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Thermal comfort evaluation using different glazing technologies in an energy model of rural housing in a cold climate

Javier Ascanio-Villabona[1*], Nicolas Orejarena-Osorio[1], Nilson Yulian Castillo-Leon[1], Brayan Eduardo Tarazona-Romero[1], Karen Tatiana Jaimes-Quintero[1]
[1] Faculty of Natural Sciences and Engineering, Unidades Tecnológicas de Santander, Bucaramanga, Colombia

*Corresponding author E-mail: Jascanio@Correo.uts.edu.co

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Abstract

Building energy efficiency, consumption and comfort are aspects to be evaluated in the energy simulation of buildings (BES). However, their results deviate from reality leading to the need to improve their accuracy through calibration. In this regard, a rural house located in a cold climate at more than 3000 meters above sea level, is energetically modeled with its subsequent calibration and evaluation of thermal comfort. The study is developed in four stages, starting with the monitoring of climatological variables and followed by the house energy modeling. Subsequently, manual and iterative calibration is conducted by means of statistical comparison and scatter plots. In this way, a model with more than 80% accuracy between monitored and simulated data is achieved. Based on the previously calibrated model, the thermal comfort is evaluated using different glazing technologies and then, the number of hours for two levels of thermal sensation are evaluated (comfortable and not comfortable). For this purpose, statistical methods such as predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) are used, which are included in the Design Builder software. This study identified that single bronze glazing technology increased thermal comfort hours by 14.2% with respect to the case study, allowing the development of a methodology that improves thermal comfort through passive heating in rural dwellings in cold climates.

Keywords: Building simulation, Energy models, Indoor temperature, Model calibration, Comfort, Glazing, Passive heating

1. Introduction

Global warming and climate change are intensifying the hot and cold seasons, which has a direct impact on the dwelling's comfort. Considering this situation, in 2015, the United Nations (UN) established objectives, the aim that cities and human settlements should not only guarantee habitable conditions but also be sustainable [1]. This is particularly relevant given that energy consumption in buildings represents 30% of the world's total [2]. Therefore, the efficiency analysis of dwellings is an important scope of study for the achievement of global sustainability objectives.

In this sense, building energy simulation (BES) models are essential tools for analyzing energy consumption and efficiency in modern architecture, having a major role in design, optimization, and regulatory compliance. Some of the prominent tools in this field include DOE-2, EnergyPlus, TRNSYS, and ESP-r [3]. DOE-2 is free software that estimates energy consumption and associated costs per hour based on meteorological data, building geometric description, and HVAC system conditions. EnergyPlus, meanwhile, offers detailed simulation, including multi-zone airflow and a wide range of HVAC specifications, making it one of the most widely used programs, with a prevalence of 37.2% in previous studies. TRNSYS specializes in the simulation of transient systems and can model everything from simple components such as fans and pumps to more complex multi-zone building systems. Finally, ESP-r, allows the integration of thermal, visual, and acoustic modeling, providing a holistic view of building energy performance [3], [4].

Building energy simulation has attracted a growing interest; nevertheless, the disagreement between simulated models and real data has been a constant in previous studies [5], [6]. The complexity of energy-building models arises from the variety of input data and the influence of the modeler's expertise. In order to increase the reliability of these models, calibration is essential - a process endorsed by the International Performance Measurement and Verification Protocol (IPMVP). This procedure adjusts the simulation inputs to closely approximate the results to reality [7], [8]. Although there is no standard calibration methodology established, the literature highlights four main approaches. The first is the manual and iterative calibration, which involves repetitive input data modification, a process that can be time-consuming but has been used widely in research between 2013 and 2023. The second approach is based on graphical methods, such as time series and scatter plots, which provide a visual comparison of results, including 3D plots and calibration signatures [7], [8]. Another approach is analytical, including invasive testing, short-term monitoring, inspections, and calculations. Finally, automated calibration approaches, based on analytical, mathematical, and statistical approaches, such as Bayesian calibration, meta-modeling, and optimization-based methods, have gained relevance due to advanced computational capabilities [8], [9].

According to the approach used, calibration levels have been outlined according to the degree of information collected. These levels range from the most elementary, which is based merely on utility bills and does not require on-site visits, to level 5, which represents the most comprehensive degree of monitoring. The latter level involves long-term data collection by using energy meters, along with specific inspections and measurements performed directly in the building. Table 1 clearly shows the differentiation between the different levels of calibration [10], [11]. Once the appropriate approach and the scope of each calibration level have been decided, it is important to select appropriate criteria for model fitting and validation. In this context, statistics proves to be the preferred tool for assessing calibration accuracy. A comparison is made between the simulated data set and the actual measured or monitored data of the dwelling, using statistical techniques to calculate precision indicators such as the mean bias error (MBE), the normalized mean bias error (NMBE), the coefficient of variation of the root mean square error C_v(RMSE), and the coefficient of determination (R^2) [12]. Besides, existing reference guides such as ASHRAE, as well as international organizations such as IPMVP and the M&V guidelines for FEMP, suggest calibration limits based on these indicators, providing recognized standards for the validation of calibration models [8].

Table 1. Calibration level as a function of input data available [7]

Calibration levels	Building description and performance data available for calibration					
	Utility bills (one year)	As built data	Site visit or inspection	Detailed audit	Short-term monitoring	Long-term monitoring
Level 1	X	X				
Level 2	X	X	X			
Level 3	X	X	X	X		
Level 4	X	X	X	X	X	
Level 5	X	X	X	X	X	X

The application of energy modeling in buildings to mitigate greenhouse emissions, improve comfort in dwellings, and reduce energy consumption costs has led to the research being conducted, ranging from reviews to case study evaluations, for example; a review of modeling techniques emphasizes the models that are or could be used to model the energy consumption of the residential sector. The energy consumption models in this research involve an approximation of the residential stock and a method for the energy consumption estimation for both old and new residential stock [13]. Another review covers methods for fitting building energy simulation models to measured data, and presents a detailed review of the current techniques for modeling and fitting models, highlighting the importance of the uncertainties in the process. It includes a review of the analytical and statistical methods that experts have applied and discusses the advantages and challenges of these methods. It is concluded that buildings are complex systems with a high dependence on a large number of variables. The design, analysis, and improvement of modern building systems would be greatly improved by the implementation of simulation tools. They evaluate the energy performance of buildings in each phase of their life cycle. Nevertheless, differences have been detected between the energy consumption estimated by models and that measured in real situations, indicating that there is still scope for further development in the use of these simulation tools [3]. Weerasinghe et al. discuss several aspects related to the retrofitting of existing buildings to achieve net zero carbon (NZC) emissions. Based on 125 carefully selected articles to better understand the benefits, challenges, and measures of NZC retrofitting, the study provides a deep understanding of the NZC retrofitting field and serves as a useful reference for future practice and improvement in the industry [14].

Some research has been conducted on case studies, which allow the development of calibrated models. One of them was conducted by Mozina et al. based on the measurement of the dry bulb temperature (DBT) and the external wall surface temperatures. A hybrid method for calibration was developed and it is a two-phase method: introductory and core phases. In the first phase, the known parameters are incorporated into the model, and in the second phase, three iterative steps are conducted; modeling in the graphical Design Builder interface which is based on the EnergyPlus software, secondly, a statistical and graphical comparison of measured and simulated results and finally, verification of compliance with recommended uncertainty ranges. Thus, after 28 calibration steps, a model with high accuracy and low uncertainty was obtained [13]. In this study approach, a new calibration method based on the combination of thermal imaging and CFD simulation is proposed and the calibration was implemented automatically [15]. In further research, an indoor temperature-based EnergyPlus simulation model was successfully calibrated for overheating assessment using genetic algorithms. It identified the optimal parameters for calibration and provided a robust and automatized methodology for calibrating energy simulation models, which is essential for overheating assessment and planning of heat mitigation strategies [16].

In this area of research, Hong et al. focused on the automatic calibration of building energy simulation models using an optimization algorithm. It automatically reduced the coefficient of variation of root mean square error (CV(RMSE)) from 18.10% to 12.62%, improving the agreement between real and simulated energy data, representing a significant advance in the calibration of building energy simulation models, offering a more efficient and less laborious methodology than previous manual and iterative methods [4].

In addition, the objective of implementing energy efficiency studies in buildings is to reduce energy consumption and greenhouse gas emissions, while improving occupant comfort. In the study of Blazquez et al, the calibration of energy models to improve the accuracy in predicting the energy performance of buildings was studied. This is crucial for energy retrofitting and the achievement of energy efficiency targets set by policies such as Horizon 2020. It is concluded that energy retrofitting is an essential part of the transition to a more sustainable future and is especially relevant in the context of climate change and the need to reduce our carbon footprint [17]. In the study entitled, "Validation of a new model for fast, multidimensional simulation of building energy from combined heat and air infiltration" is based on the need for accurate models to simulate the energy performance of buildings, considering both heat transfer and air infiltration. The findings of the study indicate that the new model offers a significant improvement in relative accuracy, reducing the error compared to CFD analysis to less than 4.5%, while requiring less than 1% of the time required for complex hygrothermal analysis. The conclusions highlight the effectiveness of the new model for fast and accurate simulations, which could have a considerable impact on the building industry, leading to energy assessments for energy retrofit [18]. In addition, a design that addresses a comprehensive analysis of a net zero energy building (NZEB) in the context of sustainable urban development was evaluated. The methodology for studying NZEBs includes modeling the building energy and simulating its performance under different scenarios using EnergyPlus and RETScreen software. It is considered factors such as energy efficiency, renewable energy generation, and integration of sustainable technologies. The study proposed an innovative multi-generator system for hospital buildings using an air-to-water heat pump and a bio-fueled gas turbine power plant where the daily cooling and freshwater demands of a large benchmark end-user were met by the AWHP and HDH desalination cycle. The total electrical energy utilization of the indoor evaporator fan, compressor, and other equipment was obtained by the biogas-driven gas turbine cycle [19].

In regards to the comfort analysis, some research discusses the use of passive strategies to improve energy efficiency in an environmentally responsible manner. Jaouaf et al. reduced annual energy consumption (AEC) by 11% with a 60° shading angle and a window-to-wall ratio (WWR) of 30% in the analysis of a school in Algeria. In addition, it identified that Double-Low E glazing reduced the AEC by 14% [20]. Furthermore, Zoure and Genovese [21] identified that the type of glazing plays an important role considering different types of glazing such as low emissivity (Low-E) clear 6 mm glass, clear 6 mm glass, double Low-E clear 6 mm/13 mm and ral blue color tinted 6 mm glazing, considering the latter as the most affordable and best performing in reducing the excess amount of solar radiation inside the building. Usta and Zengin [22] also compare clear glazing and low emissivity glazing with thicknesses of 4 and 6mm and conclude that with low emissivity glazing less cooling energy is required due to its high solar energy reflectance coefficient. Fathi and Kavoosi [23] investigated high office buildings in Iran by comparing electrochromic windows with low emissivity (Low-E) double glazing and clear double glazing separated with air and argon under different climatic conditions. It is concluded that the tinted reflective electrochromatic low-E double glazing has the best energy-saving performance, especially in cold locations.

In general, research has highlighted the need for calibration of building energy models (BES) in order to achieve reliable results. However, in the literature, there are no specific case studies where energy models are evaluated in rural houses and in climates of steady cold. In the present research, the energetic model of a rural house located in a cold climate at more than 3000 meters above sea level is evaluated. For this purpose, the dwelling unit is modeled in Design Builder, and the climatic variables are monitored. Subsequently, these data are processed by EnergyPlus, and with an analytical approach together with an iterative method and statistical techniques the energy model is calibrated. In parallel the calibration uncertainties are calculated. The structure of this document is divided into five sections. The first section provides a detailed description of the case study, covering aspects such as the predominant climate, the type of dwelling examined, and the characteristics of the building materials. These features are essential to define the input data required for the simulation of the energy model. In the second section, the methodology is presented, detailing the monitoring systems implemented, the generation of energy models, and the model calibration process. This part is key to understanding how the model was built and adjusted to accurately reflect real conditions. The third section is devoted to the analysis and evaluation of the results obtained, as well as the discussion of the work performed. Here the uncertainties associated with the energy model are identified and quantified, providing a critical view of its accuracy and reliability.

In the fourth section, thermal comfort is evaluated using the calibrated model as a basis for different glazing technologies and, using the statistical methodology predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD), calculating the hours for different levels of thermal sensation. Finally, the fifth section presents the conclusions derived from the study, summarizes the key findings, and reflects on their impact in the field of energy efficiency in buildings.

2. Case study

The dwelling to be studied is located at an altitude of 3400 meters above sea level, in a geographical area classified as a high mountain moor type. Its location coordinates are 7.15, -72.91, which corresponds to the rural area of the village of Berlín, in the municipal district of Santander in Colombia. This area, which has few houses and is mainly dedicated to agriculture, is considered to have a low population density. It should be pointed out that the house is located on a hillside oriented from east to west, thus favoring cross ventilation by natural ventilation. The maximum temperatures seldom exceed 20°C, while minimum temperatures rarely drop below 10°C. In addition, during the months of January and July, the lowest temperatures are recorded and in contrast, the months of February and August present warmer temperatures. The average wind speed is 4 km/h [24] and the highest rainfall occurs in May and October.

Regarding the thermal envelope of the house, it is made up of different materials: brick walls and concrete partitions, cedar wood decks, clay roof tiles, and asphalt fabric, while the floor is made of stone slabs and finally, the living room has glazed walls with wooden frames (see Figure 1). Despite the absence of mechanical or hybrid ventilation systems as well as air conditioning, the house has few air leaks, evidencing a high degree of airtightness. The thermal envelope characteristics are considered in the energy model together with meteorological data. The latter is monitored through a weather station and its console, which are located outside and inside the house, respectively. The monitoring of data along with its actual occupancy conditions will take place from March 21, 2023, to April 29, 2023. This period corresponds to the average temperatures from 2011 to 2022 according to on-site meteorological data (see Figure 2).

Figure 1. Aerial, front, side and rear view of rural housing in the case study

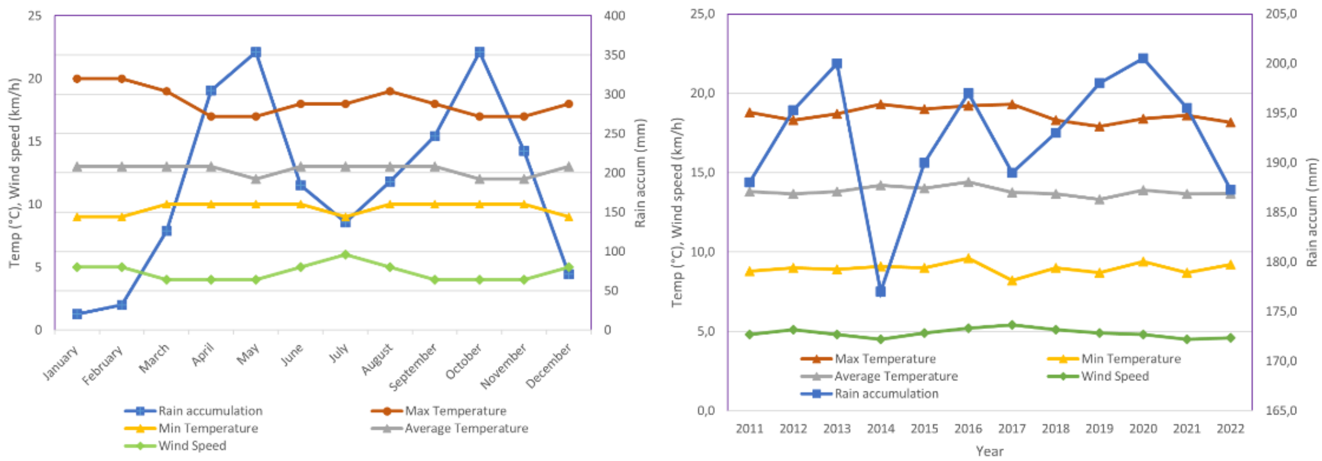

Figure 2. Monthly seismogram of the year of study and historical seismogram in the municipality of Berlín/Santander, Colombia

3. Methodology

To analyze the thermal comfort of the rural housing energy model, a four-stage methodology was implemented. In the first stage, a weather station and its console were installed outside and inside the house, respectively. During one month, variables such as UV solar radiation, temperature, humidity and wind speed were monitored by the outdoor station, while relative humidity and dry temperature were measured by the indoor console. At the same time, the occupancy and operating conditions of the house were recorded. In the second stage, based on the dimensions, materials and physical characteristics of the house, an energy model was built using the Design Builder interface together with Energy Plus. It is remarkable that with EnergyPlus, from the monitored external climate data, the indoor temperature was simulated and compared with what was recorded by the indoor console. This process led to the third stage, in which the associated uncertainties were identified and quantified through the manual and iterative calibration method that led to the selection of the ideal model, in other words, the one that guaranteed the validity and accuracy of the energy model (see Figure 3). Finally, in stage four, based on the calibrated energy model and as a passive heating methodology, different glazing technologies were simulated. The results obtained as the global coefficients of heat transfer, humidity, and internal temperature were used to evaluate the thermal comfort based on the statistical methodology predicted mean cote (PMV) and predicted percentage of dissatisfied (PPD). These assessed the number of hours for two levels of thermal sensation together with global heat transfer coefficients. Each of these steps played an important role in achieving a reliable energy model that also allowed us to evaluate the thermal comfort of a rural dwelling in cold weather and thus propose improvements with passive heating methodologies.

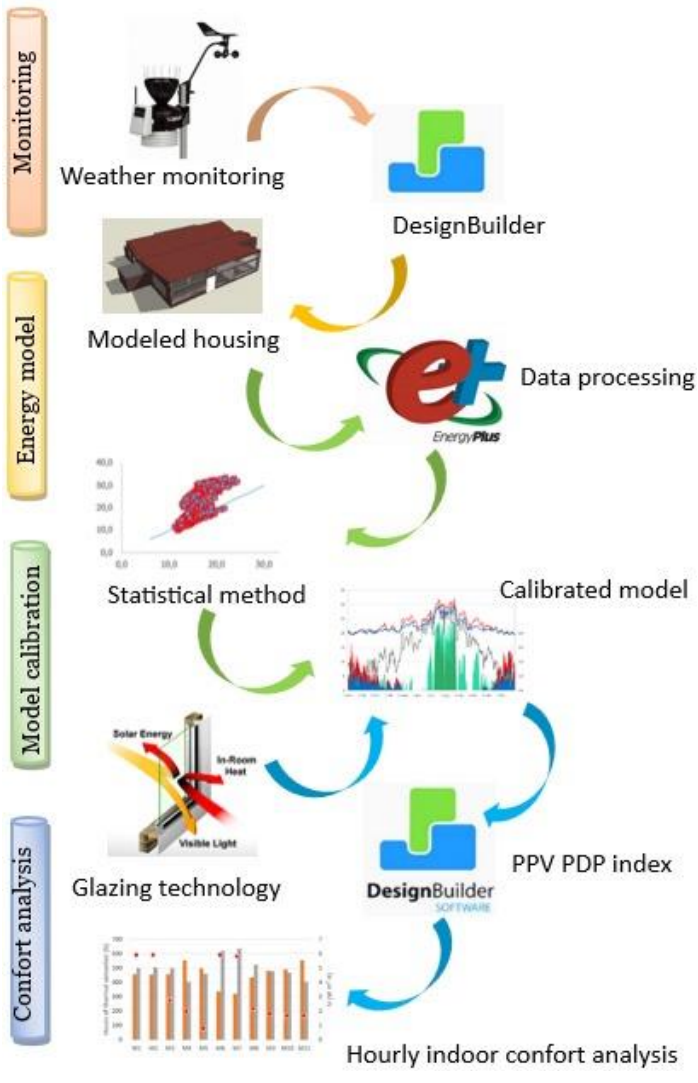

Figure 3. Methodology used in the study

3.1. Monitoring

Monitoring of environmental data both inside and outside the house was carried out using a Davis Vantage Pro2 weather station and its wireless sensors (see Figure 4). The parameters measured included relative humidity and air temperature inside the house, as well as humidity, solar radiation, wind speed, probability of rain, barometric pressure, UV index, and wind direction outside the house. These data were recorded at 15-minute intervals over a one-month period (March 21, 2023, to April 29, 2023), which provided the data for the energy modeling analysis of the dwelling.

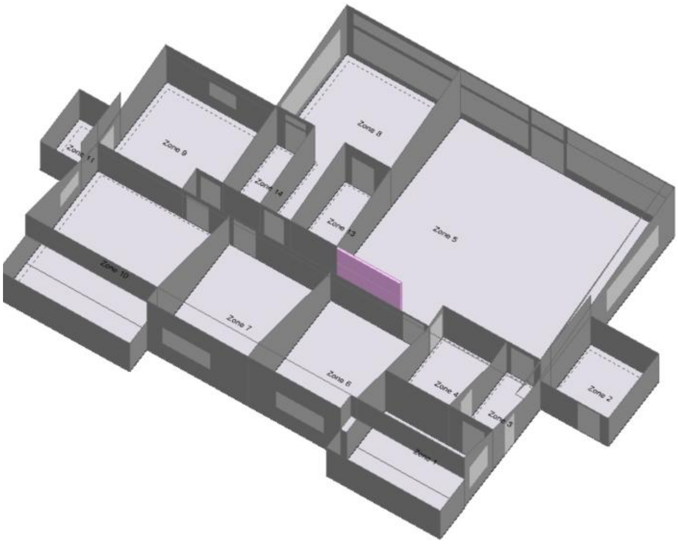

Figure 4. Sensor and weather station locations

3.2. Energy model

The energy model (Figure 5) was developed in the Design Builder modeling interface (v.5.5.2.007) integrated into the EnergyPlus simulator, which is free and was developed by the National Renewable Energy Laboratory (NREL) and the U.S. Department of Energy (DOE) [25][26]. The energy model represents the dwelling object of the case study, considering the specific climatic conditions of the village of Berlín, the jurisdiction of the municipality of Tona (Santander). In addition, meteorological data obtained during monitoring were incorporated and the physical characteristics of the house were taken into account, such as room dimensions, doors, windows, roofs, structure geometry, construction materials, and orientation (see Table 2). The simulated results were compared with the real values obtained in the console located inside the house, by using statistical criteria, thereby obtaining those characteristics that are relevant or most influential in the simulation. In this way, the types of layers to be worked and visualized in the model were selected, obtaining the complete energy model of the house.

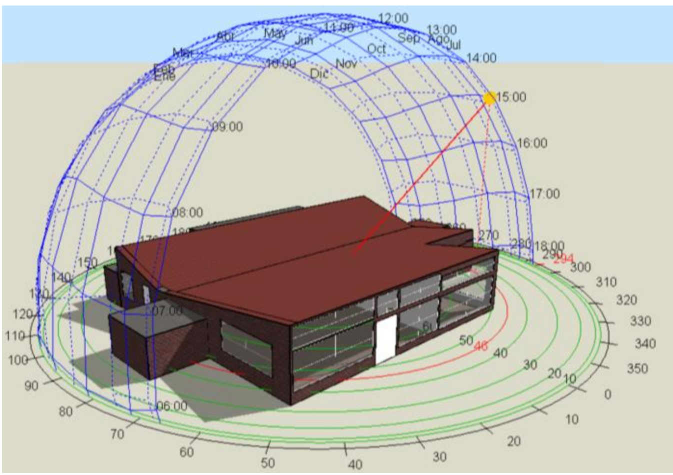

Figure 5. Model housing

Table 2. Physical characteristics of the house

Items	Characteristics
Latitude	7.15
Length	72.91
Full occupancy	1
Area	266 m^2
Glazing area	15 m^2
Type of glazing	3mm single glazing - clear glass
Zone	Living room
Walls and partitions	100 mm brick, 100 mm concrete
Cover	200 mm cedar Wood, 25 mm clay roof tiles, 5 mm asphalt cloth
Floor	Flagstone

3.3. Energy model calibration

Using the external weather station and its internal console, 959 data sets of conditions are recorded at the monitoring stage. The data obtained from the external station was fed to the dwelling energy model and the result obtained from the internal temperature was compared with that measured at the console through an analytical approach. For this purpose, the sensitivity was analyzed through manual iteration of eight parameters: occupancy, thermal loads, infiltrations, thermal transmittance, openings, natural ventilation, schedules, and lighting. From the above 53 models were implemented through DesignBuilder whose simulated internal temperature results are compared with those recorded in the console. These comparisons are made within the statistical framework using Pearson's correlation coefficient, R2 coefficient of determination, sample standard deviation, average absolute error, and relative error. From these, the model with the lowest uncertainty was determined, in other words, the ideal or calibrated model.

3.4. Formulation to determine correlation percentage

The statistical indicators used for the calibration of the energy model are shown below [27]. The average temperature, also known as the arithmetic mean, is calculated by summing the sample data and dividing by the total number of sample data as shown in Equation 1. This value describes the representative value of the data set.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i = \frac{x_1 + x_2 + \ldots + x_n}{n} \tag{1}$$

The difference between a value considered accurate and its approximation is known as the absolute error and is calculated in Equation 2.

$$E = Vm - Vs \tag{2}$$

A linear dependency measure between two quantitative random variables is Pearson's linear correlation coefficient, as shown in equation (3), which is calculated by dividing the sum of the products XY by the individual roots of the sums of squares of X and Y. This gives a dimensionless coefficient of linear correlation between two quantitative random variables. This results in a dimensionless coefficient according to the author [27] whose result varies between -1 and 1, the former indicating related variables, but in opposite directions, while the latter implies a high association.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{3}$$

One metric that evaluates the quality of the regression model is the coefficient of determination R2 shown in Equation 4. It indicates how much of the total variability could be accounted for by the linear relationship between the independent variables and the dependent variable. R2 ranges from 0 to 1: a value close to 1 indicates that the model fits the data well, while 0 indicates that it does not fit well and does not explain much variation.

$$R^2 = \frac{\sum_{t=1}^{n}(\hat{Y}_t - \bar{Y})^2}{\sum_{t=1}^{n}(\hat{Y}_t - \bar{Y})^2} \tag{4}$$

On the other hand, the measure of the dispersion of a data set is represented by the standard deviation. Indicated in Equation 5, states that less dispersion and higher precision will be obtained for values close to 0.

$$s = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}} \tag{5}$$

Finally, the expression given in Equation 6 describes the ratio between the absolute error and the reference value of a quantity and is called relative error.

$$E_r = \frac{x_i - x_t}{x_t} * 100\ \% \tag{6}$$

3.5. Comfort evaluation with passive heating method

Once the housing energy model was calibrated, eleven glazing technologies were selected for the purpose of improving heating through passive techniques. The glazing technologies include single glazing with clear glass, double glazing, triple glazing, air and argon separations, Building Integrated Photovoltaics or BIPV, and four glazing among others. Therefore, each glazing technology was implemented in the calibrated model, resulting in eleven models to be analyzed (Table 3). As a result of simulating each model, the temperature and humidity inside the house and the global heat transfer coefficient are obtained. It is then determined the number of hours for two levels of thermal sensation, comfortable and uncomfortable. For this purpose, the ASHRAE Standard 55 method is used, based on statistical methods such as predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD), which are included in the Design Builder software. Based on this method, different glazing technologies are analyzed and evaluated for the purpose of heating improvement, by considering the real dwelling as the reference model (MR).

Table 3. Simulated models

Models	Description
Model MR	3mm single glazing (clear glass)
Model 2	Dbl Blue 6mm/13mm Air
Model 3	Dbl Clr Low Iron 3mm/13mm Air
Model 4	Project BIPV Window (Building Integrated Photovoltaics o BIPV)
Model 5	Quadruple LoE Films (88) 3mm/8mm Krypton
Model 6	Sgl Bronze 3mm
Model 7	Sgl Bronze 6mm
Model 8	Thermochromic Glazing
Model 9	Trp Clr 3mm/13mm Air
Model 10	Trp Clr 3mm/13mm Argon
Model 11	Trp Clr 3mm/13mm Argon no shading

4. Results and discussion

In the calibration stage, the manual iteration of parameters resulted in a total of 53 energy models for the house under study. However, through Pearson's linear correlation as a statistical comparison method, the internal temperature resulting from the simulation and the actual monitored temperature obtained lower dispersion for the parameters established in model 39.

The characteristics of this energy model are: the occupancy of 4 people 24 hours a day, 7 days a week is recorded. Additionally, 38 W/m^2 as miscellaneous thermal gains per floor area and 4 W/m2 as additional gains from computer equipment are established. Because of the hermetic tightness of the dwelling with only two doors for ventilation, the air is renewed 7.5 times per hour. Thanks to the design of the house, natural ventilation is maintained at 1.5 ac/h 24 hours a day. Also, the 12 windows allow natural light to enter and a thermal transmittance coefficient of 2,661 W/m^2 K is achieved. Table 4 summarizes the characteristic parameters of model 39.

Table 4. Model 39 simulation variables

	Occupancy (people/area)	Thermal loads (W/m^2)	Air infiltrations (ac/h)	U(W/m^2.K)	Openings
M39 Lower dispersion	0,0179	OE = 0 CPT = 4 MS = 38	7,5	EW = 2,061 BGW = 0,350 FR = 0,250	AA = 15
	Ventilation	Lighting	Horary		
	OPEN 24/7; 1,5	GL = 0	08:00-18:00 Mon-Sat; OPEN 24/7; OFFICE_OPENOFF_LIGTH		

Figure 6 shows graphically the comparison, using Pearson's correlation, between the simulated internal temperature data and the monitored temperature. In the linear data set a robust relationship is shown with an accuracy of over 80%, which is a favorable fit given the complexity of the housing energy models due to the habits of the users. The statistical comparison results are shown in Table 5.

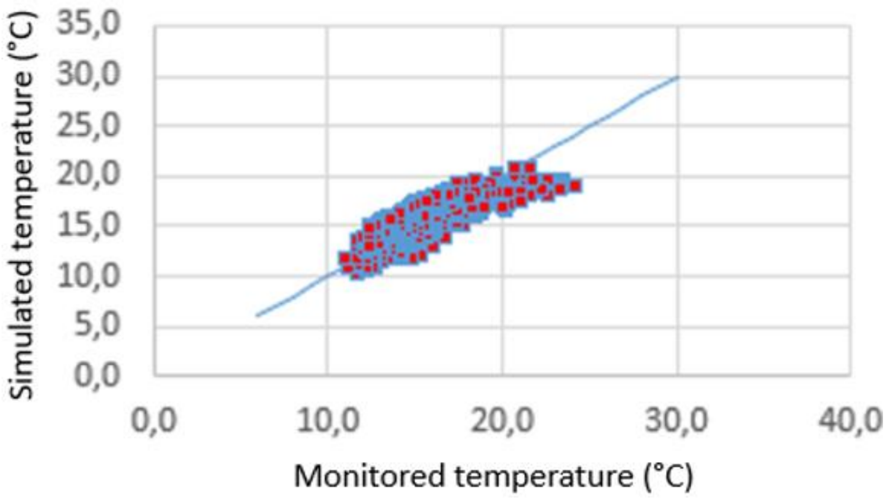

Figure 6. Scatter plots of the models 39

Table 5. Data validation of the models 39

Statistical metrics	M39
Average temperature °C	15.654
Pearson's linear correlation coefficient	0.820
Coefficient of determination R2	0.672
Sample standard deviation	1.842
Mean absolute error	0.111
Relative error %	0.7

Regarding the temperature variation inside the house over time, the plots shown in Figure 7 were obtained. The set of data corresponding to the monitored temperature is shown in blue, while the simulated data is shown in orange. It is also shown that the range of temperatures inside the dwelling oscillates between 10.7 °C and 24.2 °C. It is remarkable that the largest discrepancy between monitored and simulated data does not exceed 3.5°C and 2.2°C for higher and lower temperature ranges, respectively. This is evidence once again that the M39 model is consistent with reality.

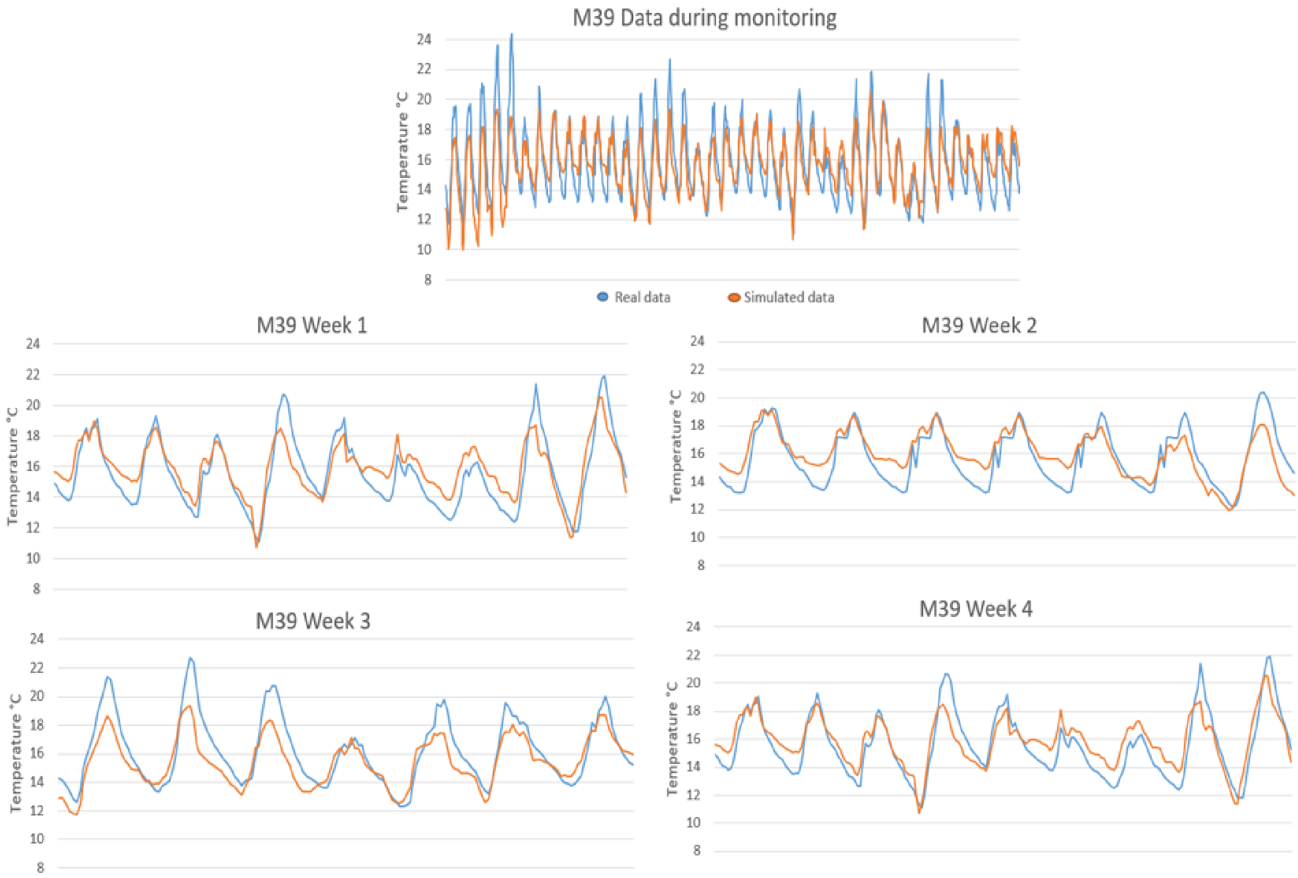

Figure 7. Comparison of simulated vs. monitored temperatures

As for the simulation of eleven models, each one with different glazing technology, and their subsequent analysis based on the methodology predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD), the global heat transfer coefficient, and the number of hours for two levels of thermal sensation were obtained. The results obtained are shown in Figure 8. It is observed that those models with single glazing and smaller caliber, like clear glass, have a high transfer coefficient (U=5.89 W/m2-K), which does not allow maintaining a constant temperature inside the house. In other words, the temperature inside the house easily changes according to external conditions.

Nevertheless, air- or argon-separated double glazing achieved a low heat transfer coefficient, which makes it possible to maintain the temperature inside the house. In addition, special glazing such as Quadruple LoE Films had low transfer coefficients (U=0.78 W/m^2-K) due to their low total solar transmittance coefficient (SHGC = 0.338). On the other hand, it is found that models M6 and M7, corresponding to bronze laminated glass, had the highest number of hours with comfortable thermal sensation with 64.7% and 66.4% of the total hours simulated, respectively. At the same time, they show a high global heat transfer coefficient of 5.83 W/m^2 K and 5.72 W/m^2 K respectively. Therefore, it allows a higher heat gain during the day and keeps the interior temperature of the house for a longer period of time, leading to more hours with a comfortable thermal sensation. By comparing these two models, the M7 model has slightly more comfortable hours due to its higher thickness. Nevertheless, the M6 provides similar performance with less thickness and lower price, which is recommended.

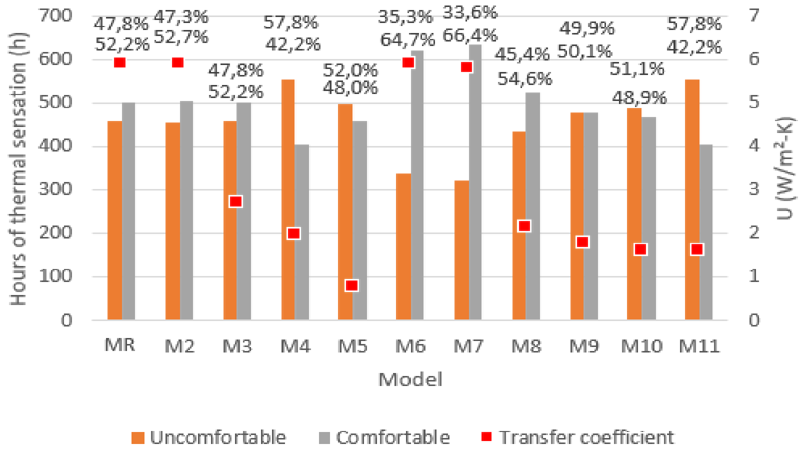

Figure 8. Comparison between the thermal sensation hours of the models

5. Conclusions

This research of thermal comfort for rural communities living in high-altitude areas with low temperatures arises due to the low habitability as a consequence of unfavorable climatic conditions, characterized not only by low temperatures but also by high solar radiation and strong winds.

The sensitivity analysis performed in this research revealed that the calibration methodology focuses on reducing the uncertainty of the parameters and evaluating their impact on the energy model. Nevertheless, manual iteration can result in a time-consuming process and, in some cases, it does not produce significant variability between parameters. Therefore, the use of numerical approaches that facilitate integration into the data validation process is recommended.

Accurate building energy model calibration is highly dependent on the accuracy of measurement of actual occupancy conditions. Occupant patterns, including practices such as natural ventilation, significantly influence the variability of internal parameters and thus the model's accuracy. In order to reduce uncertainty and improve the correlation between real and simulated data, it is important to use surveys and monitoring devices, such as window-opening contactors.

In addition, the importance of including air infiltration and natural ventilation variables in the calibration stage is pointed out. It is concluded that during the data collection period, it was observed that these variables are particularly sensitive and have a significant impact on the indoor thermal oscillation ranges, especially during temperature peaks.

Because uncontrolled air ingress introduces considerable uncertainty in performance analyses, it is recommended for future research to focus on analyzing the impact of building infiltration. A deeper understanding of this phenomenon could improve the accuracy of models and ultimately lead to more energy-efficient buildings.

On the other hand, by analyzing the other models, it is observed that the lower the heat transfer coefficient, the fewer the hours of thermal comfort. It is also shown that the interior temperature is better preserved with the use of more layers of glazing and greater separation between them, achieving a lower heat transfer coefficient.

The glazing technology that provided the highest number of hours of comfort corresponds to bronze single glazing. This technology, corresponding to models M6 and M7, presented 64.7% and 66.4% of simulated hours with comfortable thermal sensation, improving 12.5% with respect to the real or reference model.

Also, the interior temperature is better kept if less window area is used which means a lower window-to-wall area ratio (WWR). It is also reflected that it is not only possible to keep the interior temperature but also to improve self-sustainability by generating energy through BIPV (Building Integrated Photovoltaics) systems.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

The contribution to the article is as follows: Javier Ascanio-Villabona: conception and design of the study; Javier Ascanio-Villabona: data collection; Nicolas Orejarena-Osorio, Nilson Yulian Castillo-Leon, Brayan Eduardo Tarazona-Romero, Karen Tatiana Jaimes-Quintero: analysis and interpretation of results; Javier Ascanio-Villabona: preparation of the draft. All authors approved the final version of the manuscript.

Informed consent Informed

Consent for the publication of personal data in this article was obtained from the participant(s).

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