



## EVALUATION OF THE VALIDATION METHODS OF SUMMER HEAT PROTECTION CALCULATIONS IN GERMANY

Luis Enrique Sanchez Vazquez<sup>1\*</sup>, Max Bachmann<sup>1</sup>, Arda Karasu<sup>2</sup>, Martin Kriegel<sup>1</sup>,  
Claus Steffan<sup>2</sup>

<sup>1</sup> Chair of Building Energy Systems (Hermann-Rietschel-Institute), Technical University of Berlin

<sup>2</sup> Chair of Building Technology and Architectural Design, Technical University of Berlin

\* corresponding author: [l.sanchezvazquez@tu-berlin.de](mailto:l.sanchezvazquez@tu-berlin.de)

### Abstract

All new and renovated buildings must comply with the verification of summer heat protection as stated in DIN 4108-2, according to the Building Energy Act (GEG). The solar gain factor (simplified method) and dynamic simulation are the two approaches now in use. Using a data set of 10,000 configurations generated in IDA ICE, the accuracy of the simplified method was determined in this study. Following that, three different regression models were performed on the data set with the aim of generating a model that better represented the dynamic simulation findings. The results demonstrate that the simplified method can improve accuracy on this data set, however the boundary conditions must be adjusted to increase representation of real buildings.

### Introduction

The University Campus Berlin-Charlottenburg (HCBC) is undergoing building renovations, as described in a previous publication (Inderfurth, et al., 2017), and several new buildings will be added to the campus. A research project funded by the German Federal Ministry of Economics and Climate Protection is currently evaluating energy-efficiency and thermal comfort proofing methods for new buildings.

In summer, high solar radiation can be expected, which directly affects the energy balance of buildings. Furthermore, this effect is intensified by global warming. Planning that ignores these factors can lead to high indoor temperatures that cause discomfort and require additional energy consumption.

Proof of summer heat protection is required for newly constructed residential and non-residential buildings. The Building Energy Act (GEG) formulates the requirements for this in five points in § 14 and refers to DIN 4108-2 Part 8 for the methods to be used. The results of a simplified method or a dynamic simulation are recognized as proof of summer heat protection.

In the simplified method, the critical room's expected solar gain factor ( $s_{\text{vorth}}$ ) must be lower than a limit value

( $s_{\text{zul}}$ ), which depends on envelope properties, climate region, orientation, windows and ventilation rate. The convenience to have a simplified method is clear because it is a quick and easy calculation that can be applied by a user without access to specialized software.

Alternatively, the over-temperature degree hours (OTDH), in Kh/a, are used to evaluate the dynamic simulation with a maximum acceptable value of 1,200 Kh/a for residential and 500 Kh/a for non-residential buildings. For this, the reference temperature is determined by the location climate.

Dynamic simulations allow tracking of other indicators that can be used to evaluate comfort, such as Predicted Percentage Dissatisfied (PPD) and indoor air quality. It also gives insight into the impact of variables including control methods, heat storage capacity, and weather. As stated in prior articles, (Freudenberg and Budny, 2022, Hoffmann and Ganji Kheybari, 2021, Elsharkawy and Zahiri, 2020) the boundary conditions given in the norm DIN4108-2 for dynamic simulations are restrictive and do not represent the operation conditions of different room uses, especially in non-residential buildings. Nevertheless, for this study the normative boundary conditions are followed.

The verification results from both methods are expected to give the same conclusions for any given scenario. This is not always the case and was observed in a previous publication (Sanchez Vazquez, et.al., 2022) in which a north oriented room has a positive outcome from the simplified method, but the dynamic simulation calculates OTDH above the limit value. For this reason, the classification accuracy of the simplified method is calculated and compared to alternative regression models using a dataset created in IDA ICE with 10,000 unique energy models.

### Methodology

The workflow of this paper is shown in Figure 1, it consists of two different sections. First, the evaluation of the methods in DIN4108-2 using a dataset from a

parametric Monte-Carlo (MC) simulation in IDA ICE. The OTDH are obtain directly from the simulated models. Parallely the input parameters for the energy models are evaluated using the simplified method.

In the second section, the dataset is used to train and evaluate three different regression models that predict OTDH using the same input parameters as the energy models.

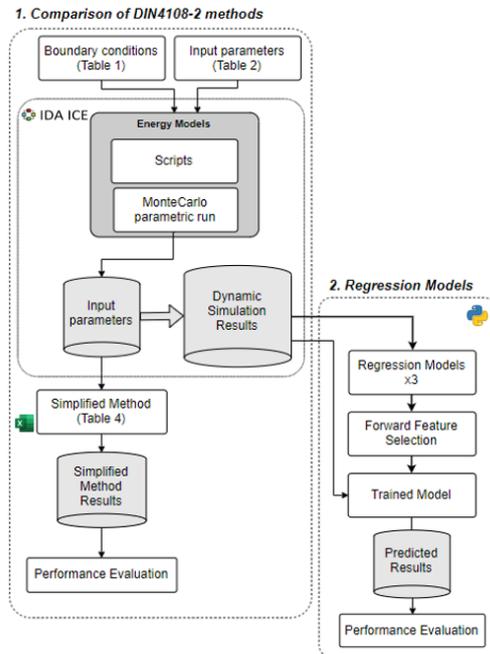


Figure 1. Workflow

### Energy Models

#### Boundary conditions

The reference energy model for this study is part of a non-residential building in Berlin, Germany and was built following the normative boundary conditions in DIN4108-2, as shown in Table 1.

Table 1: Boundary conditions.

DIN4108-2 (8.4.2)	Parameter	Value
a	Simulation Environment	IDA ICE
b	Building type	Non-residential
	Operation time	Monday-Friday 7:00 - 18:00 hrs.
c	Climate Region	B - TRY Zone 4 (2011)
d	Simulation period	1 complete year. Starting on Monday 01/Jan at 00:00hrs
e	Internal heat gains	144 Wh/(m <sup>2</sup> d)
f	Temperature Set point	21°C
g	Ventilation rate	Basic
j	Shading Control	150 W/m <sup>2</sup> (N, NW and NE) 200 W/m <sup>2</sup> (Other orientations)

The simulation environment for the analysis is IDA ICE, which has participated in the SIMQuality test series. The climate file used is the Test Reference Year (TRY) Zone 4 – Potsdam from the Deutscher Wetterdienst (DWD - 2011).

Because the other strategies proposed in DIN4108-2 (increased ventilation and night ventilation) cannot be guaranteed in practice without mechanical ventilation and advanced control, only the basic rate was studied.

For the evaluation of results, the allowed OTDH is 500 Kh/a at a reference temperature of 26°C.

#### Energy model input parameters

The input parameters for the energy models in the dataset are shown in Table 2.

Table 2: Input Parameters

Parameter	Var	Units	Range	
<b>Envelope</b>				
Density	$\rho$	kg / m <sup>3</sup>	250	2000
Specific Heat	c	J / kg K	525	2100
Thermal Conductivity	$\lambda$	W / m K	0.075	0.3
Thermal Resistivity	R	m <sup>2</sup> K / W	3	10
<b>Transparent Surfaces</b>				
Window to wall ratio	$f_{ww}$	-	0	1
g-value	g	-	0.2	1
Shading factor	Fc	-	0.2	1
<b>Geometry</b>				
Room height	h	m	2	6
Ground floor area	A <sub>G</sub>	m <sup>2</sup>	16	100
Orientation	O	°	0	360

The envelope category focuses on the room's external wall (simplified one-layer model). The material's density ( $\rho$ ) and specific heat (c) define the type of construction (light, medium or heavy) and the heat transfer coefficient is calculated with the thermal conductivity ( $\lambda$ ) and resistivity (R) of the material.

For the transparent surfaces the same variables currently used in the norm are taken: The window to wall area ratio ( $f_{ww}$ ), the solar heat gain coefficient (g) and shading factor (Fc).

For the geometry, ten different floor configurations (A<sub>G</sub>) were studied ranging between 16 and 100 m<sup>2</sup>, as Shown in Figure 2. The room height (h) ranges from 2m to 6m and the orientation (O) was also defined as variable.

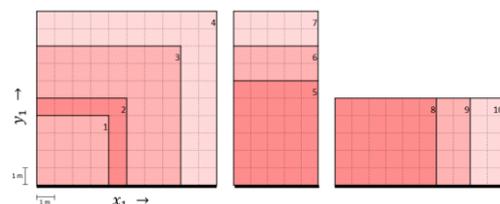


Figure 2. Ground floor areas studied

## Models scripting

Currently, IDA ICE offers the option to perform the solar heat protection analysis according to the norm DIN4108-2 in its German localization package. Nevertheless, the energy models for the dataset were created using graphical scripts. 7 scripts were used in IDA ICE to guarantee that all the models respect the boundary conditions.

## Envelope

### 1. Type of construction:

For the simplified method is important to determine in which category the model is classified. According to the external wall properties and the ground floor area, each model is classified as Light (L), Medium (M) or Heavy (S) construction.

### 2. External wall thickness:

Using the reference building principles in GEG, the U-value for the external wall is controlled to be  $\leq 0.28 \text{ W/m}^2\text{K}$ .

$$U = \frac{1}{R_{si} + \sum R + R_{se}} \left[ \frac{W}{m^2K} \right] \quad (1)$$

Using  $R_{si}$  and  $R_{se}$  from DIN-EN-ISO-6946:2008-04, the thermal resistivity can be expressed as:

$$R = \frac{d}{\lambda} > 3,4 \left[ \frac{m^2K}{W} \right] \quad (2)$$

The external wall thickness is calculated using the thermal resistance and thermal conductivity of the wall.

$$d = R\lambda[m] \quad (3)$$

## Transparent Surfaces

### 3. Window dimensions:

For all the models, the window and the external wall are concentric, and its dimensions depends on the Window-wall-ratio ( $f_{ww}$ ).

### 4. Window transmittance:

The fraction of incident radiation that passes the glazing as direct radiation is defined as 80 % of the total value of solar heat gain coefficient for all the models.

### 5. Shading control:

All models have a radiation-dependent control as shown in Table 1. Here, orientations relative to the north between  $67.5^\circ$  (ENE) and  $292.5^\circ$  (WNW) are considered as "other orientations".

## Geometry

### 7. Internal gains:

In function of the ground area, the internal gains ( $144 \text{ Wh/m}^2$ ) are calculated and distributed among the operation time. The internal gains are assumed to be constant during this period.

### 8. Ventilation rate:

All the models use the basic ventilation rate given in DIN4108-2, which is defined as:

$$n_{day} = 4 \left( \frac{A_G}{V} \right) [h^{-1}] \quad (4)$$

$$n_{night} = 0.24 [h^{-1}] \quad (5)$$

## Dataset

To optimize the creation of energy models, the parametric Monte-Carlo (MC) run included in IDA ICE was used. MC is a mathematical technique that allows data-driven decisions to be made. In this parametric study, a sample is created by assigning random values within the defined range of input parameters. The models are then created and simulated to obtain the OTDH for each scenario. A total of 10,000 models were used in this study.

Table 3 shows the Pearson correlation between the model parameters used and the over-temperature degree hours (OTDH). There is no correlation between the variables themselves, as the values were assigned randomly, but a strong correlation can be seen between the OTDH and the two parameters from the transparent surfaces: g-value and window to wall ratio ( $f_{ww}$ ). This is expected as the solar radiation has a high impact on the overheating during summertime.

Table 3: Correlation of input parameters and OTDH

Category	Parameter		Pearson correlation
Transparent Surfaces	Window to wall ratio	$f_{ww}$	0.61
Transparent Surfaces	g-value	g	0.58
Transparent Surfaces	Shading factor	$F_c$	0.14
Geometry	Room height	h	0.12
Envelope	Specific Heat	c	0
Envelope	Density	$\rho$	-0.01
Envelope	U-Value	( $\lambda$ , R)	-0.02
Geometry	Orientation	O	-0.02
Geometry	Ground_area	$A_G$	-0.11

## Evaluation of DIN4108-2 simplified method

The simplified method was conducted for each of the energy models in the dataset, the outcome classifies the models into "satisfactory" or "unsatisfactory" according to the evaluation of the  $S_{vorh}$  and  $S_{zul}$ . Table 4 shows the parameters used for this calculation.

To compare the normative methods a confusion matrix can be used. Each energy model in the dataset is labelled "True" if the conclusion from the simplified method matches the dynamic simulation, or "False" if the conclusions are different. The classification accuracy was obtained using:

$$ACC = \frac{TS+TU}{TS+TU+FU+FS} \quad (6)$$

and for the Satisfactory precision (positive predicted value):

$$PPV = \frac{TS}{TS+FS} \quad (7)$$

Where:

- TS = Number of True Satisfactory models
- TU = Number of True Unsatisfactory models
- FU = Number of False Unsatisfactory models
- FS = Number of False Satisfactory models

Table 4: Parameters used in the simplified method

Solar heat coefficient ( $S_{vorh}$ )			
Window Area	$A_W$	$m^2$	Variable
g-value	g	-	Variable
Shading Factor	$F_c$	-	Variable
Ground Area	$A_G$	$m^2$	Variable
Admissible Value ( $S_{zul}$ )			
Type of building	-	-	Non-Residential
Climate Region	-	-	Berlin, Germany (Zone B)
Type of construction	-	-	Variable
Night Ventilation	-	-	Without
Window to wall Ratio	$f_{WW}$	-	Variable
g-value	g	-	Variable
Window inclination	$f_{neig}$	-	0
Orientation	$f_{nord}$	-	Variable

### Regression Models

The dataset created in the previous section is used to generate an equation that estimates the OTDH as a function of the input model parameters, and thus the classification of the model. For this, the library sklearn was used in Python.

The dataset was divided into training data (80%) and testing data (20%) and 3 different expressions were considered for the regressions.

1. Model 1: Linear

$$y = b_0 + b_1x_1 + b_2x_2 + \dots \quad (9)$$

2. Model 2: Squared Parameters

$$y = b_0 + b_1x_1 + b_2x_1^2 + b_3x_2 + b_4x_2^2 + \dots \quad (10)$$

3. Model 3: Products

$$y = b_0 + b_1x_1 + b_2x_1^2 + b_3x_2 + b_4x_2^2 + b_5x_1x_2 + \dots \quad (11)$$

Where:

- $y$  = estimated OTDH [Kh/a]
- $b_i$  = model coefficient
- $x_i$  = input parameter

Model 1 has a total of 9 features, one for each model parameter. For Model 2 the squared value of the parameters is added into the equation, with a total of 19 features. Model 3 additionally takes into consideration the product of 2 parameters (all the possible combinations), with a total of 37 features.

### Feature Selection

To reduce the complexity of the proposed regressions a step forward feature selection was implemented. In a similar way, this methodology is used by EVO IPMVP to create the energy performance baseline of a building (EVO, 2019). The selection is an iterative methodology that test the statistical performance of each feature, selecting the best and keeping it for the next iteration. In this way, only the most important features are used.

### Performance Evaluation metrics

The model's performance ( $r^2$ ) is directly obtained in the feature selection process. Additionally, the root mean squared error (RMSE) was also studied. At the same time, the regression models were evaluated as classifiers. This means that the predicted OTDH were used to label each energy model as "Satisfactory" or "Unsatisfactory" and the classification accuracy (ACC) and satisfactory-precision (PPV) were obtained using the equations 6 and 7, respectively.

### Results.

Following the structure of the work, the results are presented in two sections. First the comparison between the methods in DIN4108-2, shown in Figure 6, and in the second section the performance of the regression models.

#### Performance of simplified method

Figure 6-a shows the dynamic simulation results. According to the findings, 25% of the energy models in the dataset will meet the requirements to avoid overheating during summer. This means, the OTDH are lower than 500 Kh/a. On the right, the distribution of the results shows a minimum value of 0 Kh/a, a maximum of 1,870 Kh/a, and an average of 820 Kh/a.

Figure 6-b shows that 39% of the dataset meets the verification criteria using the simplified method. This means that the simplified method is more optimistic and zones with OTDH above the limit are classified as Satisfactory. On the right, the correlation between the calculated solar heat gain coefficient ( $S_{vorh}$ ) and the admissible value ( $S_{zul}$ ) is shown. In this figure, two clusters that represent the room orientation are observed. The north-facing rooms are part of the right cluster and have a greater chance of being classified as "satisfactory" than the other orientations (left cluster).

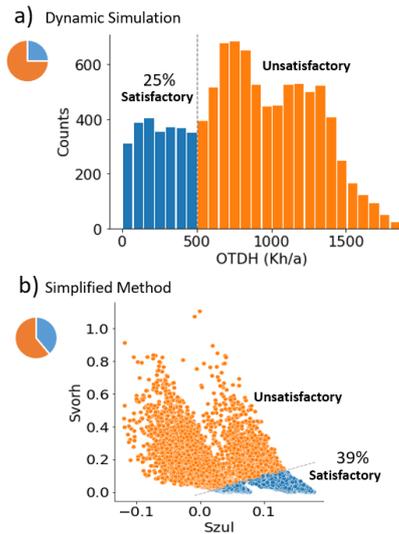


Figure 6. Standard methods comparison

### Classification accuracy

The confusion matrix is shown in Figure 7. On the vertical axis the results from the dynamic-thermal simulations and the horizontal axis represents the simplified method. The most critical energy models are the “False-Satisfactory”, represented in the top-right corner of the matrix. These models get a positive outcome from the simplified method, but the simulation shows OTDH above the admissible value (500 Kh/a). The classification accuracy for the simplified method in DIN4108-2 (in this specific dataset) is 84% and its Satisfactory precision is 61%

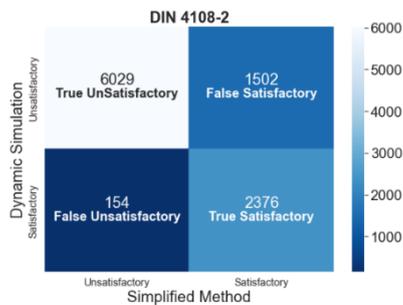


Figure 7: Confusion Matrix, Simplified method (complete Dataset)

### Regression Models evaluation

#### Model 1: Linear

Table 5 shows the order in which the features were selected using a simple linear regression.

The transparent surfaces features have the highest correlation to the OTDH (as shown in Table 3). The window to wall ratio ( $f_{ww}$ ) is the first feature selected, followed by g-value (g), shading factor ( $F_c$ ) and the ground area ( $A_G$ ). These features can also be found in the solar gain factor ( $s_{vorh}$ ) used in the simplified method in DIN4108-2. The performance of Model 1

reaches a maximum of  $r^2 = 0.75$  with just 5 features, after adding room height (h). This means that the last four features do not provide relevant information to predict OTDH.

Table 5: Feature selection, Linear

Parameter	Category	$r^2$
$f_{ww}$	TS	0.37
G	TS	0.7
$F_c$	TS	0.72
$A_G$	G	0.74
H	G	0.75
U	E	0.75
C	E	0.75
O	G	0.75
$\rho$	E	0.75

The confusion matrix (Figure 8) was obtained using the test set and shows that the classification accuracy for the linear regression model, in this specific dataset, is 88% and the Satisfactory precision is 83%

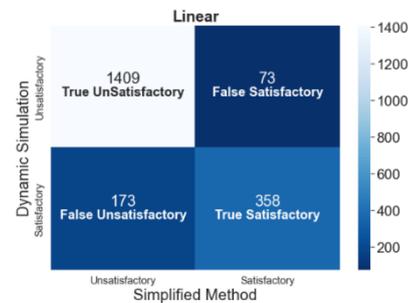


Figure 8: Confusion Matrix, Linear (test set)

#### Model 2: Squared features

In the second model the squared components for each variable were added, resulting in total 19 features. Table 6 shows the selection order. The performance of this model gets stable at  $r^2 = 0.9$  with 9 features.

Table 6: Feature selection, Model 2.

Parameter	Category	$r^2$
$f_{ww}$	TS	0.37
G	TS	0.7
$f_{ww}^2$	TS	0.76
$F_c$	TS	0.78
$g^2$	TS	0.80
$A_G$	G	0.81
h	G	0.82
$O^2$	G	0.83
O	G	0.90

The transparent surfaces are again predominant in the regression, adding the squared component of the window to wall ratio and g-value before the geometry properties of the room. The envelope properties do not have contribution in this model.

The confusion matrix (Figure 9) shows, that the classification accuracy for the squared-features regression model is 93% and the Satisfactory precision is 94%

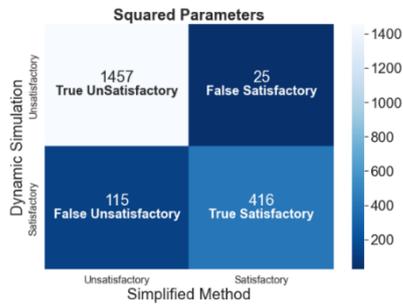


Figure 9: Confusion Matrix, Squared features

### Model 3: Products

For the model 3, the combination effect of 2 variables is added, resulting in a total of 37 possible features to use. Table 7 shows the selection order until the performance stabilizes at  $r^2 = 0.91$  with 12 features. In this regression the first feature to be added is the window to wall ratio multiplied by the g-value, followed by the  $g_{Total}$  ( $g * Fc$ ). The performance of this model increases faster but needs extra features to reach the stability.

Table 7: Feature selection, Model 3.

Parameter (s)	Category	$r^2$
$g, f_{ww}$	TS-TS	0.66
$g, Fc$	TS-TS	0.71
$h, g$	G-TS	0.72
$f_{ww}$	TS	0.74
$f_{ww}^2$	TS	0.8
$O^2$	G	0.81
$O$	G	0.81
$g$	TS	0.88
$h, A_G$	G-G	0.89
$Fc$	TS	0.9
$g^2$	TS	0.9
$g, A_G$	TS-G	0.91

The confusion matrix (Figure 10) shows, that the classification accuracy for the third regression model is 94% and the Satisfactory precision is 91%

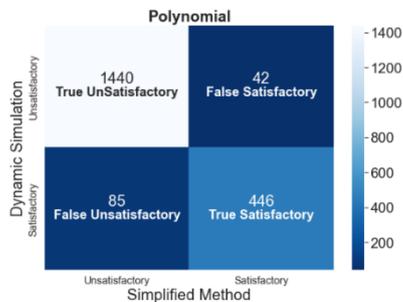


Figure 10: Confusion Matrix, Products

### Summary

The results show that the regressions proposed have a good performance ranging between  $r^2 = 0.75$  to  $0.91$ . Additionally, the classification accuracy (ACC) for this dataset can be improved from 85 % to 94 % and the satisfaction precision (PPV) can be increased from 66 % up to 94 %.

Table 8: Results.

	Classifier		Regression	
	ACC	PPV	$r^2$	RMSE (Kh/a)
Simplified method DIN4108-2	0.85	0.66	-	-
Model 1: Linear	0.88	0.83	0.75	214.8
Model 2: Squared features	0.93	0.94	0.90	134.8
Model 3: Products	0.94	0.91	0.91	127.9

### Discussion

Dynamic simulations consider the effects of crucial factors for overheating such as the effect of climate, orientation and shading control. This is important as it hints what is happening inside the studied zone. They also serve as a reference for evaluating strategies to improve performance. For example, by reducing the transitivity of the glass in the windows or by adding control strategies. At the same time, the simplified method should replicate the simulation results without the need of specialized skills.

The accuracy and replicability of the results given by simulation highly depend on how well the model represents the building's operation, the software used for simulation and the assumptions made for the operation of the building. In this paper the dataset was created following the boundary conditions in DIN4108-2, the variables were defined with Monte-Carlo and the energy models implemented in IDA ICE. To increase the dataset potential to be used as reference for validation, the degrees of freedom of the system must include other important factors like the occupancy profiles and ventilation rates.

According to the outputs, the DIN4108-2 simplified method shows low accuracy and precision in comparison with the regression models analysed. With a satisfactory-precision of 56% in this dataset, almost half of the satisfactory cases given by the simplified method are underestimated and the risk of approving a room that eventually will overheat is high.

When it comes to using regression models as a simplified method, they can not only classify the studied area but also show the expected OTDH. This can be used to make early-stage decisions.

Model 2 (squared features) shows the best performance. Using only 9 features, the dataset can be reproduced with a coefficient of determination of  $r^2 = 0.9$  and a satisfactory precision of 0.93. This

means, that only 7% of the models classified as satisfactory are wrong.

Using feature selection allows to detect the critical parameters that describe the dataset. This approach is planned to be used in future works to evaluate the sensitivity to other parameters such as occupancy profiles and ventilation rates. In this way looking to create a validated sample with real building information.

## Conclusion

Dynamic simulations show a detailed picture of a building's energy balance. They can combine the effects of multiple factors that have a direct impact on the building's energy consumption and thermal comfort. As a result, they are ideal for operational verification and evaluation of metrics like energy consumption, PPD and OTDH. However, the energy model must accurately reflect the building's expected operation. This is determined by the boundary conditions and standard values chosen for the energy models, particularly in the case of new buildings, where there is no operational data to use for calibration.

Apart from that, the importance of a simplified evaluation option lies in its ease of implementation. During the planning stage, it saves time and resources. For this, precision and accuracy are essential to avoid certifying buildings that will be affected during operation by overheating or other effects that cause discomfort and/or increase the estimated energy consumption.

Getting a simplified method that represent all possible scenarios implies a difficult task due to the large number of factors that play a key role in predicting building behaviour. However, it is possible to create a sample of energy models by defining the boundary conditions and giving the input variables a range. Then using regressions, get a simple equation that describes the simulations outcome.

This method could be used for evaluation of different parameters that describe the comfort and energy use of the dataset.

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