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Temperature Prediction for indoor environments using sensors and Linear Regression

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Informações do Artigo

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Arduino,
Built Environment,
Digital Twins.
Energy Efficiency,
Sensors.

Resumo:

A eficiência energética está sendo procurada como uma nova abordagem ao consumo de energia no ambiente construído, visando a transição energética e sustentabilidade. A recente incorporação dos avanços tecnológicos da Indústria 4.0 permite integrar diferentes dispositivos para automatizar o processo de tomada de decisão na indústria da construção. Nesta pesquisa foram utilizados um microcontrolador Arduino e um sensor de temperatura para obter registros da temperatura em um laboratório. O objetivo foi utilizar esta inovação digital para gerar dados deste espaço e permitir o desenvolvimento de estratégias de eficiência energética. Utilizando um método de Regressão Linear Múltipla, e com base em quatro horas e meia de medições, foi realizada a previsão da temperatura para o funcionamento do espaço durante o resto do dia. Verificou-se que o laboratório permaneceu em um intervalo de temperaturas entre 21ºC e 24ºC durante todo o dia, ligando o ar-condicionado apenas durante uma hora e meia, o que garante níveis de conforto e poupanças energéticas significativas. A contribuição desta pesquisa primeiramente ajuda a explorar a integração de tecnologias 4.0 no ambiente construído para o desenvolvimento de gémeos digitais de ativos físicos. Em segundo lugar, permite encontrar um ponto ideal entre o conforto interior e o consumo energético.

Abstract

Energy efficiency is being pursued as a new approach to the energetic consumption in the built environment towards energy transition and sustainability goals. The recent incorporation of technological advances from the Industry 4.0 permits to integrate different devices to automate the decision-making process in the construction industry. In this research, an Arduino Microcontroller and a temperature sensor were utilized to obtain registers about the temperature in a laboratory. The objective was to utilize this digital innovation to generate data for this space and permit the development of energy efficiency strategies. By utilizing a Multiple Linear Regression method, and basing on four and a half measurements, a prevision of temperature was accomplished for the functioning of the space during the rest of the day. It was found that the laboratory remained between 21ºC and 24ºC all over the day by only turning on the *air conditioner for one and a half hour, which ensures comfort levels and significant energy savings. The contribution of this research, firstly, helps in exploring the integration of 4.0 technologies in the built environment towards the development of digital twins of physical assets. Second, it permits to find an optimal point between indoor comfort and energy consumption.*

1. Introduction.

The new era of digitalization is expected to promote changes in the current energy systems by including optimized strategies and cost-effective solutions for future energy grids and reduce carbon emissions [1]. The utilization of Digital Twins (DT) technology and smart energy-management systems would permit to automate the energy use [2].

Energy 4.0 surges as a solution to outdated and overwhelmed grids, making them smarter and with bidirectional communication by using technological innovations. Smart grids in energy systems mean databased environment, with advanced analytical capabilities, integrated, and decentralized, including renewable energy sources. The smart monitoring process permits to acquire real-time data about voltage, current, connectivity, and temperature via wireless sensor networks [3].

In the built environment, there is a chance to include advanced technologies such as smart grids, smart management systems, renewable energy sources, and storage. Likewise, the utilization of sensors, smart meters, data sources, and wireless communication can help to achieve the integration of the above-mentioned technologies [4].

Energy consumption in the built environment depends on many aspects, such as location, use, hours of operation, equipment technology, and so on. Optimizing building energy consumption seems imperative since commercial and office sectors consume 71% of the whole global energy consumption [2].

The energy sector is one of the most important for society, where reliable and permanent operations are essential. The innovations in this sector are expected to enhance the operations and integration with other systems [3]. Energy efficiency is based on the capability to permit energy savings, and it is pointed out as the main goal to pursue when using 4.0 technologies in smart energy systems. The transition to this energy system is inevitable. It is expected to obtain 18% increase in energy efficiency by 2030, but to achieve it seems necessary to surpass the challenge of presenting a more developed data infrastructure in the smart energy systems [1].

The United Nations (UN) highlights a strong relationship between sustainability and energy transition. It is expected that the inclusion of technical advances related to digitalization in the energy sector will translate into relevant transformation in the energy sector, changing the way people trade, produce, consume, and live. However, accelerating the global energy transition represents a challenge, first, due to the high interdependency of high-carbon fossil fuels; second, due to the difficulties in transformation and adjustments in energy system’s structures; and third, due to the several concerns in terms of environmental and social aspects [5], [6], [7].

For this reason, the next research question is: What are the current possibilities of integrating 4.0 technologies in the construction industry towards energy transition? It is possible to think that testing 4.0 technologies in the built environment determines if these technologies truly encourage transition energy.

The objective of this research relies on testing if one of the 4.0 technologies permits us to develop energy-efficient measures in the built environment. It is important to deepen our knowledge about this area due to the possibilities of discovering integration strategies that the most recent technologies offer. This research is concerned in optimizing the utilization of energy and bringing a sustainable perspective for its consumption according to the most recent demands in the built environment.

2. Literature Review.

Global energy consumption has increased in the last years, highlighting the need to achieve sustainability goals to avoid negative effects. For this reason, reducing energy consumption, diversifying the energy grid, promoting behavioral change, and utilizing the latest technological trends had gained interest, making it possible to develop a whole area of research named energy transition [6], [8].

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The role of these technologies is to permit the implementation of energy-efficiency strategies, which performs a primary role in the transition to net-zero carbon emissions [6]. In the construction industry, energy efficiency is one of the most relevant cost-saving opportunities for facilities managers since it does not require huge investments or expenses [9]. As the focus of sustainability in construction is related to the energy systems, the attention relays on the operation of the built environment [2].

The strategies for reduction of energy consumption are associated, in part, to control the thermal performance of a building during operational phase of the building, considering passive and active system components. For this reason, the optimization of the HVAC systems and appliances is important to ensure an efficient energy operation [2], [9].

The integration of data in the energy systems could permit the development of Digital Twins (DT). Within them, the digital information is obtained, processed, analyzed, and can be integrated with the digital environment to improve the physical environment [10]. Real-time data exchange is one of the most important aspects of 4.0 technologies since it is relevant to obtaining information of constant and instantaneous monitoring. The data obtained from the system can be analyzed effectively and different models of the building's energy consumption can be evaluated. With this, help managers make informed decisions about energy use and saving opportunities, predict equipment failures and program maintenance activities, and quickly identify errors [2], [11].

Data collection and acquisition are one of the most important procedures to obtain energy savings. This task involves sensor selection, establishment of a communication protocol, information systems, and storage, and establishing a data prioritization protocol. The utilization of data-driven modeling methods can adapt to the uncertainties in the systems, reflecting the behavior of the real world and the introduction of smart approaches is required to execute predictive analysis [1].

The digitalization of energy systems promotes the increment of volumes of data, introduces new technologies, and contributes to revenue streams. It permits us to understand a holistic perspective of energy efficiency, including demand-side flexibility and end-use-side efficiency. Also, it ensures better information flow and the provision of electricity following the lowest emissions and costs properly [6].

However, there is a series of barriers and challenges that need to be surpassed to properly implement smart energy systems. There are significant economic and financial barriers, due to high initial costs. Also, lack of social awareness, since the inclusion of digital technologies have faced severe resistance due to less recognition and limited learning rate [6]. It is lacking a significant evaluation of the integration of technologies such as blockchain, IoT, renewable energy sources in smart grids, towards the digitalization of the energy systems. Also, more research is needed to understand how these technologies help to achieve energy efficiency [6].

Some authors conveyed that the challenges for this include the adoption of correct strategies to efficiently manage and obtain data, designing predictive models capable of managing uncertainties, and interconnecting the different components of a grid [2], [12]. For this reason, it is necessary to continue exploring energy performance analysis, as well as developing more detailed layout and configuration of buildings. Also, it is necessary to continue validating, testing and improving the models [2].

3. Methodology.

Many researchers have studied the consumption of the building's energy by the HVAC (Heat, Ventilation and Air Conditioning) systems, by developing different strategies to improve the thermal comfort of the dwellers. The general idea is to apply energy-efficient approaches, since energy savings is a critical challenge nowadays [13], [14], [15].

Some authors have identified six variables affecting thermal sensibility: temperature, humidity, air speed, average radiant temperature, metabolic rate, and clothing insulation. Smart monitoring has been developed to measure these variables, especially in the operation stage of the building [13], [16], [17].

One of the most applied techniques to measure indoor variables in the built environment affordably is by using the microcontroller Arduino with sensors [13], [15], [17], [18]. Several research has been accomplished toward creating a real-time platform for performance monitoring, utilizing piezoelectric sensors, different types of Arduino controllers, different building systems, and disposing IoT to communicate data [15], [18], [19]. Appliances connected to a microcontroller can run automatically by embedding a program into the microcontroller [20].

Essa *et al.*[15] utilized temperature, humidity, vibration, and pressure sensors to execute environmental analysis and identify occurring liabilities. They collected, organized, and saved data using an Arduino Mega Microcontroller, and a Raspberry Pi controller was utilized to process data and perform automatic decisions.

Romadhon and Widyaningrum [20] developed a system using an Arduino Mega, and three different types of sensors to make decisions over different connected devices under the concept of smart home. They tested the system's capabilities to open a gate and a garage door, measure temperature and humidity, give warnings in case of gas leakage, and turn on/off the lights.

Aleksandrovs-Moisejs *et al.* [16] worked with three types of temperature sensors to accomplish measurements under different conditions and analyze which was more sensitive. They utilized the IDE application to program the commands. Likewise, Mobaraki *et al.* [18] developed five different monitoring systems using five different sensors to evaluate their accuracy. Two different algorithms were established to capture and analyze the data using IDE programming application.

Nikitha *et al.* [21] studied the development of a smart-home system for monitoring environmental conditions (temperature, humidity and fire-detection monitoring) in the living room and a bedroom. Similarly, El-Leathey *et al.* [22] created a system using Arduino and multiple sensors, but in this case, for studying environmental conditions in office buildings towards the creation of energy-efficient strategies. The conditions analyzed were humidity, light, sound level, and temperature.

Visvesvaran *et al.* [23] developed a greenhouse monitoring system based on temperature, humidity, soil moisture, pH, and light sensors and an Arduino microcontroller, to automatically deliver nutrients to the plants. Borkowski [17] created a system for temperature monitoring in a house to permit the enrichment of a digital model towards the integration of data following the BIM methodology. With the help of sensors, an Arduino microcontroller, and the Arduino IDE programming environment, the author studied the integration with a BIM model through the MQTT protocol.

Abdalgader, Al Ajmi and Saini [19] developed a system for measuring and analyzing the effect of weather conditions on thermal insulation efficiency by measuring temperature and humidity with low-cost sensors.

Irshad *et al.* [14] studied the performance of a thermoelectric air conditioning system controlled by a IoT-based configuration for real climatic application. The goal was to maintain the temperature of the room by continuously monitoring the parameters.

Mahgoub *et al.* [24] developed an experimental Building Management System (BMS) to monitor environmental conditions to reduce energy loads during the operation of buildings. This research integrated a programmable logic controller, an Arduino, and several sensors to obtain data, as well as an ANN to make forecasts of the temperature indoors.

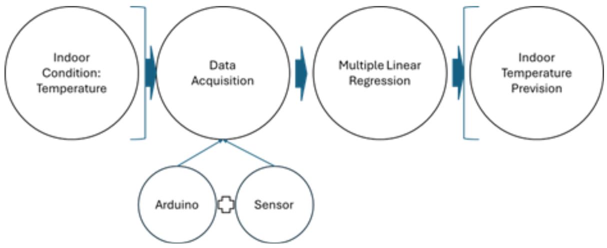
The integration of real-time data to enrich models appears as a suitable idea since it permits visualization, monitoring, and automation of the decision-making process [13], [15]. According to the amount of data, the decision-making process can be assisted by IA. For solid databases, automation algorithms can be useful to execute commands to the appliances of the system. However, for limited databases, it is necessary to accomplish forecasts of the condition's behavior or the performance of the appliances.

Artificial Neural Network (ANN) algorithm can be utilized to make forecasts related to the temperature indoors, due to its reliability, however it needs a sufficient and representative amount of data for the model training [25]. A linear or multiple regression analysis of the available data can be executed as well, especially when it is scarce.

For this reason, to accomplish forecasts of temperature data in this research, only a multiple linear regression study was performed to understand the temperature variations in a laboratory room. It was considered this space with its air conditioner unit on during a period, and also, an opened door that permitted to receive cold air from an air conditioner unit out of this space. This situation represents the normal functioning of the laboratory.

It was found the equation that leads the model, considering temperature as the dependent variable, and the periods of study as independent variables. A flowchart showing the whole process of this research can be seen in Figure 1.

Figure 1 – Flowchart of the research.



Source: Authors (2024)

For this research, only the variable temperature was considered for measurements. The microcontroller Arduino MEGA 2560 was utilized, as well as the HDC1080 sensor temperature sensor. The Arduino MEGA 2560 is one of the most popular microcontroller boards in the electronics industry, counting with 54 digital input/output pins, 16 analog inputs, 4 hardware serial ports, a 16 MHz crystal oscillator, and a USB connection. The sensor selected for the temperature measures was HDC1080 Low Power, High Accuracy, from Texas Instruments, which measures temperature, with a range from -40ºC to 125ºC and ±2ºC accuracy, and humidity with a range from 0 to 100% and ±2% accuracy.

The place chosen to execute the measurements was Laboratory Nº 1 of the GESTORE department, part of the Escola Politécnica of the Federal University of Rio de Janeiro. It is a closed underground room, with artificial lighting, windows with indoor views, 4 LED lamps with neutral lighting, and an air-conditioning unit (see Figure 2). The microcontroller was put on a table, and properly connected to the computer (see Figure 3). The arrangement of cables and the sensor can be seen in Figure 4.

Arduino Integrated Development Environment (IDE) was used to create a code to make measurements. It is open-source software that permits to write codes and upload them to the board. ClosedCube_HDC1080 library was utilized on Arduino IDE to collect temperature data from the HDC1080 sensor. This library was created specifically for this sensor and permits us to acquire measures of humidity and temperature easily; in this case, it only reads the former. The outputs of temperature measures are represented in Celsius (C), which can be seen in Appendix A. The data obtained was exported in format .csv to create a file in Microsoft Excel.

Figure 2 – Laboratory's floor-plan sketch.

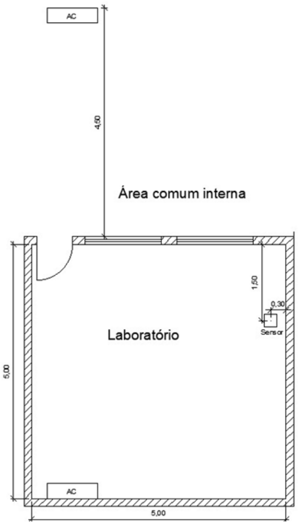


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Figure 3 – Detail of sensor arrange.

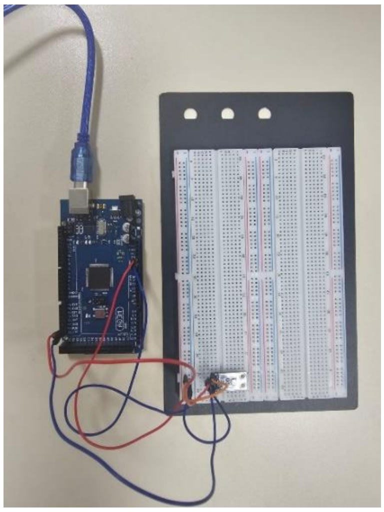

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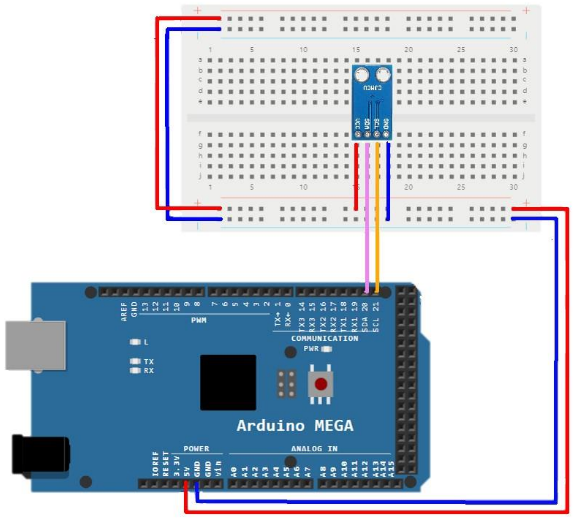
Figure 4 – Diagram of cable placement in Arduino Microcontroller.



Source: Authors (2024)

A Multiple Linear Regression analysis was applied to make predictions of the indoor temperature. To achieve this, Microsoft Excel was utilized to read the .csv file and execute the analysis. It consisted of the application of the function LinEst, which accomplishes Multiple Linear Regression to predict the outcomes of a dependent variable based on two or more dependent variables. For this study, there were defined four terms in the equation: Known_y (known temperature values), Known_x (day time and the amount of the air conditioner was on/off), const (true or false, resulting b=0 or calculated), stats (true or false, returning values of R2 and error).

The forecast of indoor temperature was necessary to understand how the temperature is expected to perform in a controlled environment based on a reduced database. The expected temperature behavior was compared to the real temperature values to understand if it is possible to make previsions for other periods based on the acquired measures.

4. Results and Discussion.

The sensor data was obtained every five minutes during a lapse of four and a half hours. The study was accomplished on October 8th, 2024. The code utilized for reading the measurements in Arduino IDE using the ClosedCube_HDC1080 library can be seen in Figure 5.

Figure 5 – Code utilized for reading the temperature.

```
#include "ClosedCube_HDC1080.h"
#include <Wire.h>

ClosedCube_HDC1080 hdc1080;

void setup() {
  Serial.begin(9600);
  hdc1080.begin(0x40);
  Wire.begin(0x40);

}

void loop() {
  float temperature = hdc1080.readTemperature();
  Serial.println(temperature);
  delay(300000);
}
```

Source: Authors (2024)

After obtaining the data of the sensor, it was converted to .csv format for its proper analysis. The data delivered was in terms of time and the temperatures registered. With the data in Microsoft Excel, two more columns were created to represent the time when the air conditioner unit was on and the time when the air conditioner unit was off.

Afterward, it was applied the LinEst function, which returns a matrix with the values of Line 1 representing the coefficients of every term that can be placed in the equation of regression:

$$y = m_1 x\, X_1 + m_2 x X_2 + m_3 x X_3 + b$$

Using the least squares method to perform linear regression, it is possible to approximate the data obtained from a model that follows the equation mentioned above. In here, the dependent variable (y) is the measured temperature, the independent variables are: time (X1), time elapsed with air conditioning off (X2), and time elapsed with air conditioning on (X3).

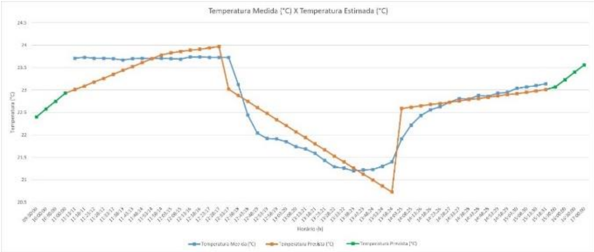
For better adjustment results, the variables relating to the functioning of the air conditioning were separated into two variables to represent the amount of time since there was a change in the device's operation, thus considering that the temperature changes gradually regarding how long it has been operating or not.

The time was normalized around 12:00h, with this being considered as 0, and the values increasing the further away they are from this time. It represents more adequately the cyclical increase in indoor temperature throughout the day. As temperatures at close times can be similar, even if separated by a change of day (for example, the temperature at 23:00h is close to that at 1:00h) this approach makes the model more accurate for predicting future temperatures. For our model, it was obtained the next equation, with an R^2 of 0.87.

$$y = -4.23x\, X_1 + 16.37xX_2 - 30.28xX_3 + 23.28$$

With this equation, it is possible to accomplish previsions for other values of temperature considering different times of the day. Figure 6 shows the series of temperatures measured in a period between 11:00h until 15:15h in a function (blue line), also it shows the function of the predicted temperature (orange line). In this case, a small prevision of temperature was executed from around 9:30h to 11:13h, and from 15:13h until 17:00h (green lines). The temperature values adjusted in the model, as well as their relative error can be seen in the Appendix A.

Figure 6 – Measured and Predicted temperatures by the sensor.

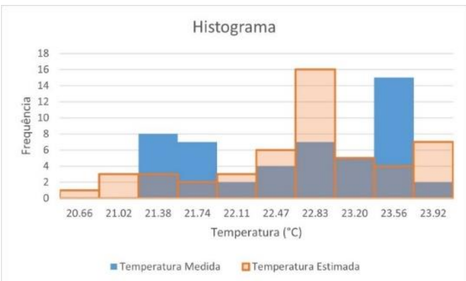


Source: Authors (2024)

In this study, the result for the variance was 0.82 was obtained for measured values, and 0.71 for estimated values. This difference may indicate that the linear regression model smoothest the dispersion of the data, not capturing all the variations in the actual measured values. This analysis is important for evaluating the model's accuracy. It is a positive indicator, since the real and estimated values were close, despite suggesting potential for improvements in the model's adjustment.

Figure 7 shows the histogram of the temperatures. The histogram of the measured temperature (blue bars) demonstrates a bimodal characteristic, being able to see the separation of two groups of data with the air conditioning on and air conditioning off, with the higher temperature measurements appearing more frequently given that during the measurement the air conditioning unit spent more time off. The estimated temperature histogram (orange bars) demonstrates the model's tendency to normalize the values, something expected for a linear regression, according to the observation of the variance being small.

Figure 7 – Histogram of the measured and predicted temperatures.



Source: Authors (2024)

The prediction of temperatures is an important aspect to consider if there is a database with a reduced number of registers. It could happen due to a series of causes, for example, for not being able to continue measuring data, for restrictions in the utilization of spaces, for loss of registers, for errors on the sensors, and so on. In front of these unexpected situations, the continuity of registers must be considered for the development of strategies to manage the appliances towards ensuring proper comfort levels and energy efficient approaches.

Indoor temperatures can be forecasted utilizing other techniques, for example, ANN. However, its reliability will depend on the size and representativeness of the database. [24]accomplished a study making previsions of temperature in a day-long study. Despite the present research did not utilize ANN, the previsions in Microsoft Excel are simpler but can be considered correct, affirming the possibility of achieving previsions following different methods.

The comfort and energy-efficient strategies in the built environment find an optimal point, for example, when an interval of temperature values is proposed as fixed, as well as the time of functioning of an air conditioner unit. In consequence, the air conditioner in the room should not permit the temperature to surpass the limits.

In this research, the analysis of the temperature indoors permitted us to understand that the utilization of the air conditioner during an interval of less than two hours allows the maintenance of the temperature between 21ºC and 24ºC, considered as comfortable for its utilization. This condition is possible in this laboratory, considering the rest of the environmental conditions in the area.

The utilization of sensors in the built environment allows us to identify these kinds of particularities in indoor spaces. With the information in this research, it is possible to think that an air conditioner unit can be utilized in intervals of around one and a half hours every two hours, reducing the energy related to its continued consumption. Likewise, the temperature can remain fixed during the period of functioning and still offer a comfortable room, has also done by Irshad *et al.* [14] in their study. The parameters of temperature comfort obtained in this research can be confirmed as correct since they are similar to the ones studied by Nikitha *et al.*, and El-Leathey *et al.* [21], [22].

Despite the utilization of sensors and an Arduino microcontroller is already used, it is highly recommended to execute a series of analyses in the built environment, due to its simplicity and low cost, as highlighted by Abdalgader, Al Ajmi and Saini [19]. The incorporation of illuminance and humidity sensors can permit to study deeper the interaction of these conditions in the comfort levels of indoor spaces, as accomplished by Essa *et al.*, Nikitha *et al.*, and El-Leathey *et al.* [15], [21], [22].

Also, the utilization of other types of sensors in other building systems following the concept of smart homes is imperative. The necessity to automate the decision-making process to increase the building-user's well-being, or the creation of digital twins of real constructions, opens ways to continue exploring the interaction between sensors and Arduino microcontrollers.

5. Conclusions and Recommendations.

The United Nations is promoting energy transition to achieve sustainable energy goals for 2030. Studies forecast that around 80% of energy consumption would come from renewable energy systems by 2050, but for this, techniques for protection and stability assessment are necessary to implement the operation of smart energy systems [26].

The objective of this research was accomplished. It permitted the utilization of 4.0 technologies in the built environment by installing sensors in an indoor environment. It was achieved in a low-cost way considering only a microcontroller Arduino and a temperature sensor. This approach permits us to prove that the integration of new technologies can be done in a simple form, and also allows the creation of data for developing efficiency strategies in the energy systems.

Since the interpretation of the data elucidates the possibilities to enhance the appliance's performance, it is possible to affirm that the research objective was achieved.

Energy-efficient measures considering an energy-transition approach are affected by the inclusion of new technologies that can promote information exchange, reduce information asymmetry, and create knowledge spillover [5]. For this reason, the incorporation of innovators that allow the creation of cyber-physical models in the energy systems of the built environment is a current topic of interest permitting professionals to think in novel approaches.

One of the limitations of this research remains on the size of the database, which only measured temperature in a short period of time of around four hours. For this reason, it is suggested to obtain more temperature measures to enrich the model and increase its reliability. Also, with a more robust database, ANN can be applied to obtain a forecast following another approach.

Likewise, it is recommended to study other indoor conditions, such as humidity or illuminance. Another research can be done considering the integration of temperature values with both abovementioned conditions to have a more holistic understanding of the laboratory room indoor behavior.

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7. Appendix.

APPENDIX A

Table 1 – Temperatures measured and estimated.

Hour	Measured Temperature (ºC)	Estimated Temperature (ºC)	Relative Error	Hour	Measured Temperature (ºC)	Estimated Temperature (ºC)	Relative Error
11:13:11	23,71	23,01	2,95%	13:18:21	21,59	21,80	0,97%
11:18:11	23,73	23,09	2,70%	13:23:21	21,43	21,67	1,12%
11:23:12	23,71	23,18	2,24%	13:28:22	21,29	21,53	1,13%
11:28:12	23,71	23,26	1,90%	13:33:22	21,26	21,40	0,66%
11:33:12	23,70	23,35	1,48%	13:38:23	21,20	21,26	0,28%
11:38:13	23,67	23,44	0,97%	13:43:23	21,22	21,13	0,42%
11:43:13	23,70	23,52	0,76%	13:48:24	21,23	21,00	1,08%
11:48:14	23,71	23,61	0,42%	13:53:24	21,30	20,86	2,07%
11:53:14	23,70	23,70	0,00%	13:58:24	21,40	20,73	3,13%
11:58:14	23,71	23,78	0,30%	14:03:25	21,91	22,59	3,10%
12:03:15	23,70	23,83	0,55%	14:08:25	22,22	22,62	1,80%
12:08:15	23,69	23,86	0,72%	14:13:26	22,43	22,65	0,98%
12:13:16	23,74	23,89	0,63%	14:18:26	22,56	22,68	0,53%
12:18:16	23,74	23,91	0,72%	14:23:26	22,63	22,70	0,31%
12:23:17	23,73	23,94	0,88%	14:28:27	22,73	22,73	0,00%
12:28:17	23,73	23,97	1,01%	14:33:27	22,81	22,76	0,22%
12:33:17	23,73	23,02	2,99%	14:38:28	22,80	22,79	0,04%
12:38:18	23,13	22,88	1,08%	14:43:28	22,88	22,81	0,31%
12:43:18	22,44	22,75	1,38%	14:48:28	22,86	22,84	0,09%
12:48:19	22,04	22,61	2,59%	14:53:29	22,93	22,87	0,26%
12:53:19	21,92	22,48	2,55%	14:58:29	22,95	22,90	0,22%
12:58:19	21,91	22,34	1,96%	15:03:30	23,04	22,92	0,52%
13:03:20	21,85	22,21	1,65%	15:08:30	23,07	22,95	0,52%
13:08:20	21,74	22,07	1,52%	15:13:30	23,10	22,98	0,52%
13:13:21	21,69	21,94	1,15%	15:18:31	23,14	23,01	0,56%

Source: Authors