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Simulation of the energy model of a rural house located in a cold climate using an in-situ monitoring system

Javier Ascanio-Villabona[1-2], N. Y. Castillo-Leon[1], Nicolas Orejarena Osorio[1], Brayan Eduardo Tarazona-Romero [1-2], K. T. Jaimes-Quintero[1]

[1] Faculty of Natural Sciences and Engineering, Unidades Tecnológicas de Santander, Student Street 9-82, Bucaramanga, 680005, Colombia

[2] University of the Basque Country, Ingeniero Torres Quevedo Plaza, 1, 48013 Vizcaya Spain

ABSTRACT

The energy simulation of buildings is presented as a tool to analyze the comfort, consumption and energy efficiency of buildings, however, the discrepancy between simulated models and real data has been a constant, for this reason, energy model calibrations are performed to increase the reliability of the predictions of the simulation. This research carried out the simulation and calibration of the energy model of a rural house, located in a cold climate at more than 3000 meters above sea level, the study was developed in three phases, starting with the monitoring of climatological variables, followed by the energy modeling and finally, the calibration of the model is achieved by applying the iterative and scatter plot methods, allowing the selection of a model where a sequence of linear data was observed, with a strong relationship of more than 80% accuracy between the monitored data and the simulated energy model.

Keywords: Building simulation, Energy models, Indoor temperature, Model calibration.

Corresponding Author:
Nilson Yulian Castillo Leon
Electromechanical Engineering Program
Unidades Tecnológicas de Santander
Student Street 9-82, Bucaramanga, 680005, Colombia.
E-mail: nycastillo@correo.uts.edu.co

1. Introduction

Climate change and global warming are intensifying the hot and cold seasons, significantly affecting the comfort inside our homes. Faced with this reality, the United Nations (UN) has highlighted the importance of developing sustainable cities and human settlements [1]. Given that the energy consumption of buildings represents approximately 30% of the total worldwide, the analysis of energy efficiency in housing emerges as a fundamental pillar to achieve global sustainability goals [2]

In the search for solutions, building energy simulation (BES) models have established themselves as indispensable tools for assessing consumption and improving energy efficiency in contemporary architecture, among the most prominent tools in this field are DOE-2, EnergyPlus, TRNSYS and ESP-r. Each of these programs has distinctive features and capabilities suitable for various energy efficiency analyses. Choosing the right tool and applying it correctly is crucial to obtaining reliable results [3], [4]

Despite the growing interest in building energy simulation, the discrepancy between simulated model results and real data poses significant challenges, influenced by the diversity of input data and the experience of the modeler [5], making the calibration of simulations an essential step to improve their accuracy and ensure reliable predictions [6]. Although much research has been conducted applying energy models to reduce greenhouse gas emissions, improve comfort and energy efficiency in buildings [7], [8], [9], there is a notable absence of studies focused on rural dwellings in consistently cold climates. This gap in the literature underscores the need to explore this area in greater depth.

In the present research the energy model of a rural house located in a cold climate at more than 3000 meters above sea level was evaluated, the residential unit was modeled in Design Builder and climatic variables were monitored, these data were processed by EnergyPlus that through an analytical approach using an iterative method together with statistical techniques calibrated the energy model and determine the uncertainties of the calibration, it is expected that the findings of this study can be applied in practice to improve energy efficiency and comfort in rural dwellings.

2. Case study

The house analyzed is located at the following coordinates 7.15,-72.91 in a rural area of the municipality of Berlín-Santander (Colombia), this geographical area is classified as a high mountain paramo type at an altitude of 3400 meters above sea level, with temperatures that drop below 10°C and maximum temperatures that rarely exceed 20°C, the hottest months are February and August and the months with the lowest temperatures are January and July. The months with the highest rainfall are May and October with an average wind speed of 4 km/hr [10]. The house is located in an area with low building density, on the top of a hillside facing east to west, which favors cross ventilation by natural draft.

The materials and components that characterize the thermal envelope of the house are composed of brick walls with concrete partitions, a roof constructed of cedar wood, clay tiles and asphalt fabric and a stone slab floor, the living room has glazed walls with wooden frames (see fig.1). The house has a high degree of airtightness, showing few air leaks; it does not have mechanical or hybrid ventilation or air conditioning systems.

Data on environmental parameters were monitored by means of an outdoor weather station and a sensor station inside the house under real occupancy conditions from March 21, 2023 to April 29, 2023, according to meteorological data from the site, this month represents the average of temperatures recorded from 2011 to 2022, see Fig. 2.

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

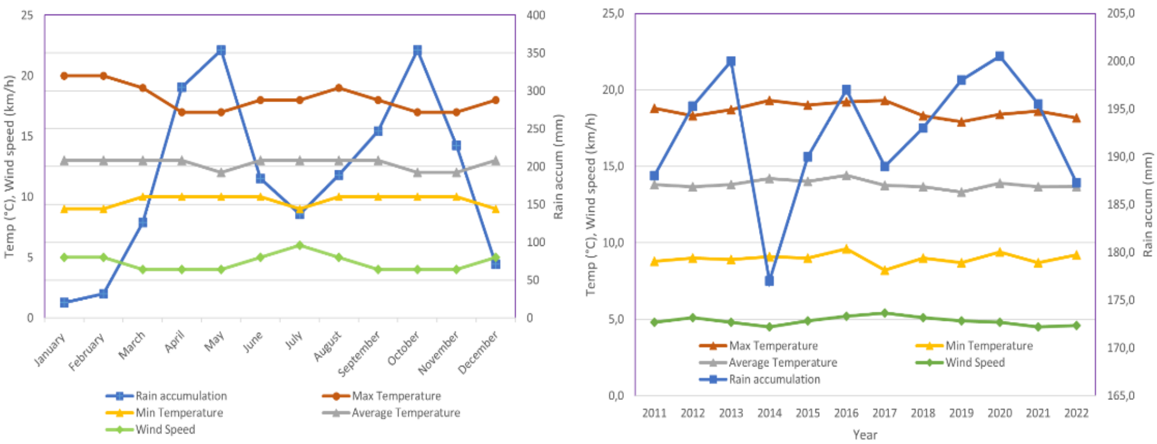

Figure 2. Monthly climogram of the year of study and historical climogram in the municipality of Berlín/Santander, Colombia

3. Methodology.

The methodology implemented for the simulation and calibration of the energy model of the rural housing object of the case study, was structured in three main phases; the first phase is the monitoring, this initial phase consists of the installation of a weather station in the house, the station operated for a month, recording data under normal conditions of occupation and operation of the house. In the second phase, we proceeded to the construction of the energy model, taking into account the dimensions, materials and physical characteristics of the house. For this purpose, the integration of specialized software, such as Design Builder and Energy Plus, was used to perform a detailed analysis of the data in comparison with the real values obtained from the weather station. The last phase involves the application of an iterative method and statistical techniques to calibrate the energy model; this process allows identifying and quantifying the uncertainties associated with model calibration and selecting the model that matches the ideal model (see Fig. 3).

Each of these phases is crucial to ensure the accuracy and validity of the energy model developed, thus allowing a reliable assessment of the energy performance of the rural housing under study. to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity that you use in an equation.

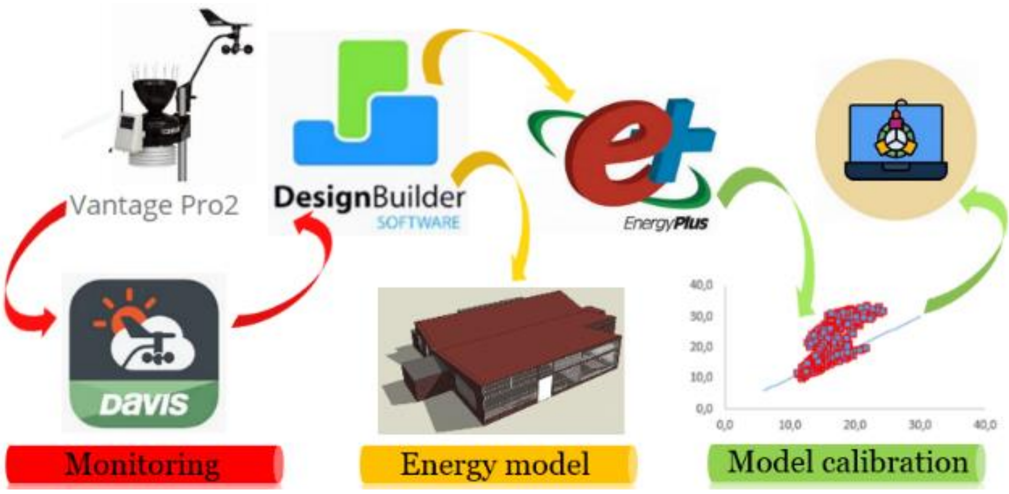

Figure 3. Methodology used in the study.

3.1. Monitoring

The monitoring of indoor and outdoor environmental data was performed by means of a Davis Vantage Pro2 weather station and its complementary wireless sensors, both indoor air temperature and relative humidity, as well as humidity, wind speed, solar radiation, probability of rain, barometric pressure, wind direction and UV index, outside the house, these data were recorded during a period of 1 month (March 21, 2023 to April 29, 2023) with 15-minute intervals, providing 959 data to the data acquisition system. (see Fig. 4).

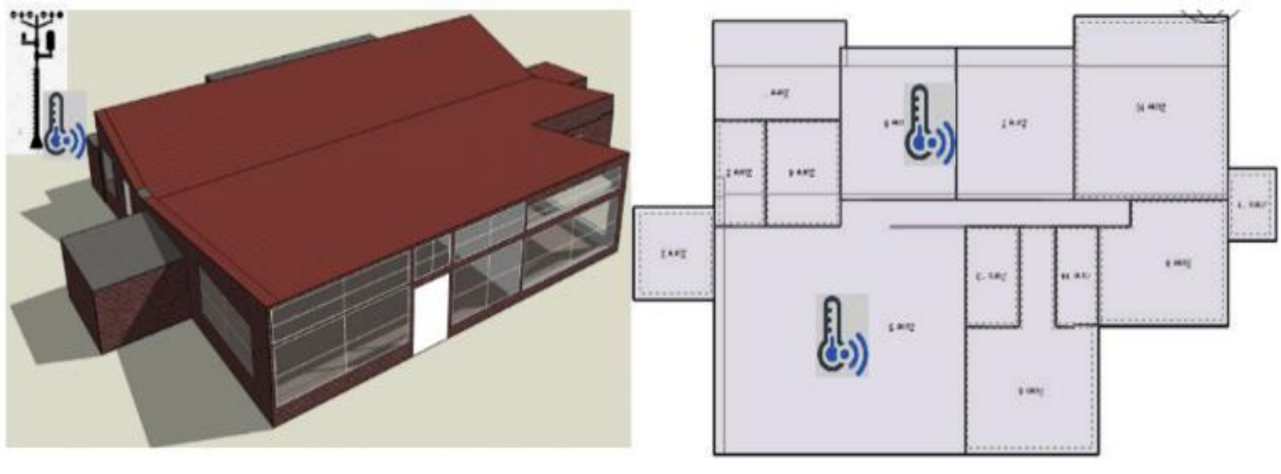

Figure 4. Sensor and weather station locations

3.2. Energy model

The energy modeling was developed with DesignBuilder (v.5.5.2.007) and energy Plus software, the latter is funded by the Building Technologies Office (BTO) of the U.S. Department of Energy (DOE) and developed by the National Renewable Energy Laboratory (NREL), several DOE national laboratories, academic institutions and private companies [11], [12]

The energy model recreates the housing object of the case study, taking into account the climatic conditions of the municipality of Berlin (Santander), the actual orientation and the meteorological data obtained in the monitoring, as well as the physical characteristics; surface dimensions of rooms and rooms, doors windows, roofs, geometry of the structure and construction materials (see table 1), which allowed a detailed analysis of the simulated data compared with the actual values obtained by the weather station, Once the climatological data is imported, the types of layers to be worked and visualized in the model are selected. At the end of this stage, the model of the house is obtained.

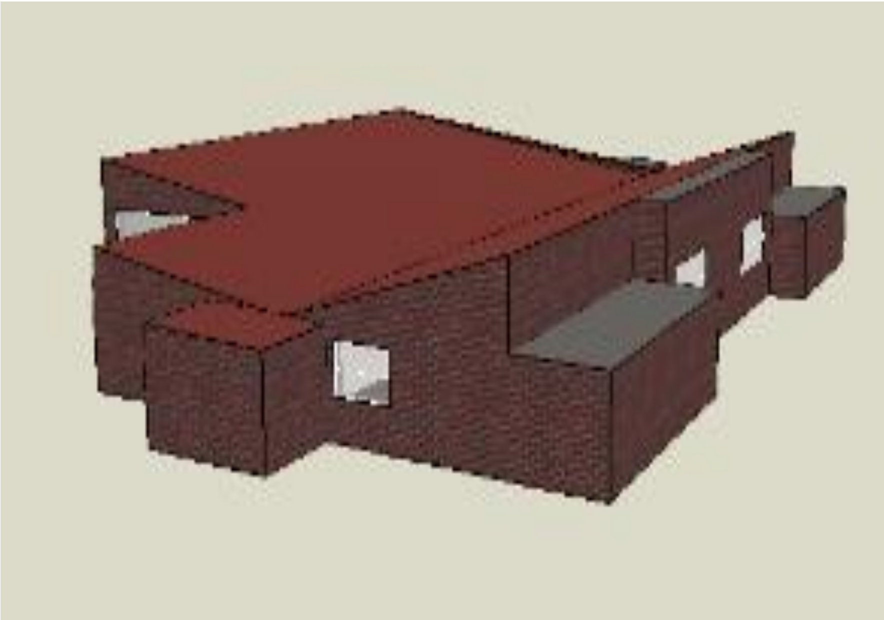

Figure 5. Model housing

Table 1. Physical characteristics of the house

Items	**Characteristics**
Latitude	7.15
Length	72.91
Full occupancy	1
Área	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

The calibration of the energy modeling of the house with respect to the real values of the meteorological station is developed through an analytical approach, the 959 data recorded in the monitoring stage were analyzed to determine the maximum correlation coefficient achievable in the modeling calibration, in the simulation were iterated in the form of sensitivity, eight parameters; occupancy, thermal loads, infiltrations, thermal transmittance, openings, natural ventilation, schedules and lighting, having as a reference point the internal temperature parameters of the house. The number of models simulated in the DesignBuilder software was 53, within the probabilistic framework of the comparison method, statistical techniques were used using metrics such as Pearson's linear correlation coefficient, the coefficient of determination R2, the sample standard deviation, the average absolute error and the relative error that determine the uncertainties of the calibration model, where the model that coincides with the ideal model is selected.

3.4. Formulation to determine correlation percentage

Next, the formulations used by the statistical technique in this study will be shown [13]. The average temperature or arithmetic mean is the sum of sample data over the number of sample data as can be seen in equation (1), providing a representative value of the data set and thus understanding the trend of the data.

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

Absolute error is defined as the discrepancy between a value considered to be accurate and the approximate value of a quantity, and is determined by equation (2).

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

Pearson's linear correlation coefficient: according to the author [13], it has a dimensionlessness as established in equation (3), by dividing the sum of squares of the product XY by the individual roots of the sums of squares of X and Y, a dimensionless index is obtained, expressed in ranges between -1 and 1, where -1 indicates that the variables have a close difference, but in opposite directions, the positive 1 implies that the variables have a high proximity in space. However, when the cosine of the function tends to 0, the variables are octagonal, indicating that they are not linearly related.

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

The coefficient of determination R2, known as R-squared is explained by the regression model. In essence, R-squared reflects the goodness of fit of a model to the variable it is intended to explain. This determination ranges between the values of 0 and 1, meaning that the closer the values are to 0, the less well fitted the values are, and the closer the values are to 1, the better the fit of the model.

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

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

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

The relative error is described as the ratio between the absolute error and the value considered as accurate of a quantity, and is found using the following mathematical expression

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

4. Results and discussion

Once the energy model used for the calibration process was developed, 53 simulations were generated and compared with the indoor temperature data of the house, the objective of this comparison being to determine which model best fits the real behavior. After obtaining the 53 energy models, they were compared according to the dispersion criterion, the most dispersed (Model 48, M48), the moderately dispersed (Model 53, M53) and the least dispersed (Model 39, M39).

For M48 the dwelling was parameterised during the monitoring time with an occupancy of 13 persons from Monday to Saturday from 08:00-18:00, a thermal load of miscellaneous gains expressed in power density of 5 W/m2 indicated by the power per zone floor area throughout the day, an infiltration rate of air that is renewed 7 times per hour, a thermal transmittance coefficient of 2.661 (W/m2. k) which is the sum of the amount of heat that is transmitted through the building materials per unit square metre, openings of 15% considering that the house has only 2 doors that allow ventilation, but more than 12 windows that allow natural light to enter.

In M53 it was indicated that the dwelling has an occupancy of 13 persons expected to be in the dwelling, a miscellaneous gain heat load expressed in power density of 80 W/m2 and computer gain of 30 W/m2, an air infiltration rate that is renewed 12 times per hour, a thermal transmittance coefficient of 2.661 (W/m2.k), openings of 15% taking into account that the dwelling has only 2 doors that allow a natural ventilation of 7 ac/h.

For model 39 it was indicated that the dwelling had during the monitoring time an occupancy of 4 persons who are expected to be in the dwelling 24/7, a miscellaneous gain thermal load expressed in power density of 38 W/m2 indicated by the power per zone floor area throughout the day and another computer gain of 4 W/m2, an air infiltration rate that is renewed 7.5 times per hour, a thermal transmittance coefficient of 2.661 (W/m2. k), openings of 15% taking into account that the house has only 2 doors that allow the entry of ventilation, but with more than 12 windows that allow the entry of natural light and a natural ventilation of 1.5 ac/h 24/7 using the openings created in the design of the house. Table 2 shows the simulation variables for models 48, 53, 39.

Table 2. Simulation variables of models 48, 53, 39.

<table>
<tr><td rowspan="6">M48
Greater
dispersion</td><td>Occupation (persons/area)</td><td>Thermal loads (W/m^2)</td><td>Air infiltrations (ac/h)</td><td>Thermal transmittance U(W/ m^2.k)</td><td>Openings</td></tr>
<tr><td rowspan="3">0,05</td><td>OE = 0</td><td rowspan="3">7</td><td>EW = 2,061</td><td rowspan="3">AA = 15</td></tr>
<tr><td>CPT = 0</td><td>BGW = 0,350</td></tr>
<tr><td>MS = 5</td><td>FR = 0,250</td></tr>
<tr><td>Ventilation</td><td>Lighting</td><td colspan="3">Timetable</td></tr>
<tr><td>0</td><td>GL = 0</td><td colspan="3">08:00-18:00 Mon-Sat; OPEN 24/7; OFFICE_OPENOFF_LIGTH</td></tr>
<tr><td rowspan="6">M53 Moderate dispersion</td><td>Occupation (persons/area)</td><td>Thermal loads (W/ m^2)</td><td>Infiltrations (ac/h)</td><td>U(W/ m^2.k)</td><td>Openings</td></tr>
<tr><td rowspan="3">0,05</td><td>OE = 0</td><td rowspan="3">12</td><td>EW = 2,061</td><td rowspan="3">AA = 15</td></tr>
<tr><td>CPT = 30</td><td>BGW = 0,350</td></tr>
<tr><td>MS = 80</td><td>FR = 0,250</td></tr>
<tr><td>Ventilation</td><td>Lighting</td><td colspan="3">Timetable</td></tr>
<tr><td>OPEN 24/7; 7</td><td>GL = 0</td><td colspan="3">08:00-18:00 Mon-Sat; OPEN 24/7; OFFICE_OPENOFF_LIGTH</td></tr>
<tr><td rowspan="6">M39
Less dispersion</td><td>Occupation (persons/area)</td><td>Thermal loads (W/ m^2)</td><td>Infiltrations (ac/h)</td><td>U(W/ m^2.k)</td><td>Openings</td></tr>
<tr><td rowspan="3">0,0179</td><td>OE = 0</td><td rowspan="3">7,5</td><td>EW = 2,061</td><td rowspan="3">AA = 15</td></tr>
<tr><td>CPT = 4</td><td>BGW = 0,350</td></tr>
<tr><td>MS = 38</td><td>FR = 0,250</td></tr>
<tr><td>Ventilation</td><td>Lighting</td><td colspan="3">Timetable</td></tr>
<tr><td>OPEN 24/7; 1,5</td><td>GL = 0</td><td colspan="3">08:00-18:00 Mon-Sat; OPEN 24/7; OFFICE_OPENOFF_LIGTH</td></tr>
</table>

OE. Office Equipment, CPT. Computers, MS. Miscellaneous, EW. External Walls, BGW. Bellow Grade Walls, FR. Flat Roof, AA. Glazing Area, GL. General Lighting

Table 3. Data validation of the models 48, 53,39

Statistical metrics	M48	M53	M39
Average temperature °C	20.85	18.166	15.654
Pearson's linear correlation coefficient	0.791	0.811	0.820
Coefficient of determination R2	0.626	0.658	0.672
Sample standard deviation	6.305	2.250	1.842
Mean absolute error	-4.820	-2.401	0.111
Relative error %	-30.6	-15.2	0.7

It is complex to obtain 100% accuracy between the simulated model and the real data, mainly due to the habits of the users, however, this study analyzed the indoor temperature ranges and trends, identifying that the model that came closest to the real data recorded by the weather station was the M39, (see Fig. 6) where a sequence of linear data was observed, with a strong relationship of more than 80% accuracy.

Figure 6 shows the temperature graphs inside the house, where the blue line represents the monitored temperature data and the orange line the temperature provided by the simulation. It can be seen that the temperature range is between 10.7 and 24.2 °C, where the greatest difference between the real data and the model data does not exceed 3.8°C in the areas of higher temperature and 2.2°C in the lower temperature ranges, showing that the M39 model is consistent.

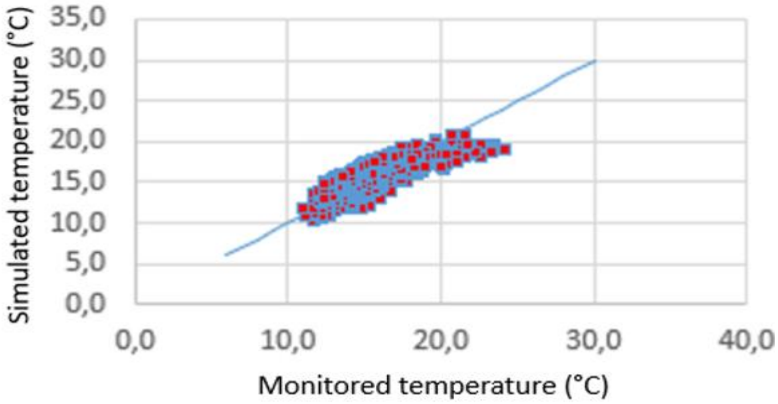

Figure 6. Scatter plots of the models 39.

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.

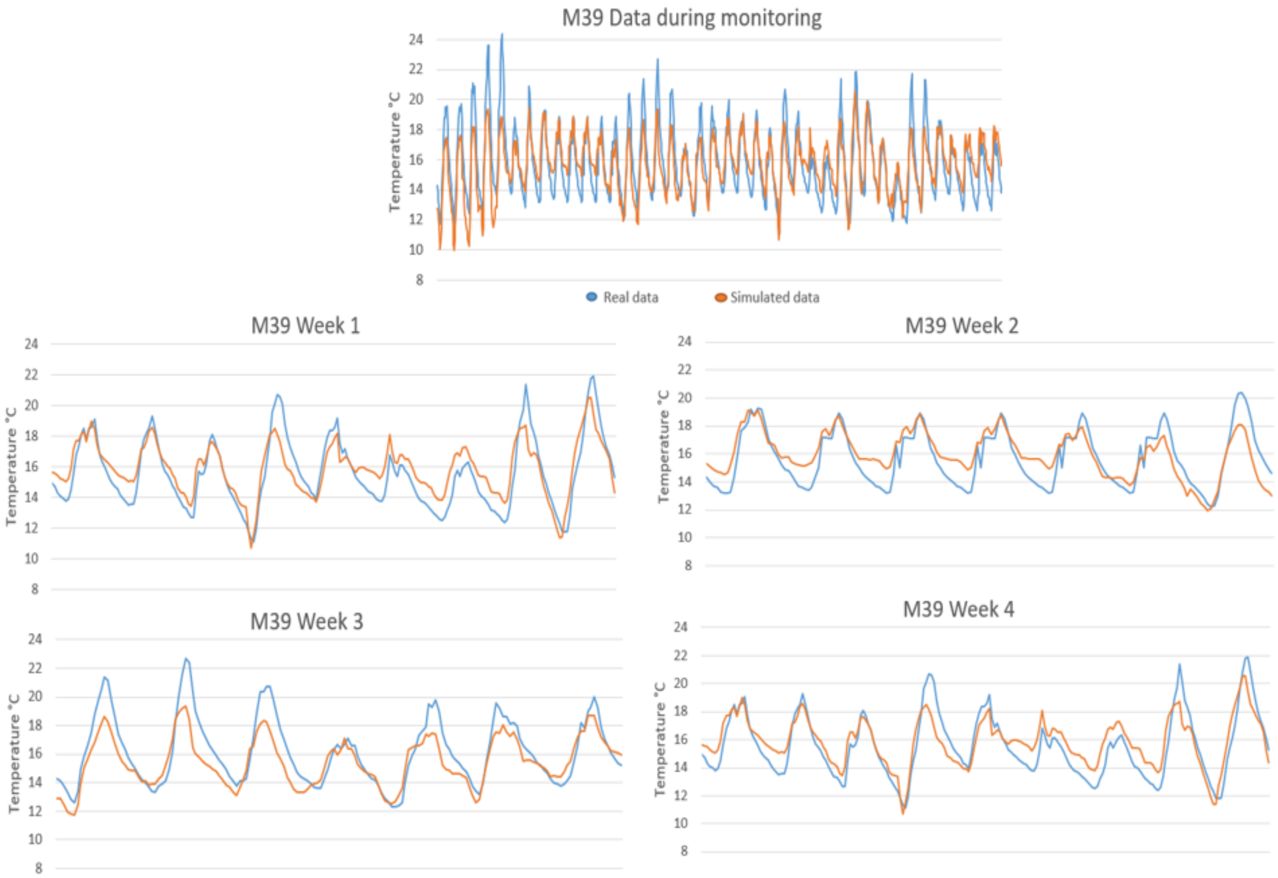

Figure 7. Comparison of simulated vs. monitored temperatures

5. Conclusions

The data monitored during the research reflect the adverse climatic conditions in a rural high mountain area with low temperatures, high solar radiation and high wind speeds, making it a sparsely inhabited area of Colombia, which motivates the development of thermal comfort studies for these populations. The calibration methodology developed in this research reveals that the adjustments are directed to reduce the uncertain parameters and evaluate their effect on the energy model through a sensitivity analysis, however, the manual iteration ends up deriving in an extensive process and sometimes without considerable variations from one parameter to another, based on this, it is recommended the use of numerical approaches that allow the integration in the data validation process.

Accuracy in the measurement of actual occupancy conditions is crucial for the calibration of building energy models. The influence of users and their behavior, such as natural ventilation, plays a significant role in the variability of internal parameters and thus in the accuracy of the model. The implementation of surveys and monitoring devices, such as window opening contactors, can reduce uncertainty and improve the correlation between real and simulated data.

It has been observed that infiltration and natural ventilation variables are particularly sensitive and have a considerable impact on indoor thermal oscillation ranges, as demonstrated during the temperature peak in the data collection period. This underscores the importance of considering these variables in the calibration of energy models. For future research, it is recommended to focus on the analysis of the impact of building infiltration. The amount of uncontrolled air introduces a large uncertainty in performance analyses, suggesting that a deeper understanding of this phenomenon could lead to more accurate models and ultimately more energy efficient buildings.

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