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Identifying Key Parameters in Building Energy Models: Sensitivity Analysis Applied to Residential Typologies

Sofía Gervaz * and Federico Favre

Instituto de Ingeniería Mecánica y Producción Industrial, Facultad de Ingeniería, Universidad de la República de Uruguay, Montevideo 11300, Uruguay; ffavre@fing.edu.uy
* Correspondence: sofiag@fing.edu.uy

Abstract: Building energy modeling tools play a crucial role in quantifying and understanding the energy performance of buildings. These tools require substantial amounts of data, which can be challenging to obtain and are often associated with significant uncertainties. The incorporation of sensitivity analysis is a crucial step toward developing reliable models as it identifies the most critical parameters that require meticulous characterization. In this study, a sensitivity analysis based on the Morris method was conducted to assess the relevance of 14 input parameters affecting thermal loads across four dwelling typologies modeled in EnergyPlus. Different numbers of Morris trajectories and levels were considered to analyze the impact of the user-defined values of r and p when employing the Morris method. Convergence was achieved at $r = 200$ and $p = 12$, which are higher than the typically employed values ($r = 10$ and $p = 4$). Roof solar absorptivity, setpoint temperatures, orientation, and the roof conductance rank among the top five most influential parameters affecting thermal loads in all four of the studied typologies. Occupancy was also among the top five most relevant parameters in three of the four typologies.

Keywords: building energy model; sensitivity analysis; building simulation

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1. Introduction

Given the significant contribution of buildings to global energy consumption, there is increasing interest in quantifying and understanding their energy performance. Within this context, the use of building energy model (BEM) tools has become increasingly popular in evaluating and assessing building energy performance [1–4]. These tools are usually data-intensive, and the information needed to develop reliable models is difficult to obtain and is often subject to significant uncertainties [5,6]. This lack of information often leads to large mismatches between measured and simulated output data [7]. Therefore, for BEM tools to be employed with confidence, it is necessary for the models to be calibrated to represent the actual behavior of the building under study [8].

As pointed out by Reddy et al. [9], standardized methods for calibrating BEMs involve defining a set of influential parameters. In this regard, the use of sensitivity analysis (SA) techniques can be useful for improving the understanding of the relationship between model inputs and outputs, as well as for determining the most relevant parameters affecting building thermal performance [3,10]. Thus, a SA of BEM input parameters represents an important step in the model calibration process, thereby increasing confidence in the model results [6].

The methods for SA applied in BEM can be divided into local and global approaches. Sensitivity measures in local sensitivity analysis (LSA) are calculated by changing one parameter while keeping the others constant at their reference value [4]. The main advantage of this method is that it is easily applied, and its results are easily interpreted. However, it only explores a reduced space of the input factors around a base case, and interactions between factors cannot be considered [11]. On the other hand, global sensitivity analysis

(GSA) focuses on the influence of uncertain inputs over the entire input space, and it is thus able to include effects from correlated input parameters. This category covers a range of methods employing different techniques, which usually evaluate the effect of an input parameter on the output by varying not only the parameter in question, but also the other parameters chosen for the analysis [12]. This approach makes GSA methods more reliable but more computationally demanding than LSA.

Firth et al. [13] conducted an LSA for BEMs of six dwelling archetypes in the United Kingdom, aiming to assess the impact of input uncertainty on the predicted CO_2 emissions of a housing stock model. Their analysis revealed that the heating setpoint, length of the daily heating period, external air temperature, story height, and gas boiler efficiency were the most influential parameters affecting CO_2 emissions across most of the six archetypes. Similarly, Kavgic et al. [14] performed an LSA for dwelling archetypes in Serbia, identifying indoor temperature, heating system efficiency, and external air temperature as key parameters influencing space heating demand and, consequently, CO_2 emissions. In another study, Lam et al. [15] conducted an LSA to examine the impact of 10 parameters on the electricity use of 10 air-conditioned office buildings in Hong Kong. They found the cooling setpoint, equipment loads, and lighting loads to be the most relevant parameters affecting electricity use.

Demir Dilsiz et al. [16] carried out a GSA to analyze the annual cooling and heating consumption for various building forms across different climates in the United States. Their findings highlighted that setpoint temperatures, infiltration rate, and the transmittance of walls, floors, and roofs were the input parameters with the most significant impact. In another study, Zhu et al. [17] conducted a GSA as part of a BEM calibration process for a three-story office building in Colorado, United States. In this analysis, they determined that the cooling setpoint and equipment and lighting power densities played key roles in cooling demand, while the heating setpoint, occupancy density, and the solar heat gain coefficient (SHGC) of windows were critical factors affecting heating demand. Wang et al. [18] performed a GSA on a fictitious building in the Netherlands as a first step toward the calibration of an urban-scale energy model. The authors examined the influence of 14 parameters on heating demand and concluded that the setpoint temperature, wall transmittance, and infiltration rate were the parameters with the highest impact. Xuanyuan et al. [19] conducted a global sensitivity analysis (GSA) as a preliminary step before an optimization process for a three-story office building in Hangzhou, China. Their study identified solar shading, window-to-wall ratio (WWR), and the cooling setpoint as the most influential parameters affecting total energy consumption for heating loads, with some differences depending on the building orientation.

The screening-based method is a specific group of GSA methods in which the primary objective is often to fix some input factors from a large number of factors without reducing the output variance [11]. GSA methods of this type are considered useful for qualitatively identifying key design variables to which the model output is most sensitive, providing a computationally efficient alternative when a rough ranking of the parameters is desired [12]. The drawback of these methods is that they cannot quantify the effects of different factors on outputs, thus preventing the identification of how much of the total variance of outputs has been considered in the analysis [11]. The screening method described by Morris [20] is one of the most widely used methods for SA in BEM [3,4,6,12,21,22]. It can handle a large number of parameters while simultaneously requiring fewer simulations compared to other methods, and it easily provides interpretable results [10,11,21]. However, it is important to acknowledge that users of the Morris method often overlook the minimum number of simulations required to ensure result convergence.

The Morris method is also widely used for SA in applications other than BEM. King and Perera [23] applied it to detect important variables in an urban water supply system, while Janse van Rensburg et al. [24] used it to approach the complexity of developing a physics-based model of a battery. Reuge et al. [25] used the method to identify the most sensitive parameters affecting a physicochemical model of chloride-induced corrosion of concrete in marine environments. Ben Touhami et al. [26] applied the Morris method to examine the sensitivity of a pasture simulation model, while Han et al. [27] used it to identify key inputs in a biochemically-based photosynthesis model. Ujjwal et al. [28] analyzed the uncertainty in a fire spread model, Aumond et al. [29] examined relevant parameters affecting a traffic noise model, and Wang et al. [22] identified key parameters for a passive residual heat removal system.

In this study, the Morris method was applied to determine the most relevant parameters affecting cooling, heating, and total thermal loads in four residential building typologies modeled in EnergyPlus. In Section 2, an overview of the Morris method is provided, along with a brief review of some previous studies that applied it to BEM. Additionally, there is a description of the Morris method parameters used in the present study. In Section 3, there is a description of the four case studies and the hypotheses considered in their EnergyPlus models. In Section 4, the convergence of the SA results with the user-defined parameters of the Morris method is analyzed, and the results are presented and discussed. Finally, in Section 5, the conclusions of this study are presented.

The novelty of this research lies in its pioneering approach toward developing high-fidelity BEMs tailored to the Uruguayan housing stock. The case studies are modeled with a level of detail not typically seen in comparable research, making them more representative of real-world conditions. These models encompass multiple thermal zones, incorporate occupancy schedules that dictate HVAC operation, account for occupant behavior in using solar protections and natural ventilation based on interior and exterior conditions, and utilize a comprehensive model (i.e., the EnergyPlus airflow network model) to simulate ventilation and infiltration loads, including the airflow from both the exterior and adjacent zones.

In terms of SA, special consideration was given to the impact of user-defined parameters in the Morris method, which is not common practice when employing this approach. Among the parameters studied, factors such as the solar absorptivity of surfaces—often overlooked in similar studies—were identified as highly relevant.

2. Methodology

A sensitivity analysis (SA) was conducted to identify the relevant parameters in residential building energy models (BEMs) in Uruguay. This study involves four different building archetypes: three of them are the typical buildings defined by Curto-Risso et al. [30], and the fourth is a social interest archetype modeled by Pena et al. [31]. For the analysis, the global sensitivity analysis (GSA) technique introduced by Morris [20] was implemented.

2.1. Morris Method for Sensitivity Analysis

In the Morris method, the user must define the number of parameters under study (k) and their range of possible values. This determines Ω, a k-dimensional input space consisting of the model inputs $X = (X_1, X_2, \ldots, X_k)$. Ω is discretized into a p-level grid where each X_i for $i = 1, 2, \ldots, k$ may assume values within the grid.

For a given value of X, the elementary effect (EE) of the ith input factor is defined as the magnitude of variation in the model output due to a variation in the ith parameter (as shown in Equation (1)). By randomly sampling different X from Ω, the finite distribution of EE_i (denoted F_i) is obtained.

$$EE_i = \frac{Y(X_1, \ldots, X_{i-1}, X_i + \Delta, X_{i+1}, \ldots, X_k) - Y(X)}{\Delta}. \quad (1)$$

In Equation (1), $X = (X_1, X_2, \ldots, X_k)$ represents any selected value within Ω, $Y(X)$ is the model output, and Δ is a predetermined multiple of $1/(p-1)$.

The method assumes that F_i follows a Gaussian distribution and uses its mean (μ) and standard deviation (σ) as indicators of the significance of the ith input. The mean, μ, evaluates the overall influence of the factor on the output, while the standard deviation, σ, estimates higher-order effects such as non-linearity or interactions with other inputs.

Therefore, the Morris method identifies the inputs that can be categorized as having the following effects:

1. Negligible (low μ and low σ).
2. Linear and additive (high μ and low σ).
3. Non-linear or involved in interactions with other inputs (high σ).

A revised version of the measure μ, denoted as μ^*, was proposed by Campolongo et al. [32]. This measure represents the mean of the distribution of the absolute values of the elementary effects (EEs). The use of μ^* addresses a potential issue that may arise when F_i includes both positive and negative elements, as may occur in non-monotonic models. In such cases, calculating μ might lead to some effects canceling each other out, resulting in a low value even for an important factor. When μ^* is used in place of μ, Garcia Sanchez et al. [3] have suggested that the value of σ/μ^* can identify the following inputs:

1. Almost linear ($\sigma/\mu^* < 0.1$).
2. Monotonic ($0.1 < \sigma/\mu^* < 0.5$).
3. Almost monotonic ($0.5 < \sigma/\mu^* < 1$).
4. Non-monotonic or with high interactions with other factors ($\sigma/\mu^* > 1$).

To estimate the sensitivity measures μ (or μ^*) and σ, the r elementary effects (EEs) from each F_i are sampled. The Morris method proposes a sampling strategy that involves generating r trajectories, each composed of $(k+1)$ points within the input space Ω. At each point, one EE is computed for one input factor, resulting in a total of $r(k+1)$ sample points. This translates to simulating $r(k+1)$ building models.

Each trajectory is constructed by randomly selecting a base value from the p-level grid Ω. Subsequently, all trajectory points are generated by incrementing (or decrementing) one of its k components at a time by Δ. This design results in a trajectory comprising $(k+1)$ sampling points $X^{(1)}, \ldots, X^{(k+1)}$, where consecutive points differ in only one component by Δ, and where each component has been increased (or decreased) once. This procedure is repeated r times, each time with a randomly selected starting point.

Therefore, when employing the Morris method for SA, the user is required to specify not only the parameters to be analyzed and their ranges of possible values, but also the number of levels (p), the number of trajectories (r), and the value of Δ. Morris [20] suggests that p should be an even number and that Δ should be set as $\Delta = p/[2(p-1)]$. This choice ensures an equal probability of sampling from each F_i.

2.2. Previous Studies Using the Morris Method in BEM

Neale et al. [4] implemented the Morris method to identify a subset of the most influential parameters affecting electricity consumption and heating load in five Irish building archetypes: a two-story detached dwelling, a two-story semi-detached dwelling, a single-story detached dwelling, a mid-floor apartment, and a top-floor apartment. They selected 24 parameters for the analysis, including building construction parameters (U-values), building energy use, building equipment parameters, ventilation, and occupancy. For the apartment archetypes, some of these parameters were not examined (e.g., the floor and roof U-values for the mid-floor apartment), resulting in 19 and 22 parameters to evaluate in the mid-floor and top-floor apartments, respectively. The study employed a triangular distribution to describe the parameter input space, except for orientation, which was assigned a uniform distribution. They used a value of $r = 10$, resulting in 200–250 models for each archetype to be simulated in EnergyPlus. No information was provided regarding the values used for p and Δ.

Garcia Sanchez et al. [3] conducted an SA using the Morris method on a seven-story residential building with 32 dwellings. They employed the ESP-r energy calculation software to model the building. In their analysis, the authors examined the impact on the heating load of 24 parameters. These parameters encompassed building design aspects (such as building and window sizes, orientation, and insulation thickness), operational factors (including temperature setpoints, occupancy levels, and ventilation rates), and meteorological variables (external temperature, solar radiation, ground reflectivity, and wind speed). To ensure the analysis was representative of apartment buildings at a national level, the authors defined rather broad intervals for possible parameter values. In their study, they set $p = 10$, $\Delta = 5/9$, and $r = 10$.

Maučec et al. [33] utilized the Morris method in six different timber building models developed in EnergyPlus. A total of 15 parameters were subjected to the analysis to assess their impact on heating and cooling thermal loads. These parameters included building geometry, insulation characteristics, glazing ratio and distribution, shading control, and setpoint temperatures. The following three locations were considered, each with different climatic conditions: moderate, warm, and cold. They evaluated the EE in $r = 10$ trajectories, resulting in 160 simulations for each model. This led to a total of 2880 simulations when considering the six building models and the three climate zones. No information was provided regarding the values used for p and Δ.

De Wit and Augenbroe [21] employed the Morris method in a naturally ventilated office located in the Netherlands. They subjected 89 parameters to the SA to evaluate their relative importance in assessing the uncertainty of a thermal comfort indicator, which was defined as the number of hours per year where more than 10% of the occupants are dissatisfied with the climatic conditions in the building. The authors assumed normal distributions for all parameters. They conducted simulations using two thermal building model tools: ESP-r and BFEP. For the SA, they assessed five independent samples of the EE on the comfort performance indicator ($r = 5$), resulting in a total of 450 simulation runs. No information was provided regarding the values used for p and Δ.

Petersen et al. [12] conducted a study to examine the impact of the choice of p and r on the results obtained from the Morris method. They compared these results with those obtained using the Sobol method. The case study was a one-story office building modeled in EnergyPlus. The authors found that, in order for the Morris method to identify the same cluster of parameters as the Sobol method, it required a higher value of r than what is typically applied. The authors commented on the limited attention given to the effect of the user-defined values for p and r when applying the Morris method in BEM. As a result of their study, they recommended using $p \geqslant 4$ and conducting simulations in steps of $r = 100$ to qualitatively analyze convergence.

Menberg et al. [6] utilized the Morris method in a case study employing TRNSYS as the simulation tool. Their study focused on the Architecture Studio at the University of Cambridge, using the annual heating demand of the first floor as the quantity of interest in the SA. The authors selected 11 uncertain parameters within the TRNSYS model and defined broad ranges for their possible values. The aim was to assess the performance of the SA method in situations with limited information about the actual parameter values. All parameters were assumed to follow uniform distributions. The researchers explored the method using different numbers of trajectories to identify the minimum value of r required for a robust ranking of parameters. They performed 10 independent evaluations of the Morris method, each with 10 trajectories, and observed significant variations in both μ^* and σ across the 10 independent evaluations. Their conclusion was that the method performed reasonably well when $r \geqslant 120$.

Nouri et al. [34] conducted a meta-model-based sensitivity analysis (SA) using the Morris method to identify the 44 most influential parameters out of 105 in a simplified hypothetical building, with variations of $\pm 10\%$ and uniform distributions for all parameters. The building, modeled in Modelica, was a single-zone shoe-box with one window, no shading, and no occupancy or HVAC schedules, and it was modeled using climatic data from Denver, USA. After applying the Morris method, machine learning algorithms were used to develop meta-models, enabling a more computationally efficient Sobol SA on the 44 previously identified parameters. The results of the Sobol SA identified the cooling setpoint, the SHGC of the window, and the window area as the most significant factors influencing thermal loads. No information was provided regarding the number of levels and trajectories used for the Morris method.

2.3. Implementation

In this study, the Morris method was employed to assess the influence of 14 uncertain parameters ($k = 14$) on the annual heating and cooling requirements of four dwelling typologies. The buildings were modeled and simulated using EnergyPlus, while Python functions were utilized for designing the Morris samples, generating and executing the models, and processing the SA results. Considering the assessment by Petersen et al. [12] regarding the importance of analyzing the impact of the selected values for p and r, four different levels were explored ($p = 4, 8, 12$, and 16) in $r = 400$ trajectories. This is a higher number of trajectories than is typically chosen by Morris method users and resulted in 6000 simulations for each building typology and each value of p, leading to a grand total of 96,000 simulations.

Given that the aim of this analysis was to identify the input parameters crucial for describing the building stock as accurately as possible at the national level, broad ranges were defined for the parameters under study, and uniform distributions were considered. The selected parameters and their variation ranges are presented in Table 1. The term conductance, denoted as U_c, represents the inverse of the sum of conduction resistances. The air permeability of windows was characterized by the air mass flow coefficient when the opening was closed per unit length at 1 Pa (denoted C'_q). The window blinds activation criterion establishes the level of solar irradiation on the windows above of which blinds are activated when the cooling system is in operation.

Table 1. The parameters subject to SA and their ranges.

Parameter	Acronym	Unit	Min	Max
Exterior wall conductance	$U_{c,walls}$	W/m^2K	0.5	6.0
Roof conductance	$U_{c,roof}$	W/m^2K	0.5	25.0
Window conductance	$U_{c,windows}$	W/m^2K	6.0	350.0
Wall thermal capacitance	C_{walls}	kJ/m^2K	200	400
Roof thermal capacitance	C_{roof}	kJ/m^2K	100	580
Window-to-wall ratio	WWR	%	10 15 10 5	30 50 30 25
Front facade orientation	Orientation	º	0	$360(p-1)/p$
Wall solar absorptivity	α_{walls}	-	0.1	1.0
Roof solar absorptivity	α_{roof}	-	0.1	1.0
Heating setpoint	HSP	ºC	18	22
Cooling setpoint	CSP	ºC	23	27
Window air permeability	C'_q	g/sm	0.096	0.898
Windows blinds activation criteria	Blinds	W/m^2	0	1000
Occupancy	Occupancy	number of people	1 1 1 1	3 7 15 8

The ranges for conductances, thermal capacitances, and air permeability were determined based on the minimum and maximum values defined for the Uruguayan housing stock in Curto-Risso et al. [30]. The air permeability values used for windows ensured that the global permeability (attributed to the permeability of the roof and windows in the models) corresponded to reasonable n50 values for Uruguayan dwellings, as reported by Pena et al. [31], Pena et al. [35], Romero [36], and Rodríguez-Muñoz et al. [37]. For orientation and solar absorptivities, the ranges encompassed all possible values, while for the blind activation criteria, a broad range was defined. In the case of the heating and cooling setpoints, narrower ranges were considered to prevent distorting the problem, ensuring that, for example, the cooling setpoint was not lower than the heating setpoint.

Regarding the WWR and occupancy, the ranges were set as wide as possible while remaining reasonable for each typology. This resulted in different ranges for the four different case studies. The criteria for determining the WWR range involved maximizing (or minimizing) the size of existing windows, with the exception of bathroom windows, wherever possible. For occupancy, a minimum floor area of 8 m^2/person was established.

The value used for Δ was set as $p/[2(p-1)]$, as recommended by Morris [20]. The only exception was the value of Δ used to vary the orientation, which was set to $1/(p-1)$. The rationale behind this exception was that, for orientation, $\Delta = p/[2(p-1)]$ results in angle variations of around 180º. In most of the case studies, due to the location of windows and exposed walls, there has been a cyclical relationship between energy consumption and orientation with a period of 180º. Therefore, using $\Delta = p/[2(p-1)]$ for orientation could lead to a low μ^* value even when the orientation significantly impacts energy consumption. This approach aligns with the suggestion by Morris [20] to assign different values of Δ to certain inputs when some prior knowledge of the function Y makes it desirable. Additionally, since orientation is a circular parameter (a step of Δ from the maximum value returns the orientation to 0º), equal probability sampling is ensured regardless of the value used for Δ.

2.4. Limitations of the Research

The selected SA approach provides a qualitative identification of input factors to which thermal loads are more sensitive, but it does not quantify the effects of the different parameters on the outputs.

This study was limited to the four typologies analyzed and focused on identifying the most relevant parameters affecting thermal loads among the 14 proposed parameters. Climatic factors such as exterior temperatures, irradiation, wind speed and direction, and precipitation were not considered. Additionally, the configuration of the surroundings, such as neighboring buildings or vegetation, was not included in the analysis. The design and dimensioning of the heating and cooling systems, as well as their efficiency, were also not considered. The behavior of occupants was only accounted for through temperature setpoints and window blind activation criteria.

3. Case Studies

This study employed three of the building archetypes developed by Curto-Risso et al. [30] and a social interest building modeled by Pena et al. [31] and Favre et al. [38]. These archetypes were as follows:

- A 27 m^2 single-story detached dwelling, hereafter referred to as the "house-studio".
- A 53 m^2 two-story attached dwelling, hereafter referred to as the "two-story".
- A 117 m^2 single-story detached dwelling, hereafter referred to as the "ranch".
- A 66 m^2 single-story detached dwelling, hereafter referred to as the "bungalow".

The case studies are illustrated in Figures 1–4. The EnergyPlus models of these four typologies were used for the SA, with the weather file being the Typical Meteorological Year (TMY) for Montevideo, Uruguay, i.e., a city with a temperate climate. In the models, the thermal zones of the dwellings were consistent with their original definitions in Curto-Risso et al. [30], Pena et al. [31], and Favre et al. [38]. The inside and outside convection coefficients were calculated using the default *TARP* and *DOE-2* models. Solar distribution was modeled as *FullExterior*, and a simulation time step of 10 min was utilized. The HVAC systems were only considered in the occupied zones and were modeled with the *IdealLoadsAirSystem*, which has infinite heating and cooling capacities. This is a simplified model that is used when studying the performance of a building without the need to model a full HVAC system.

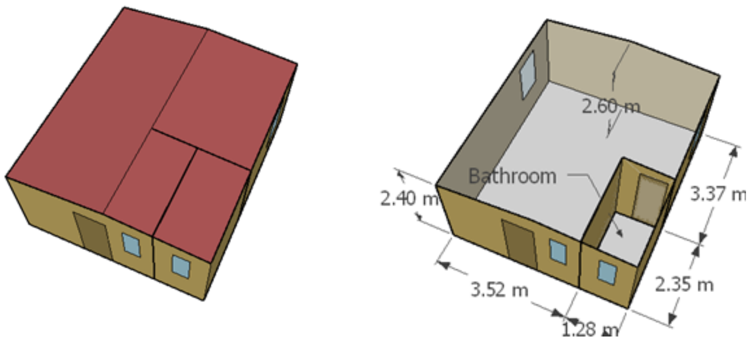

Figure 1. House-studio.

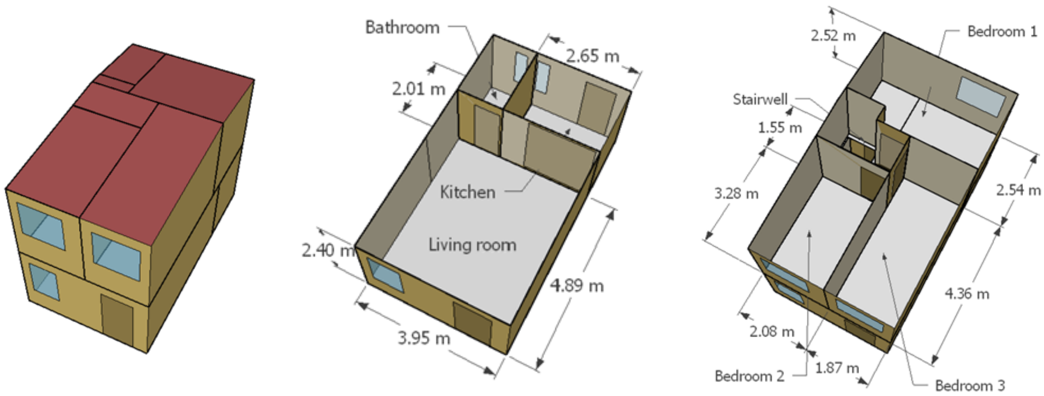

Figure 2. Two-story.

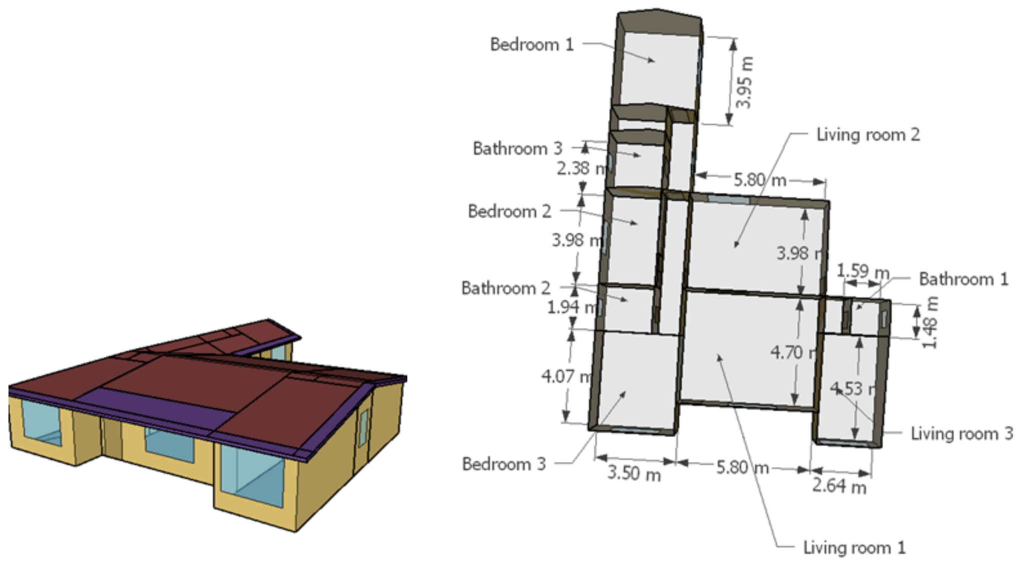

Figure 3. Ranch.

The occupancy criteria were as follows: the main living room (denoted as Living Room 1 when there is more than one living room) was occupied by 50% of the dwelling's occupants from 14:00 to 18:00 and by 100% from 18:00 to 22:00. The bedrooms were occupied from 22:00 to 08:00, with two occupants using the largest bedroom (denoted as Bedroom 1), and the remaining occupants were distributed among the other bedrooms. For example, in a case with three people and two bedrooms, two people occupy the largest bedroom while one person occupies the other. In a case with three people and three bedrooms, two people occupy the largest bedroom, one person occupies the second largest, and the third bedroom remains unoccupied. No occupancy was considered for living rooms other than Living Room 1, bathrooms, and the kitchen. The thermal loads from occupants, lighting, and appliances were based on the technical standard NBR15575 ([39]).

The occupancy schedules are crucial because the HVAC system operates only when the zone is occupied, meaning that an unoccupied bedroom does not consume energy from the HVAC system, at least directly. Therefore, when varying the occupancy parameter during the SA, not only do the thermal loads from occupants change, but there may also be changes in the conditioned area of the dwelling. For instance, a bedroom that is not conditioned under one occupancy scenario might be conditioned under another.

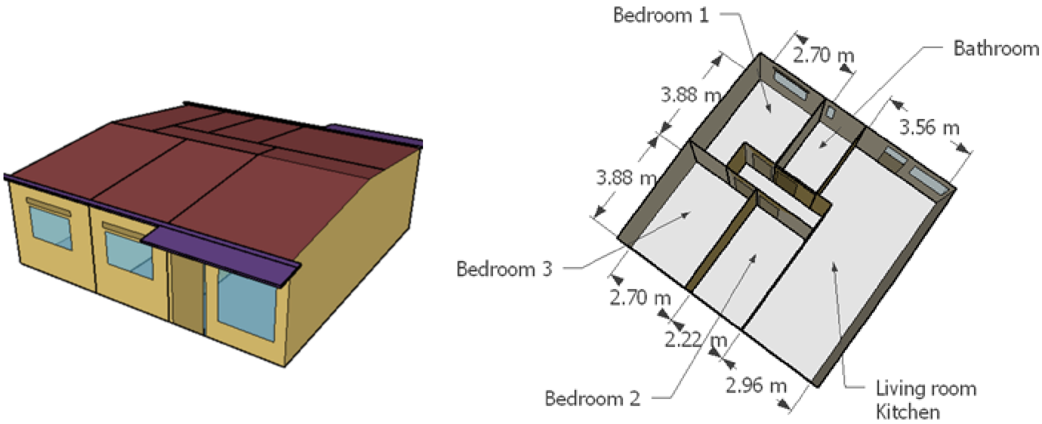

Figure 4. Bungalow.

The construction materials for floors, interior walls, ceilings, and doors remained consistent with their original definitions in Curto-Risso et al. [30] and Pena et al. [31]. However, for the exterior walls, roofs, and windows, new fictional materials were defined. These materials were adjusted in terms of conductivity, density, and solar absorptivity to meet the required conductances, thermal capacitances, and solar absorptivities.

The ventilation and infiltration loads were calculated using the *AirflowNetwork* model. When the temperature in an occupied zone exceeded both the outside temperature and the setpoint temperature, the windows within the zone were opened. The window opening factors were adjusted to maintain consistent ventilation flows as the WWR varied. For the infiltration loads, the permeability of the roof and windows was considered. The roof permeability remained as originally defined in Curto-Risso et al. [30] and Pena et al. [31], while, for the windows, the air mass flow coefficient when the opening was closed was adjusted according to the value of the air permeability parameter.

All exterior windows were equipped with blinds. In the occupied zones, the blinds were activated when cooling was on and the solar irradiation exceeded the specified threshold defined by the blind activation criteria parameter. In unoccupied zones, the blinds were activated when the zone temperature exceeded 23 ºC and solar irradiation exceeded the specified threshold parameter.

4. Results and Discussion

Considering the assessment by Petersen et al. [12] regarding the importance of analyzing the impact of the selected values for p and r on the sensitivity analysis (SA) results, four levels were evaluated (p = 4, 8, 12, and 16) across a total of $r = 400$ trajectories. In this study, the classification of parameters by order of importance is based on the value of $\sqrt{\mu^{*2} + \sigma^2}$, as will be elaborated later. Thus, to analyze the number of trajectories required, the $\sqrt{\mu^{*2} + \sigma^2}$ for each parameter was assessed in increments of $r = 10$ to visually analyze its convergence. The impact of p was studied qualitatively by observing the resulting ranking of the parameters for the different values of p considered.

For the four studied typologies, up to $r = 100$, there were significant variations in the results (see Figures 5 and 6 for the results of cooling and heating requirements, respectively). From $r = 200$, the results appeared to have converged. Ranking changes that occur at higher values of r are between parameters with very similar final $\sqrt{\mu^{*2} + \sigma^2}$ values, and should therefore be considered as equally relevant.

Figure 5. The $\sqrt{\mu^{*2} + \sigma^2}$ convergence with r for cooling loads across the four typologies.

Regarding the impact of the defined number of levels (p), the findings revealed that changes in the obtained ranking occurred up to $p = 16$ (see Figures 7 and 8). However, the most substantial variations were observed up to $p = 12$. Changes in the results between $p = 12$ and $p = 16$ primarily involved parameters with very similar $\sqrt{\mu^{*2} + \sigma^2}$ values, suggesting their roughly equal relevance.

It is important to note that for $r = 10$, which is a number of trajectories frequently employed in SA when using the Morris method, a convergence of results was not achieved in this study. This observation raises significant concerns regarding the computational cost of the Morris method. While this method is often commended for its computational efficiency, the findings of this study suggest that achieving convergence and reliable results may require a substantially higher number of trajectories, such as $r = 200$. Nevertheless, it is noteworthy that the number of simulations typically required for the Morris method with $r = 200$ remains significantly lower than the number of simulations typically required by other methods. For instance, studies employing the Sobol method for SA in BEM have demanded between 10,000 and 250,000 simulations per model [4,6,12,40].

For $r = 400$ and $p = 16$, the cooling, heating, and total thermal loads in the four typologies fell within the ranges presented in Table 2. The considerable variability in the results for different combinations of input parameters underscores the significant impact of the selected parameters on the thermal loads, at least for the wide ranges of variation considered.

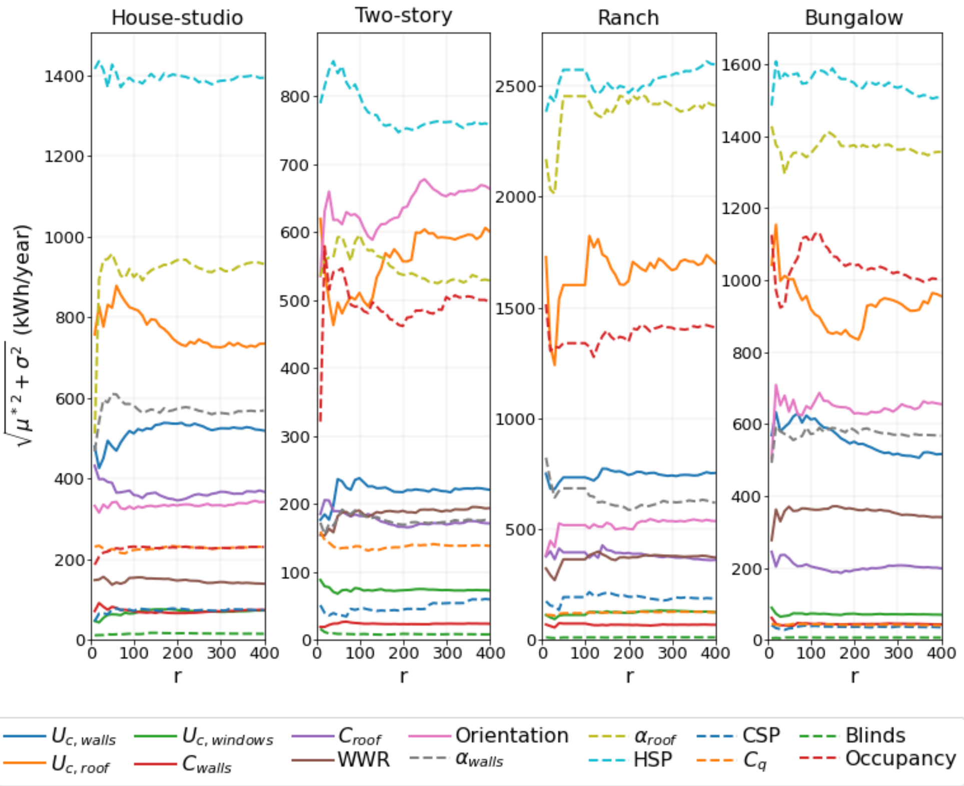

Figure 6. The $\sqrt{\mu^{*2}+\sigma^2}$ convergence with r for heating loads across the four typologies.

Table 2. Simulation result ranges for the Morris method samples across the four typologies.

		Cooling (kWh/year)	Heating (kWh/year)	Total (kWh/year)
House-studio	mean	2104	1282	3385
	min	79	48	815
	max	6201	4176	7634
Two-story	mean	1876	592	2468
	min	175	0	515
	max	5501	2742	6174
Ranch	mean	5305	1926	7231
	min	115	21	1082
	max	17,748	8068	18,746
Bungalow	mean	2510	1192	3701
	min	36	38	513
	max	8899	4533	9363

The results from the Morris method are visualized by plotting the μ^* and σ values of the EE for the parameters under study for cooling, heating, and total thermal loads. Low values of both μ^* and σ indicate a non-influential parameter, while the greater the distance from (0,0), the more relevant the parameter becomes. Reference circles centered at (0,0) are plotted for visual guidance. Additionally, the lines where $\sigma/\mu^* = 0.1$, 0.5, and 1 are drawn to delineate the zones associated with linear, monotonic, almost monotonic, and non-monotonic or high-interaction parameters.

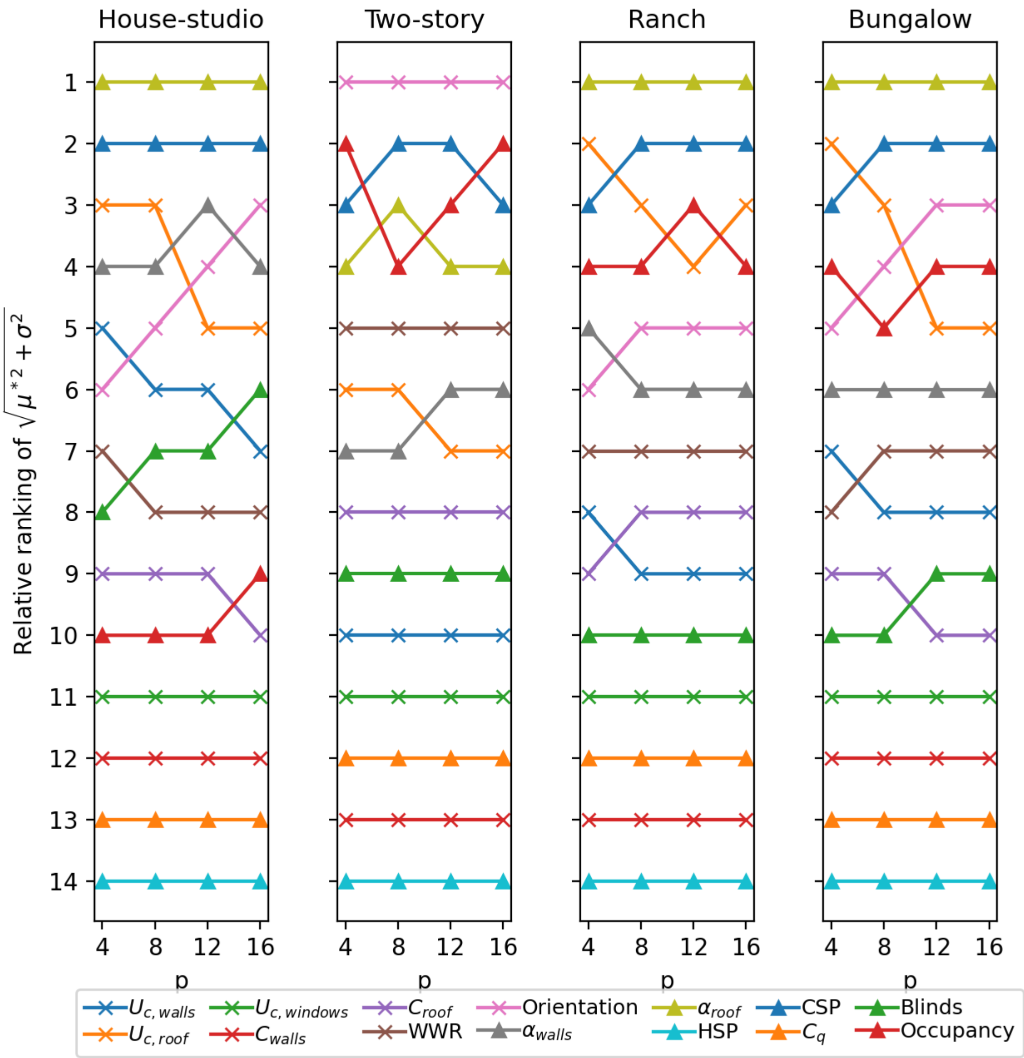

Figure 7. Relative ranking of the 14 parameters according to their $\sqrt{\mu^{*2} + \sigma^2}$ value with respect to the cooling loads after $r = 400$ for all investigated p across the four typologies.

For the house-studio typology (see Figure 9), the parameters with the highest impact on cooling loads included roof solar absorptivity, cooling setpoint, wall solar absorptivity, orientation, and roof conductance. The first three parameters fell within the monotonic region ($0.1 < \sigma/\mu^* < 0.5$), while the orientation and roof conductance were categorized as either non-monotonic or involved in significant interactions with other factors ($\sigma/\mu^* > 1$). For heating loads, the most influential parameters were the heating setpoint, roof solar absorptivity, roof conductance, wall solar absorptivity, and wall conductance; all were within the monotonic to almost-monotonic regions ($0.1 < \sigma/\mu^* < 1$). Finally, when considering the total thermal loads (cooling + heating), the most relevant parameters were roof solar absorptivity, cooling setpoint, roof conductance, heating setpoint, and orientation. The first four fell within the monotonic or almost-monotonic regions ($0.1 < \sigma/\mu^* < 1$), whereas the orientation remained either non-monotonic or heavily involved in interactions with other factors ($\sigma/\mu^* > 1$).

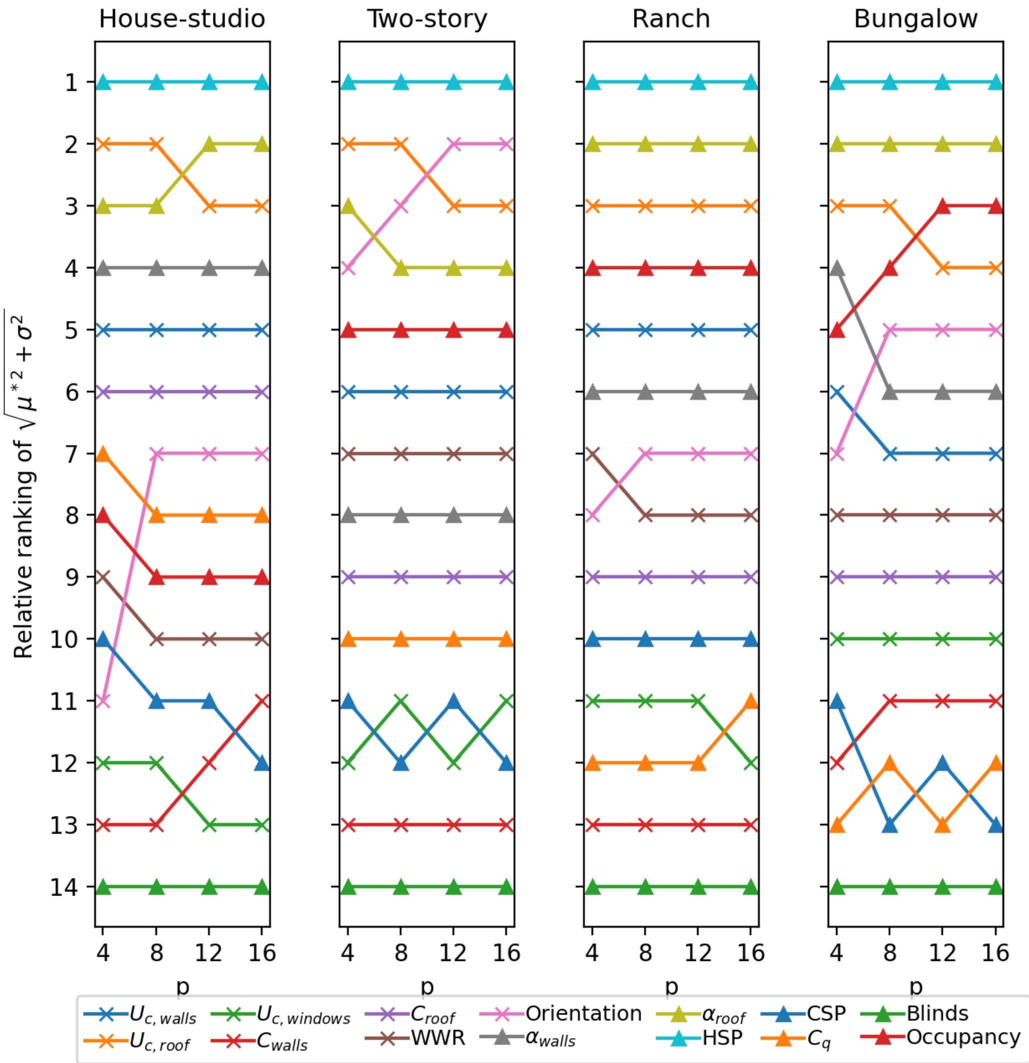

Figure 8. Relative ranking of the 14 parameters according to their $\sqrt{\mu^{*2}+\sigma^2}$ value with respect to the heating loads after $r = 400$ for all investigated p across the four typologies.

For the two-story typology (see Figure 10), the parameters with the highest impact on cooling loads included orientation, cooling setpoint, occupancy, roof solar absorptivity, and window-to-wall ratio. All these parameters fell within the monotonic region ($0.1 < \sigma/\mu^* < 0.5$) except for the orientation, which was either non-monotonic or involved in interactions with other factors ($\sigma/\mu^* > 1$). For the heating loads, the key parameters were the heating setpoint, orientation, roof conductance, roof solar absorptivity, and occupancy. Here, the orientation and occupancy were non-monotonic or involved in interactions with other factors ($\sigma/\mu^* > 1$), while the other three parameters were either monotonic or almost monotonic ($0.1 < \sigma/\mu^* < 1$). When considering the total thermal loads, the most influential parameters were the orientation, occupancy, cooling setpoint, roof solar absorptivity, and heating setpoint. All were in the monotonic or almost monotonic regions ($0.1 < \sigma/\mu^* < 1$), with the exception of the orientation.

The results for the ranch typology (see Figure 11) indicate that roof solar absorptivity, cooling setpoint, occupancy, and roof conductance are the key parameters for cooling loads; the first three fell within the monotonic region while the roof conductance was non-monotonic or involved in interactions with other factors ($\sigma/\mu^* > 1$). For the heating loads, the heating setpoint, roof solar absorptivity, roof conductance, and occupancy were the most influential, all residing within the monotonic or almost monotonic regions ($0.1 < \sigma/\mu^* < 1$). When considering the total thermal loads, the most relevant parameters included roof solar absorptivity, cooling setpoint, roof conductance, occupancy, and heating setpoint, all of which were positioned in the monotonic or almost monotonic regions ($0.1 < \sigma/\mu^* < 1$).

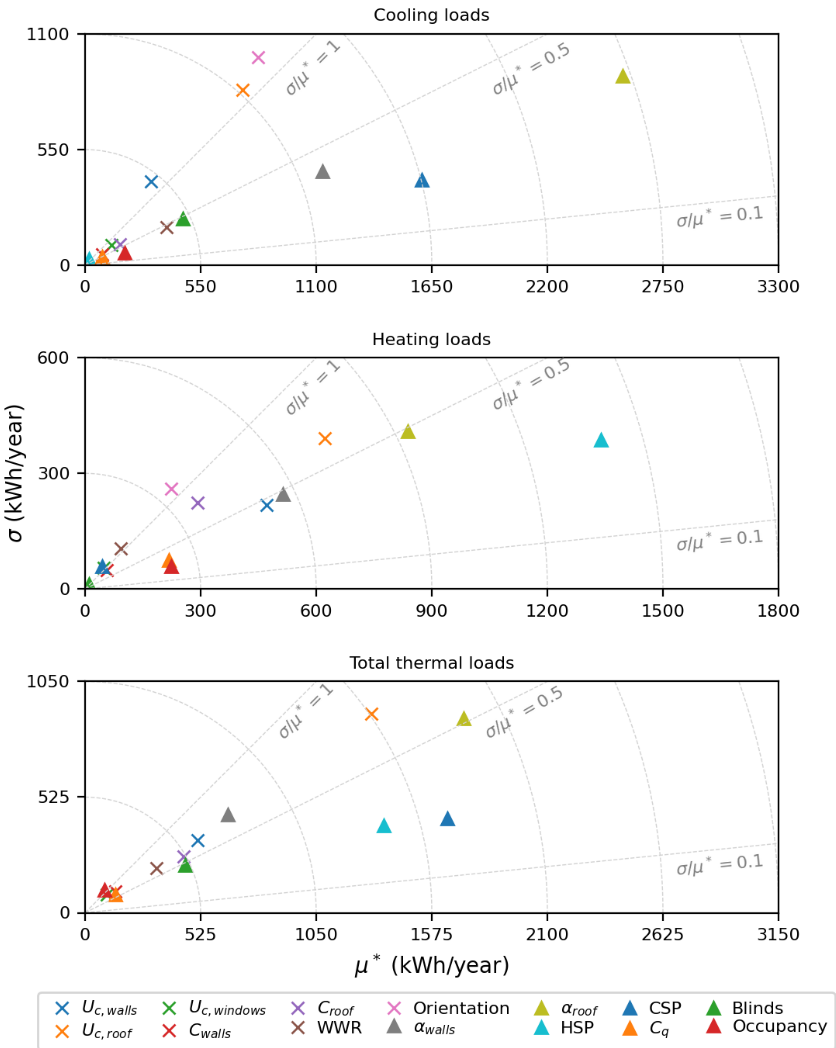

Figure 9. Morris method results of the μ^* and σ for cooling, heating, and the total thermal loads for the house-studio typology with $r = 400$ and $p = 16$.

The results from the EE analysis for the bungalow typology (see Figure 12) indicate that roof solar absorptivity, cooling setpoint, orientation, occupancy, and roof conductance are the key parameters for cooling loads. The orientation and roof conductance were categorized as non-monotonic or involved in significant interactions with other factors ($\sigma/\mu^* > 1$), while the remaining parameters fell within the monotonic or almost monotonic regions ($0.1 < \sigma/\mu^* < 1$). For the heating loads, the heating setpoint, roof solar absorptivity, and roof conductance were primarily influential within the monotonic or almost monotonic regions ($0.1 < \sigma/\mu^* < 1$), whereas occupancy was either non-monotonic or involved in interactions with other parameters ($\sigma/\mu^* > 1$). Considering the total thermal loads, the most relevant parameters included roof solar absorptivity, occupancy, orientation, cooling setpoint, and roof conductance. All were generally in the monotonic or almost monotonic regions ($0.1 < \sigma/\mu^* < 1$), with the exception of orientation, which remained either non-monotonic or significantly interacted with other parameters ($\sigma/\mu^* > 1$).

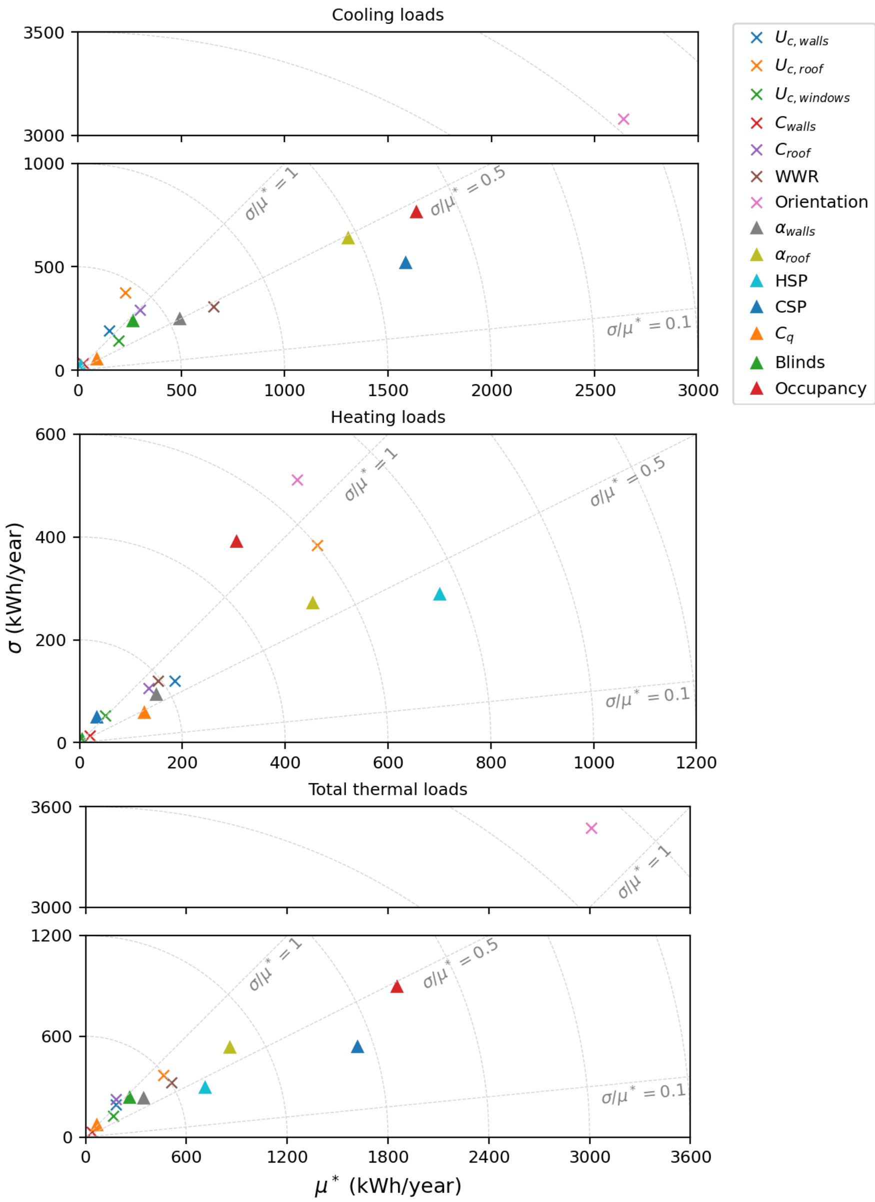

Figure 10. Morris method results of the μ^* and σ for cooling, heating, and the total thermal loads for the two-story typology with $r = 400$ and $p = 16$.

In analyzing the EE results for all four case studies, for both cooling and heating loads, the roof solar absorptivity, setpoint temperatures, orientation, and roof conductance consistently emerged as the parameters with the greatest impact, regardless of the typology. Conversely, window conductance, wall thermal capacity, and window air permeability had the lowest impact on cooling, heating, and total thermal loads across all case studies.

Occupancy exerted a high impact on cooling, heating, and the total thermal loads for all typologies except the house-studio. This is reasonable, considering that, in the house-studio, occupancy varied within a narrower range than in the other typologies (see Table 1). Additionally, there was only one area for thermal conditioning in the house-studio, whereas, in the other three typologies, the conditioned area changed with the number of occupants, depending on how many bedrooms are occupied.

The orientation parameter appeared to have a more significant impact on the two-story and bungalow typologies. This distinction can be attributed to the fact that these typologies only featured windows on the front and rear facades, whereas the other typologies had windows facing all four directions. Moreover, the two-story model was attached on both sides, further emphasizing the relevance of orientation.

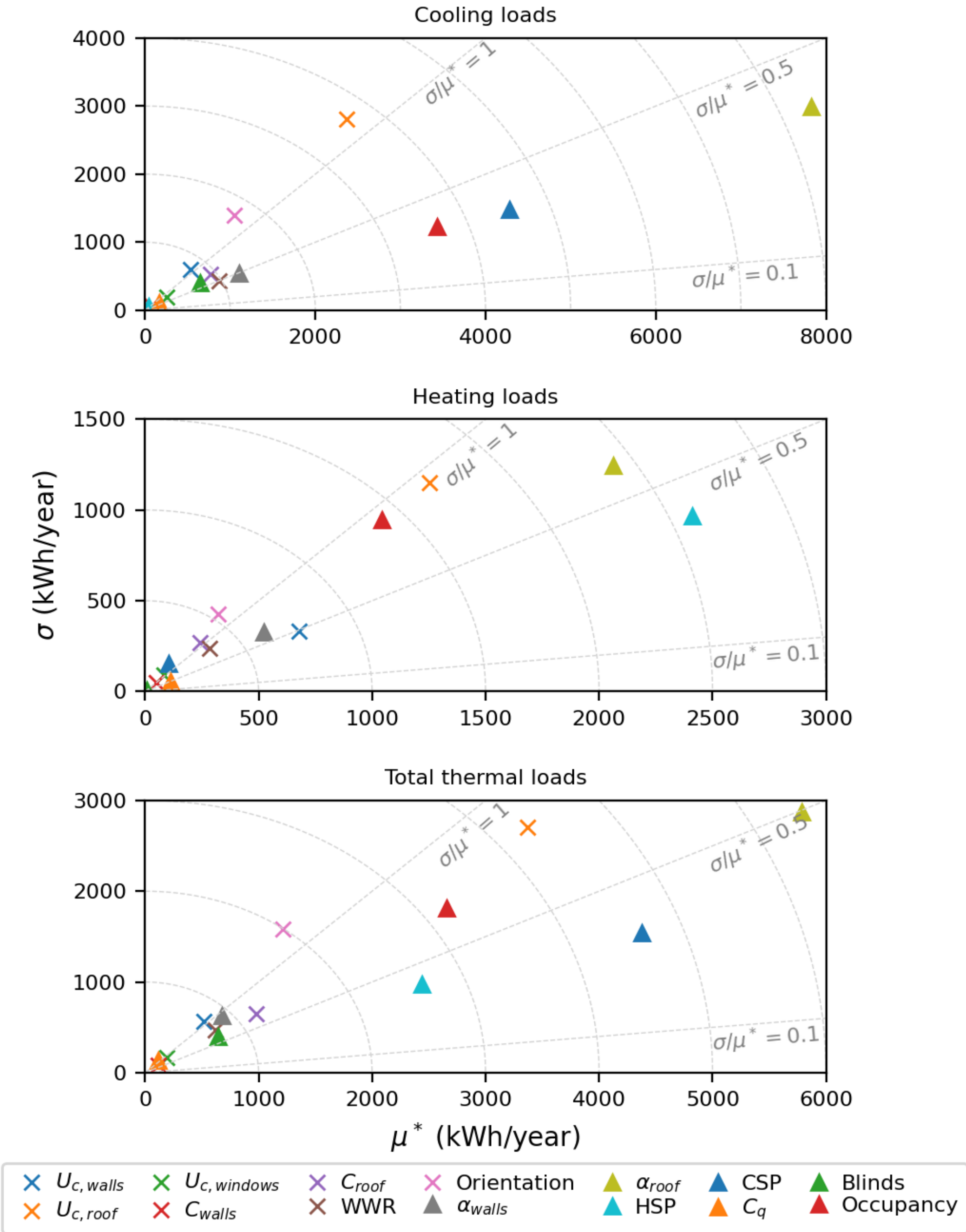

Figure 11. Morris method results of the μ^* and σ for cooling, heating, and the total thermal loads for the ranch typology with $r = 400$ and $p = 16$.

Wall and roof conductances have a greater impact on heating loads than on cooling loads; conversely, WWR and blind activation criteria are more relevant for cooling loads. The prominence of conductances for heating loads might be due to the greater temperature difference between inside and outside in winter, leading to higher heat transfer through walls and roofs for a given U-value. WWR has a more pronounced impact on cooling loads given that there are more energy gains through windows in summer than in winter, especially in east-, south-, and west-facing windows, which have relatively small (zero for south) solar gains during winter. It is also logical for blind activation criteria to be more relevant for cooling loads as the blinds are activated if the cooling is on or if there is high temperature in an unoccupied zone.

As a synthesis, the top 5 most influential parameters for cooling and heating loads across the four typologies, as determined by the Morris method, are presented in Table 3. The roof solar absorptivity, setpoint temperatures, orientation, and roof conductance consistently ranked among the most influential parameters in all the studied typologies. Occupancy also ranked in the top 5 most relevant parameters for all typologies, except for the house-studio.

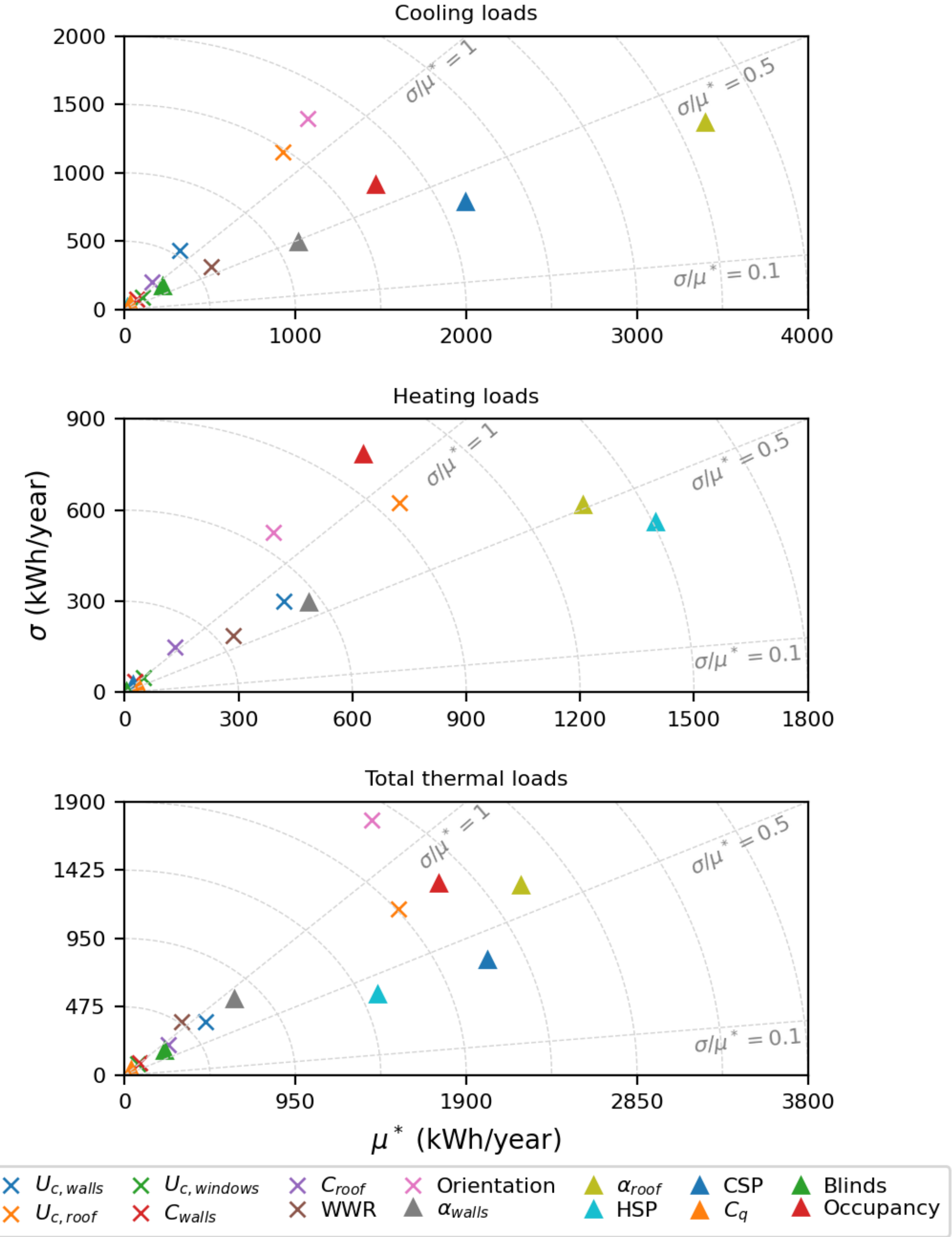

Figure 12. Morris method results of the μ^* and σ for cooling, heating, and the total thermal loads for the bungalow typology with $r = 400$ and $p = 16$.

Table 3. The Morris top 5 most relevant parameters for cooling and heating loads across the four typologies.

	House-Studio	Two-Story	Ranch	Bungalow
Cooling	α_{roof} CSP α_{walls} Orientation $U_{c,roof}$	Orientation CSP Occupancy α_{roof} WWR	α_{roof} CSP Occupancy $U_{c,roof}$ Orientation	α_{roof} CSP Orientation Occupancy $U_{c,roof}$
Heating	HSP α_{roof} $U_{c,roof}$ α_{walls} $U_{c,walls}$	HSP Orientation $U_{c,roof}$ α_{roof} Occupancy	HSP α_{roof} $U_{c,roof}$ Occupancy $U_{c,walls}$	HSP α_{roof} Occupancy $U_{c,roof}$ Orientation

Comparison with Previous Work Using GSA in BEM

Neale et al. [4], when analyzing a residential typology in Ireland similar to the bungalow in this study, identified heating setpoint, occupancy, and roof transmittance as crucial parameters affecting heating loads. However, unlike in this study, they found window transmittance to be quite relevant, whereas roof solar absorptivity was not emphasized. These differences could stem from the distinct climatic conditions, as Irish winters experience less solar irradiation and lower exterior temperatures compared to those in Uruguay.

Petersen et al. [12], when examining a Danish one-story attached office, determined that orientation significantly impacts both heating and cooling loads, a finding that is consistent with this study where orientation proved to be a critical factor in the attached typology. Additionally, heating and cooling setpoints and roof insulation were highlighted as important parameters, aligning with the significant role of roof conductance observed here. Notably, their study did not consider solar absorptivities, which contrasts with their importance in this research.

Neale et al. [4] and Petersen et al. [12] identified ventilation rates, equipment loads, and the solar heat gain coefficient (SHGC) of windows as significant parameters, which were not included in this study. Nouri et al. [34], when analyzing a simplified single-zone hypothetical building in Denver, USA, also highlighted the SHGC of the windows as a crucial parameter. Ventilation rates were omitted from the sensitivity analysis because, in Uruguayan dwellings, ventilation is primarily managed by occupants through window operation rather than by central systems. As noted earlier, natural ventilation was considered in this study, with window operation dependent on zone temperatures, thus making the implementation of fixed ventilation rates impractical. Equipment loads were not included based on the assumption of minimal variation in this parameter among Uruguayan dwellings, contrasting with Neale et al. [4], who considered a broad range of equipment loads in a single-family dwelling. The SHGC of windows was also not examined due to the infrequent use of treated window panes for managing solar gains in Uruguay. The prominence of the SHGC as a key parameter in the studies by Neale et al. [4], Petersen et al. [12], and Nouri et al. [34] may reflect the lack of solar protections in those studies, an aspect that was deliberately considered in this research.

In the study by Garcia Sanchez et al. [3], which focused on a residential apartment building, the authors identified the temperature setpoint and the number of occupants as key parameters influencing heating loads. This finding was consistent with the results from this study and those reviewed from other research. Additionally, Garcia Sanchez et al. [3] emphasized the importance of insulation thickness in walls, which is particularly relevant in a seven-story building where wall heat transfer is more significant compared to the roof.

Menberg et al. [6] similarly highlighted the temperature setpoint as a critical parameter affecting heating loads. However, they also noted that the infiltration rate was one of the most significant factors, a finding that contrasts with this study, where the air permeability of windows was not significantly impactful.

In the study by De Wit and Augenbroe [21], the emphasis was on environmental factors, which were not considered in this study. Consequently, their findings may not align directly with the results presented here.

5. Conclusions

This study employed the Morris method to conduct a sensitivity analysis (SA) on four typologies representative of the Uruguayan housing stock, each modeled using EnergyPlus. The primary objective was to identify which parameters necessitate detailed characterization to develop accurate energy models. In total, 14 parameters were examined, with each being subjected to wide ranges of variation and uniform distributions.

An advancement in this research is the detailed examination of the impact of user-defined parameters in the Morris method; an aspect that is frequently overlooked in similar studies. This enhancement, combined with the comprehensive modeling of multiple thermal zones, occupancy schedules, and natural ventilation, has resulted in a more accurate representation of the Uruguayan housing stock. The findings indicate that achieving convergence and reliable outcomes with the Morris method for SA might require a higher number of trajectories and levels than is commonly used, such as $r = 200$ and $p = 12$. Nevertheless, the number of simulations needed remains lower compared to other methods, such as the Sobol method.

The EE analysis consistently identifies key parameters that rank as most relevant across all case studies, including setpoint temperatures, roof solar absorptivity, roof conductance, and orientation. Occupancy emerged as a pivotal parameter for all typologies, with the exception of the house-studio. Regarding heating loads, wall solar absorptivity, and wall conductance were also identified as significant factors.

The identification of setpoint temperatures, roof conductance, orientation, and occupancy as some of the most relevant parameters is consistent with findings from previous research. However, roof solar absorptivity, which emerged as a significant parameter in this study, was often overlooked in the majority of the reviewed studies.

The observed differences in results compared to other studies can likely be attributed to varying climatic conditions, differing building characteristics, thermal conditioning systems, and cultural aspects related to housing use. This emphasizes the challenge of extrapolating sensitivity analysis results to different countries and underscores the importance of conducting localized studies.

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Data Availability Statement: The input files for this study are available at https://github.com/sofiger/SensitivityAnalisis_BEM.git (accessed on 4 August 2024). Further details can be obtained from the corresponding author, Sofía Gervaz, upon reasonable request.

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

Abbreviations

The following abbreviations were used in this manuscript:

List of abbreviations

BEM	Building Energy Model
EE	Elementary Effect
GSA	Global Sensitivity Analysis

HVAC	Heating Ventilation and Air Conditioning
LSA	Local Sensitivity Analysis
SA	Sensitivity Analysis
SHGC	Solar Heat Gain Coefficient
TMY	Typical Meteorological Year
List of symbols	
C	Thermal capacitance
C'_q	Air mass flow coefficient when the opening is closed per unit length at 1 Pa
CSP	Cooling setpoint temperature
EE_i	Morris method ith input elementary effect
F_i	Finite distribution of EE_i
HSP	Heating setpoint temperature
k	Number of parameters under study in Morris method
p	Morris method levels
r	Morris method trajectories
U	Transmittance
U_c	Conductance: the inverse of the sum of conduction resistances
WWR	Window-to-wall ratio
X_i	Morris method ith input
Y	Morris method output
α	Solar absorptivity
Δ	Morris method increment
μ	Mean
μ^*	Absolute mean
Ω	Morris method k-dimensional input space
σ	Standard deviation

References

1. Corrado, V.; Mechri, H.E. Uncertainty and sensitivity analysis for building energy rating. *J. Build. Phys.* **2009**, *33*, 125–156. [CrossRef]
2. Fabrizio, E.; Monetti, V. Methodologies and advancements in the calibration of building energy models. *Energies* **2015**, *8*, 2548–2574. [CrossRef]
3. Garcia Sanchez, D.; Lacarrière, B.; Musy, M.; Bourges, B. Application of sensitivity analysis in building energy simulations: Combining first- and second-order elementary effects methods. *Energy Build.* **2014**, *68*, 741–750. [CrossRef]
4. Neale, J.; Haris, M.; Mangina, E.; Finn, D.; O' Donnell, J. Accurate identification of influential building parameters through an integration of global sensitivity and feature selection techniques. *Appl. Energy* **2022**, *315*, 118956. [CrossRef]
5. Heo, Y.; Choudhary, R.; Augenbroe, G.A. Calibration of building energy models for retrofit analysis under uncertainty. *Energy Build.* **2012**, *47*, 550–560. [CrossRef]
6. Menberg, K.; Heo, Y.; Choudhary, R. Sensitivity analysis methods for building energy models: Comparing computational costs and extractable information *Energy Build.* **2016**, *133*, 433–445. [CrossRef]
7. Li, S.; Deng, K.; Zhou, M. Sensitivity Analysis for Building Energy Simulation Model Calibration via Algorithmic Differentiation. *IEEE Trans. Autom. Sci. Eng.* **2017**, *14*, 905–914. [CrossRef]
8. Coakley, D.; Raftery, P.; Keane, M. A review of methods to match building energy simulation models to measured data. *Renew. Sustain. Energy Rev.* **2014**, *37*, 123–141. [CrossRef]
9. Reddy, T.; Maor, I.; Panjapornpon, C. Calibrating Detailed Building Energy Simulation Programs with Measured Data—Part I: General Methodology (RP-1051). *HVAC R Res.* **2007**, *13*, 221–241. [CrossRef]
10. Heiselberg, P.; Brohus, H.; Hesselholt, A.; Rasmussen, H.; Seinre, E.; Thomas, S. Application of sensitivity analysis in design of sustainable buildings. *Renew. Energy* **2009**, *34*, 2030–2036. [CrossRef]
11. Wei, T. A review of sensitivity analysis methods in building energy analysis. *Renew. Sustain. Energy Rev.* **2013**, *20*, 411–419.
12. Petersen, S.; Kristensen, M.H.; Knudsen, M.D. Prerequisites for reliable sensitivity analysis of a high fidelity building energy model. *Energy Build.* **2018**, *183*, 1–16. [CrossRef]
13. Firth, S.K.; Lomas, K.J.; Wright, A.J. Targeting household energy-efficiency measures using sensitivity analysis. *Build. Res. Inf.* **2010**, *38*, 25–41. [CrossRef]
14. Kavgic, M.; Mumovic, D.; Summerfield, A.; Stevanovic, Z.; Ecim-Djuric, O. Uncertainty and modeling energy consumption: Sensitivity analysis for a city-scale domestic energy model. *Energy Build.* **2013**, *60*, 1–11. [CrossRef]
15. Lam, J.; Wan, K.; Yang, L. Sensitivity analysis and energy conservation measures implications. *Energy Convers. Manag.* **2008**, *49*, 3170–3177. [CrossRef]
16. Demir Dilsiz, A.; Ng, K.; Kämpf, J.; Nagy, Z. Ranking parameters in urban energy models for various building forms and climates using sensitivity analysis. *Build. Simul.* **2023**, *16*, 1587–1600. [CrossRef]

17. Zhu, C.; Tian, W.; Yin, B.; Li, Z.; Shi, J. Uncertainty calibration of building energy models by combining approximate Bayesian computation and machine learning algorithms. *Appl. Energy* **2020**, *268*, 115025. [CrossRef]
18. Wang, C.; Peng, M.; Xia, G. Sensitivity analysis based on Morris method of passive system performance under ocean conditions. *Ann. Nucl. Energy* **2020**, *137*, 107067. [CrossRef]
19. Xuanyuan, P.; Zhang, Y.; Yao, J.; Zheng, R. Sensitivity Analysis and Optimization of Energy-Saving Measures for Office Building in Hot Summer and Cold Winter Regions. *Energies* **2024**, *17*, 1675. [CrossRef]
20. Morris, M.D. Factorial sampling plans for preliminary computational experiments. *Technometrics* **1991**, *33*, 161–174. [CrossRef]
21. De Wit, S.; Augenbroe, G. Analysis of uncertainty in building design evaluations and its implications. *Energy Build.* **2002**, *34*, 951–958. [CrossRef]
22. Wang, C.K.; Tindemans, S.; Miller, C.; Agugiaro, G.; Stoter, J. Bayesian calibration at the urban scale: A case study on a large residential heating demand application in Amsterdam. *J. Build. Perform. Simul.* **2020**, *13*, 347–361. [CrossRef]
23. King, D.; Perera, B. Morris method of sensitivity analysis applied to assess the importance of input variables on urban water supply yield—A case study. *J. Hydrol.* **2013**, *477*, 17–32. [CrossRef]
24. Janse van Rensburg, A.; van Schoor, G.; van Vuuren, P. Stepwise Global Sensitivity Analysis of a Physics-Based Battery Model using the Morris Method and Monte Carlo Experiments. *J. Energy Storage* **2019**, *25*, 100875. [CrossRef]
25. Reuge, N.; Bignonnet, F.; Bonnet, S. Sensitivity analysis of a physicochemical model of chloride ingress into real concrete structures subjected to long-term exposure to tidal cycles. *Appl. Ocean Res.* **2023**, *138*, 103622. [CrossRef]
26. Ben Touhami, H.; Lardy, R.; Barra, V.; Bellocchi, G. Screening parameters in the Pasture Simulation model using the Morris method. *Ecol. Model.* **2013**, *266*, 42–57. [CrossRef]
27. Han, T.; Feng, Q.; Yu, T. Parameter sensitivity analysis for a biochemically-based photosynthesis model. *Res. Cold Arid. Reg.* **2023**, *15*, 73–84. [CrossRef]
28. Ujjwal, K.; Aryal, J.; Garg, S.; Hilton, J. Global sensitivity analysis for uncertainty quantification in fire spread models. *Environ. Model. Softw.* **2021**, *143*, 105110.
29. Aumond, P.; Can, A.; Mallet, V.; Gauvreau, B.; Guillaume, G. Global sensitivity analysis for road traffic noise modelling. *Appl. Acoust.* **2021**, *176*, 107899. [CrossRef]
30. Curto-Risso, P.; Favre Samarra, F.; Gervaz Canessa, S.; Galione Klot, P.; Romero Barea, J.; Picción Sánchez, A.; López Salgado, M.; Pereira Ruchansky, L.; Camacho Roberts, M.; Rodríguez Muñoz, J.; et al. *Eficiencia Energética en el Sector Residencial: Situación Actual y Evaluación de Estrategias de Mejoramiento para Distintas Condiciones Climáticas en el Uruguay*; Technical Report; Universidad de la República: Montevideo, Uruguay, 2021.
31. Pena, G.; Favre, F.; Galione, P.; Gervaz, S.; Romero, J.; López, M.; Pereira, L.; Camacho, M.; Picción, A.; Scavino, S.; et al. *Evaluación de Desempeño Térmico y Energético de Viviendas MEVIR. Análisis Comparativo de la Tipología "Cardal" en dos Sistemas Constructivos*; Technical Report; MIEM-MEVIR-UDELAR: Montevideo, Uruguay, 2023.
32. Campolongo, F.; Cariboni, J.; Saltelli, A. An effective screening design for sensitivity analysis of large models. *Environ. Model. Softw.* **2007**, *22*, 1509–1518. [CrossRef]
33. Maučec, D.; Premrov, M.; Žegarac Leskovar, V. Use of sensitivity analysis for a determination of dominant design parameters affecting energy efficiency of timber buildings in different climates. *Energy Sustain. Dev.* **2021**, *63*, 86–102. [CrossRef]
34. Nouri, A.; van Treeck, C.; Jérôme, F. Sensitivity Assessment of Building Energy Performance Simulations Using MARS Meta-Modeling in Combination with Sobol' Method. *Energies* **2024**, *17*, 695. [CrossRef]
35. Pena, G.; Kosut, J.; Favre, F.; De León, D.; Garín, L.; López, M.; Pereira, L.; Gutiérrez, L.; Ezquerra, P.; Wilkins, A.; et al. *Estudio Interdisciplinario para la Validación de Criterios de Diseño de Eficiencia Energética en los Programas de Vivienda*; Technical Report; Universidad de la República (Uruguay): Montevideo, Uruguay, 2022.
36. Romero, J. Modelado de Infiltraciones y Ventilación Natural en Simulaciones Energéticas de Edificaciones. Master's Thesis, Universidad de la República (Uruguay), Facultad de Ingeniería, Montevideo, Uruguay, 2022.
37. Rodríguez-Muñoz, J.; Sevrini, A.; Gil, G.; Bove, I. Estudio experimental de la permeabilidad al aire de edificios en Uruguay. *EnerLAC* **2020**, *4*, 76–91.
38. Favre, F.; Pena, G.; Galione, P.; López, M.; Pereira, L.; Rodríguez, J. Análisis energético de una tipología de vivienda de interés social en dos soluciones constructivas. In Proceedings of the XXXIX Congreso Argentino de Mecánica Computacional—I Congreso Argentino Uruguayo de Mecánica Computacional, Salto, Uruguay, 6–9 November 2023; p. 11.
39. Associação Brasileira de Normas Técnicas. *NBR15575. Edificações Habitacionais—Desempenho. Parte 1*; Technical Report; Comitê Brasileiro da Construção Civil: Sao Paulo, Brasil, 2013.
40. Mosteiro-Romero, M.; Fonseca, J.A.; Schlueter, A. Seasonal effects of input parameters in urban-scale building energy simulation. *Energy Procedia* **2017**, *122*, 433–438. [CrossRef]