Energy Savings
Project Default Utility Rates												
Project Default Utility Rates	--	--	$0.06	$0.007	--	--	--	--	--	--		
Base Run												
Shape1_Rect	100	679.5	$0.06	$0.007	$849	$132	$982	13,923	17,823	--		
Alternate Run(s) of Shape1_Rect												
Shape1_Rect_ASHRAE 90.1-2010	100	676.4	$0.06	$0.007	$851	$130	$980	13,945	17,437	--		
WWR - Northern Walls_95% -- Window Shades - North_No change -- Window Glass Types - North_No change	100	700.5	$0.06	$0.007	$893	$129	$1,022	14,637	17,358	--		
WWR - Northern Walls_95% -- Window Shades - North_No change -- Window Glass Types - North_Sgl Clr	100	774.7	$0.06	$0.007	$1,011	$132	$1,143	16,570	17,814	--		

Figure A9. Revit 2022. (2021). Autodesk. Insight. (2021). Autodesk. Green Building Studio. (2021). Autodesk.

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