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Hygrothermal and Economic Analysis of an Earth-Based Building Using In Situ Investigations and Artificial Neural Network Modeling for Normandy's Climate Conditions

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Abstract: This paper investigates the in situ hygrothermal behavior of a cob prototype building equipped with multiple sensors for measuring temperature, relative humidity inside the building, and water content within its walls. The experimental results show that the earth-based prototype building presents interesting thermal insulation performance. Without any heating system, the indoor temperature was found to remain stable, near 20 °C, despite large fluctuations in the outdoor temperature. This study also illustrated the ability of cob to absorb and regulate indoor relative humidity. The use of a neural network model for predicting the hygrothermal behavior of the cob prototype building was an additional objective of this work. This latter was centered on investigating the indoor ambience and moisture content within the walls. In this sense, a long short-term memory model (LSTM) was developed and trained. The validation results revealed an excellent agreement between the model predictions and experimental data, with R^2 values of 0.994 for the indoor air temperature, 0.960 for the relative humidity, and 0.973, 0.925, and 0.938 for the moisture content at three different depths in the building's walls. These results indicate that the LSTM model is a promising approach for predicting the indoor ambience of an earth-based building, with potential applications in building automation and energy management. Finally, an economic discussion of the CobBauge system is presented.

Keywords: earth construction; cob; moisture; prediction; artificial neural network

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1. Introduction

The growth of the construction sector has led to an increase in large-scale cement production. Cement production is responsible for a large proportion of global CO_2 emissions [1,2]. The European Commission launched the "Green Deal" at the end of 2019 with the intention of placing the European Union (EU) on the right path to climate neutrality by 2050 [3]. The European Union drafted a legislation known as the "European Climate Act", which came into effect on 9 July 2021 and intends to reduce greenhouse gas emissions in the EU by at least 55% by 2030 (compared to 1990 levels) [4]. Also, to be in accordance with the French regulation RE2020 and comply with the COP21 recommendations [5], it is necessary to reduce energy consumption and move toward the use of more environmentally friendly materials.

This regulation aims to decarbonize the construction sector by promoting the use of materials from organic and/or marine agriculture. The building sector, the second-most polluting sector after transport, accounted for over 25% of France's greenhouse gas emissions in 2019. As a result, limiting CO_2 emissions is an important issue to meet national targets, in particular the National Low Carbon Strategy [6]. The new RE2020 regulation is built on the national positive energy/reduction in CO_2 (E+C−) experiment initiated by the French public authorities in November 2016.

The creation of the "Projet National Terre" (Earth National Project) under the guidance of the public authorities demonstrates France's determination to promote the larger-scale deployment of raw earth construction [7]. Participating associations have published practical guidelines for raw earth construction, covering a variety of building techniques such as rammed earth, adobe, cob, and light earth. These associations are also working on drafting future environmental regulations that integrate an environmental assessment of earthen constructions. Specialists are also joining forces at the European level for training purposes, such as the European Leonardo and Pirates projects. These projects have created a common repository for demonstrating earth construction know-how.

In the context of global warming, the development of raw earth construction can present a real alternative for reducing the CO_2 emissions of the building sector [1,2]. However, this age-old material must be able to guarantee good mechanical resistance, adequate water resistance, and provide occupants with hygrothermal comfort under the particularly severe conditions imposed by the regulations in force.

The most common earthen construction technique in Normandy and southwest England is cob, which combines sand, clay, vegetable fibers, and water. The amount of fiber in a fresh cob is normally between 20 and 30 kg/m^3, with a fiber length of 30–50 cm [8]. Sandy soil is mixed with water until it reaches a plastic consistency, and traditionally, fibers are then worked underfoot by cattle's hooves, whereas currently, machine mixing is used. The cob is then stacked in multiple layers of up to 0.7 m high. One or two days later, when the mass of the cob layers has the right moisture content, the wall faces are cut vertically with a spade or paring iron and then left to dry. The density of traditional cob is generally between 1200 and 1700 kg/m^3 [8]. Because it uses locally available soil fibers and requires very little energy, traditional cob manufacturing is environmentally friendly and sustainable [9].

A UK–France collaborative project aiming to improve the ancient method of cob construction was launched in 2017. The European project CobBauge seeks to develop cob construction to meet European challenges, particularly those related to reducing CO_2 emissions. Therefore, traditional cob has been adapted in order to meet the French regulation RT2012 while maintaining its structural character. Indeed, RT2012 (regulation in force before RE2020) imposes three modulated criteria that must be satisfied: conventional bioclimatic need (Bbio max), conventional energy consumption (Cep max), and conventional indoor temperature (TIC ref). Bbio is a coefficient that characterizes the full impact of design on a building's energy performance. Cep is the conventional primary energy consumption (with an average maximum value of 50 kWhpe/m^2/year). TIC is the conventional indoor temperature, representing the maximum hourly value of the operating temperature reached in a room in summer during the period of occupancy. After preliminary studies revealed the impossibility of achieving a mixture that simultaneously fulfills both load-bearing and thermal resistance functions, the walls are made up of a double layer: a structural layer on the internal part and an insulating layer on the external part [10].

A CobBauge prototype building was constructed on the territory of the Cotentin and Bessin Marshes Regional Natural Park (Normandy, France) [10]. The earth–fiber walls are built on a 70 cm high composite sub-base made of lightweight concrete and lightweight aggregate. During construction, sensors were installed within the walls to evaluate the drying behavior of the material and the hygrothermal performance of the walls during the life of the building. In addition, a weather station was installed near the building. This station allows the measurements of outside temperature, ambient hygrometry, solar radiation, wind speed and direction, rainfall, and intensity of precipitation.

The use of bio/geo-based materials in construction has recently garnered attention due to their potential sustainability as renewable resources. However, their complex hygrothermal behavior poses challenges in building component applications. Accurate prediction is essential for energy-efficient designs. Traditional physical models struggle to capture material–moisture–heat interactions, while data-driven methods like artificial neural networks (ANNs) hold promise in modeling these behaviors due to their ability to handle non-linear relationships and learn from extensive datasets without explicit mathematical formulations.

The existing literature on neural network modeling of hygrothermal behavior in bio-based building materials is limited, with only a few studies (Table 1) available. Notably, reference [11] by May Tzuc et al. employed ANNs and global sensitivity analysis to model the hygrothermal behavior of a concrete wall in a green facade exposed to Nordic climate conditions. In a related study, Tijskens et al. [12] introduced convolutional ANNs for assessing the hygrothermal properties of timber frame walls, while their earlier work [13] concentrated on ANNs for metamodeling building components' hygrothermal behavior. These articles highlight data-driven models' potential to predict bio- and geo-sourced construction materials' behavior accurately, offering prospects for more sustainable and energy-efficient building designs.

Table 1. Summary of work using data-driven models for hygrothermal prediction.

Study	Model	Type of Materials	Scale of the Study
May Tzuc et al. [11]	ANN	Double-skin green facades	Wall
Tijskens et al. [12]	CNN	Timber frame wall with brick veneer and sidings	Wall
Tijskens et al. [13]	CNN and LSTM	Massive masonry wall	Wall

Furthermore, existing studies have primarily focused on small-scale wall experiments conducted under controlled climatic conditions, lacking research on data-driven modeling for earthen materials at the building scale. Thus, this article aims to develop a data-driven model for predicting the hygrothermal behavior of earthen materials at an actual building scale. This study intends to establish the relationships between input and output variables using machine learning techniques applied to experimental data. The resulting model undergoes validation to assess its predictive capabilities and practical applicability. These objectives will contribute to advancing sustainable building practices by enabling precise predictions of earthen-based materials' hygrothermal behavior, promoting their broader adoption in modern construction.

In this paper, we present a comprehensive model for the hygrothermal behavior of a CobBauge double-walling system using long short-term memory (LSTM). We will highlight the strengths and limitations of this LSTM-based modeling approach and provide insights into the challenges and opportunities in developing accurate and efficient models for the sustainable use of bio/geo-based materials in construction.

The LSTM model demonstrates several strengths in hygrothermal forecasting at the wall scale [13]:

(i) It can capture complex nonlinear relationships between the input and output variables.
(ii) It can handle missing data and noisy data effectively, enhancing robustness in real-world applications.
(iii) It is computationally efficient, enabling rapid predictions and iterative model development.
(iv) It is highly adaptable to various data sources, including sensor data and weather data.
(v) It can be trained using historical data to yield precise predictions of future hygrothermal behavior.

Compared to physical models, LSTM-based models do not require in-depth knowledge of the underlying physical processes. They can capture system behavior without explicitly modeling each of its components [14,15]. This is advantageous in cases where physical models are computationally expensive or lack sufficient data for precise parameterization. LSTM-based models can also handle complex scenarios with multiple inputs and outputs, such as predicting a building's temperature and humidity under varying external conditions.

In this study, we propose a combination of two walling layers utilizing natural fibers and soils (cob and light earth) to meet European building regulations. Notably, most studies have focused on laboratory-scale investigations, neglecting in situ behavior. These two layers consist of a load-bearing layer with a higher density and an insulating layer with a high fiber content. This dual walling technology aligns with current thermal construction regulations in France and the UK. Additionally, the CobBauge project aims to enhance the technical efficiency and commercial viability of cob and light earth by substantiating their performance and measurements. The project's objectives encompass the development and characterization of innovative construction materials and systems that reduce CO_2 emissions and enhance energy efficiency. Challenges include ensuring the recyclability of the construction materials at their end of life by utilizing local and readily available resources.

This study endeavors to provide a comprehensive understanding of the hygrothermal behavior of CobBauge construction and its interaction with the surrounding environment. Data collected from the sensors installed in the walls undergo analysis to assess CobBauge construction's performance and develop a data-driven model for predicting hygrothermal behavior, encompassing indoor ambience and wall moisture. The insights gained from this study will contribute to the advancement of sustainable building practices and promote the wider adoption of bio/geo-based materials in modern construction.

2. Experimental Methodology

2.1. Material Composition and Mixture Preparation

Three types of soil were employed in crafting the cob and light-earth mixtures. Initially, the cob was formulated by blending soil 1 (sandy), composed primarily of natural quartz, with soil 2, which contained small quantities of illite, goethite, rutile, huntite, and kaolinite. Soil 1 consisted of 54.8% quartz, followed by muscovite (26.2%), montmorillonite (6.9%), and albite (4.2%). In contrast, soil 3, used for the light-earth layer, comprised quartz (40.6%), kaolinite (32.3%), albite (15.1%), and calcite (10.1%). In terms of natural fibers, raw flax straw was selected for the traditional cob, as it is not valorized due to its origin from oleaginous flax cultivation or its inadequate quality for the textile industry. For the light-earth mixture, reed was chosen, which was sourced from the maintenance of natural areas and similarly not valorized.

The combination of soil 1 and soil 2 was opted for the traditional cob mixture owing to its high silt fraction (>70%). This mixture contained a 2% fiber content. Conversely, in the case of the light-earth mixture, soil served as a binder between the reed aggregates. Thus, soil 3 was selected due to its larger clay fraction and the specific surface of its clays. A 50% mass addition of fiber in relation to the soil's dry mass was used. Hygrothermal and mechanical properties of these materials have been extensively studied and documented in reference [16].

2.2. Prototype Building and Study Site

A prototype building was erected within the Cotentin and Bessin Marshes Regional Natural Park in Normandy, France. This prototype building boasts a total area of approximately 23.1 m^2, with an interior surface of 12.9 m^2, including a mezzanine spanning 6.6 m^2. Notably, it features a front door on its eastern side and a large door on the southern side, strategically positioned to maximize solar gains. Additionally, two small windows grace its northern wall, one near the base and another closer to the top, ensuring adequate illumination and ventilation for the entire structure, including the mezzanine (see Figure 1 for an illustrated view of the prototype building from various angles).

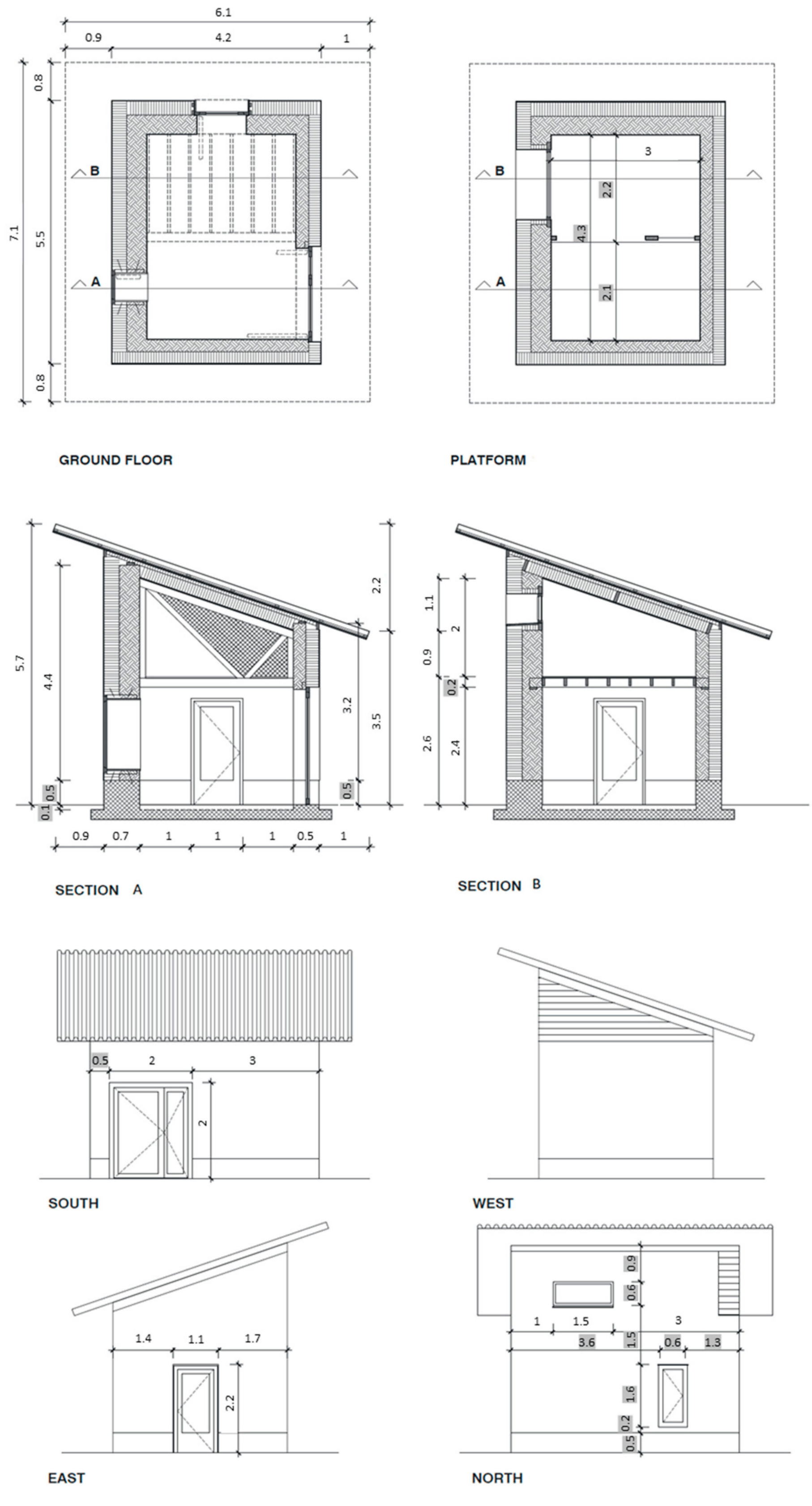


Figure 1. Architectural plans of the prototype building. Sections A and B were obtained at positions A and B indicated on the views of the ground floor and platform.

As is typical for CobBauge buildings, this prototype employs a double-walling system [17], where each wall seamlessly combines cob and light-earth materials. Wall thicknesses generally range from 50 to 70 cm. In this specific prototype, the south and west walls measure 50 cm in thickness, while the east and north walls have a robust 70 cm thickness (refer to Figure 2 for a visual representation). Construction involved incremental building of successive 70 cm high lifts, with each lift resting on a sub-base composed of lightweight concrete. This structural approach serves the dual purpose of protecting the earth–fiber walls from capillary rise and maintaining consistent thermal resistance, ensuring minimal impact on the building's overall properties.

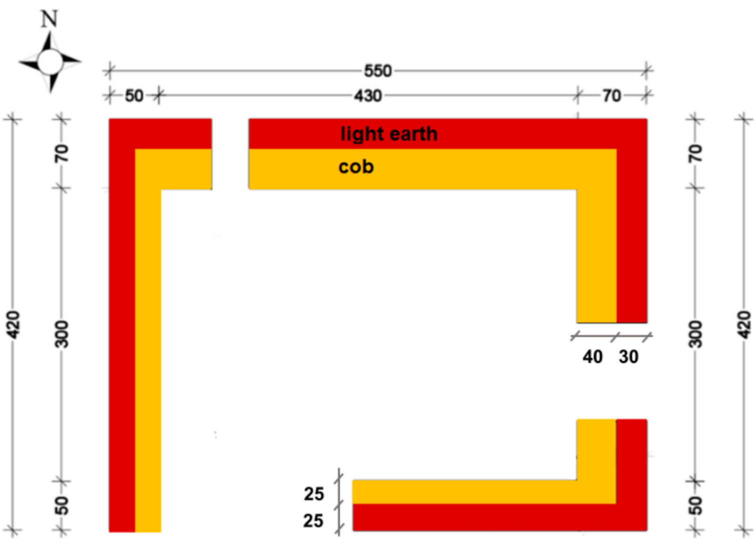


Figure 2. Scheme representing the two layers constituting each wall of the prototype building (dimensions are in cm).

Figure 3 provides a comprehensive view of the prototype building and the instrumentation implemented in situ. The roof is insulated with wood fiber and covered with galvanized iron board. Throughout the construction process of the prototype, volumetric water content (VWC) sensors were strategically installed in the walls to monitor the drying process of the building's wall materials.

Figure 3. View of the prototype building and the in situ implemented instrumentation.

2.3. *Temperature, Relative Humidity, and Moisture Monitoring*

The WS-GP1 weather station records outside temperature and relative humidity data at 15-min intervals, as depicted in Figure 4. Additionally, Figure 4 displays the NEMo XT station from Ethera-labs, which monitors indoor conditions, including temperature and relative humidity, at 10-min intervals. Section 4 provides a detailed presentation of the temperature and relative humidity data collected by both systems.

Figure 4. Monitoring of temperature and relative humidity inside and outside the prototype building.

The temperature range measured falls between −55 °C and 125 °C, with a precision of ±2 °C. Relative humidity (RH) can be measured within the range of 5% to 95%, with a precision of ±3% (between 11% and 89%) and ±7% outside this range.

To monitor moisture content in the cob and light-earth layers and at their interfaces, Campbell Scientific CS655 sensors were employed. These sensors operate based on the dielectric permittivity of the materials and exhibit an accuracy of approximately ±3% (±1% with specific soil calibration) [18]. The sensors in both layers were horizontally positioned at the same heights and depths. They were placed parallel to the wall surfaces at a height of 25 cm from the base of the second lift. This position roughly corresponds to the central part of the western wall of the prototype building. This wall was selected because it lacks openings (minimizing edge effects) and is exposed to significant temperature and humidity variations.

The probes within the cob and light-earth layers were situated at a depth of 12.5 cm, measured from the inner surface (cob layer) and from the outer surface (light-earth layer). This depth corresponds to the midpoint between the two layers. The data collected by the CS655 sensors were logged using a CR1000X data logger, with data recorded at 15-min intervals. Figure 5 illustrates the positions of the volumetric water content sensors within the walls of the prototype building.

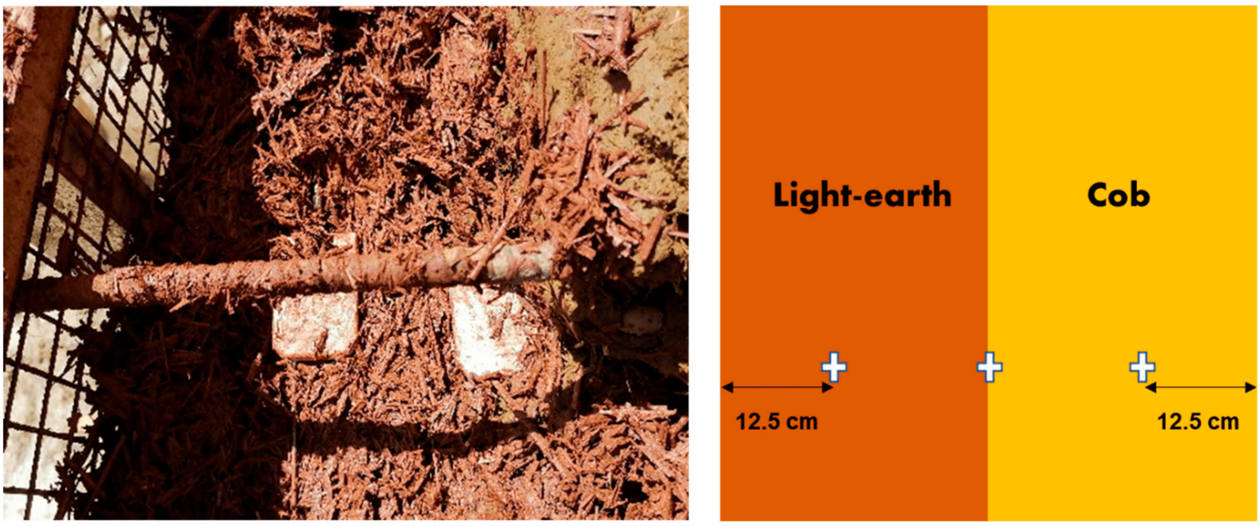


Figure 5. Position of the volumetric water content sensors in the prototype building's walls.

3. Modeling Methodology: Artificial Neural Network

In the realm of building heating efficiency analysis, artificial neural networks (ANN) are frequently employed to construct data-driven models. These ANN models are built upon a simplified abstraction of biological neurons, which are translated into numerical representations, as depicted in Figure 6. These neurons are conceptualized as mathematical entities capable of information processing [19]. The standard architecture of an ANN model consists of three primary components:

- **Synapses**: these components establish connections with associated weights.
  A processing element referred to as a "summing junction": this element combines input data from the synapses, considering their synaptic weights, and incorporates an adjustment from a bias variable (b_k).
- **An activation function**: this function governs the strength of the signal as it leaves the neuron.

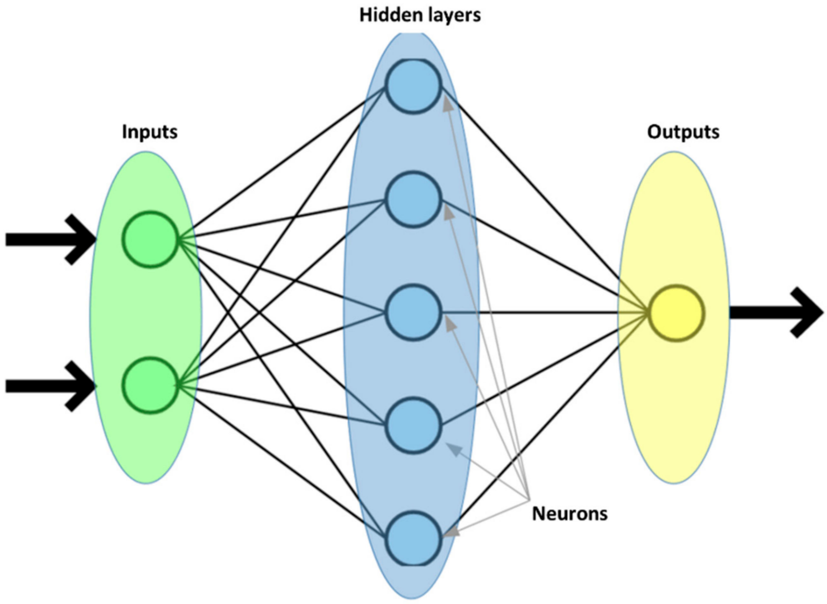


Figure 6. Basic ANN model design.

Long short-term memory (LSTM) is a type of recurrent neural network specifically designed for effectively handling sequential data. It excels in understanding temporal relationships, as illustrated in Figure 7a,b. While it shares some similarities with the classical architecture of recurrent neural networks, LSTM introduces a unique cell-state element that facilitates the flow of information across consecutive temporal stages.

The LSTM model consists of three distinct gates: the input gate, the forget gate, and the output gate. These gates govern the flow of information within the cell-state element by determining what information is added, erased, and outputted at each time step. The LSTM model is defined using the following equations [19]:

$$f_t = \sigma\left(W_f h_{t-1} + U_f X^t + b_f\right) \tag{1}$$

$$X^t = \sigma\left(W_X h_{t-1} + U_X X^t + b_X\right) \tag{2}$$

$$c'_t = \sigma\left(W_c h_{t-1} + U_c X^t + b_c\right) \tag{3}$$

$$c_t = f_t \circ c_{t-1} + X^t \circ c'_t \tag{4}$$

$$Y^t = \sigma\left(W_Y h_{t-1} + U_Y X^t + b_Y\right) \tag{5}$$

$$h_t = o_t \circ tanh(c_t) \quad (6)$$

where the outputs of the three sigmoid functions are f_t, X^t, and c'_t. Their values range from 0 to 1, and they regulate the information that is forgotten in the old cell-state C_{t-1}, stored (C'_t) in the new cell-state C_t, and output (h_t) from the cell, respectively. The weights used for the concatenation of the new input X^t and the output h_{t-1} from the preceding cell are W_f, W_x, W_C, and W_Y. The equivalent biases are b_f, b_i, b_C, and b_o.

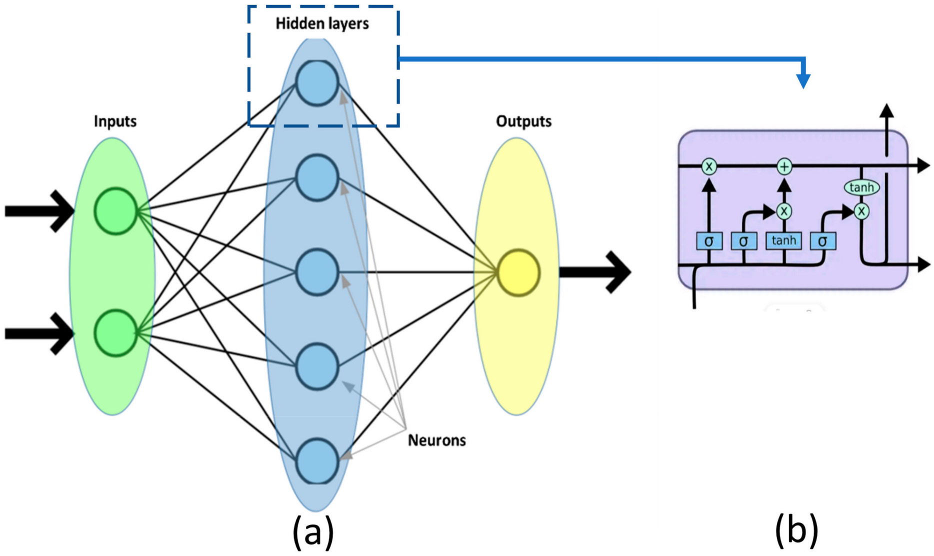


Figure 7. (**a**) Illustration of the configuration of a recurrent neural network featuring concealed neurons. (**b**) Typical architecture of a long short-term memory (LSTM) cell as an illustrative example.

The LSTM algorithms generate internal variables, such f_t, X_t and c'_t, that are used to compute $c(t)$ and $h(t)$ in the hidden layer. It is crucial to note that these equations require recalibration for each successive time step, as the provided formulas pertain to a single cycle. For a series spanning three timesteps, these equations would need to be solved three times. The weight matrices (W_f, W_X, W_Y, W_c, U_f, U_X, U_Y, U_c) and biases (b_f, b_X, b_Y, b_c) used in the model are constant and not time-dependent.

Consequently, the same matrices are used to derive results across multiple time steps. The ANN model functions through three stages. In the initial stage, the model is trained to minimize the error function by iteratively adjusting the weight factors. This adjustment is based on statistical comparisons between the experimental and simulation outputs. Finally, the model's outcomes are evaluated using metrics such as determination coefficient (R^2), root-mean-square error (RMSE), and mean squared error (MSE), as shown in Equations (7)–(9), to assess their applicability:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{n} (\bar{y}_i - y_i)^2} \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n} (\hat{y}i - yi)^2} \quad (8)$$

$$MSE = \frac{1}{n} \times \sum_{i=1}^{n} (\hat{y}i - yi)^2 \quad (9)$$

where y_i represents the observed values of the dependent variable; $\hat{y}_i$ represents the predicted values of the dependent variable based on the regression model; n is the number of data points; and $\bar{y}_i$ represents the mean (average) of the observed values of the dependent variable.

To predict future time steps, the LSTM model is fed a sequence of past data as the input. It utilizes this information to discern patterns and trends within the data. Once trained, the model can generate predictions for future time steps by inputting the most recent data point and leveraging the patterns it has learned to make predictions for the subsequent time step. This iterative process can be repeated for as many future time steps as needed.

Prior to being used as the input features, the lagged time-series data underwent preprocessing, which included data normalization. This normalization step was applied because the measurements were taken at different recording frequencies (10 min and 15 min) in our LSTM model. The purpose of normalization was to standardize the input features to a common scale. This facilitated the training process of the model by preventing certain variables from dominating due to differences in magnitudes. Data splitting into training and testing sets was carried out within the data partitioning function. This division ensured that the model was trained on one subset of the data and tested on another independent subset to assess its performance.

The selection of independent variables for the model was based on their potential influence on indoor temperature and humidity. Among the chosen variables were external temperature, outdoor humidity, solar radiation, and moisture content within the two layers of the walls. These variables were identified as significant factors that affect indoor environmental conditions. They were integrated into the LSTM model to capture their impact on the target variables. Regarding water content in the walls, the inputs were derived from weather conditions, specifically external temperature, outdoor humidity, and solar radiation. Additionally, the forecast horizon was determined, specifying how many future data points the model should predict. The forecast step, which denotes the interval between consecutive predictions, was set to 10 min.

4. Results and Discussions

4.1. Experimental Results

4.1.1. Building Walls' Moisture

Figure 8 illustrates the volumetric water content (VWC) within the cob and light-earth layers that make up the west wall of the CobBauge prototype building during the period from 16 September to 6 November 2022. During this timeframe, it is assumed that the water content equilibrium was reached in the prototype building's walls, particularly in the light-earth layer. The observed oscillations in the light-earth VWC are presumed to reflect the day–night alternation pattern.

In the case of cob, as depicted in Figure 8, the practical water content level was not completely attained. This is consistent with previous findings reported by Touati et al. [10], indicating that the VWC continued its slow drying process between 15 September and 14 October. On 14 October, the heating system was activated (with a setpoint at 20 °C), and a meeting involving four individuals took place within the prototype building from 8:50 a.m. to 12:05 p.m. CET. This activation of the heating system and human presence introduced both heat and humidity into the indoor environment, as shown in Figure 9, which the cob walls then absorbed. This absorption likely accounted for the increase in VWC observed after 14 October. One week later, the modest drying process resumed, and the VWC decreased until the cob reached its practical water content. At that point, its behavior was expected to resemble that of the light-earth layer. A similar behavior has been reported in another earth-based material, specifically rammed earth, as referenced in [20].

It is worth noting that absolute water content values, especially those pertaining to light earth (comprising clay soil and fibers), should be critically evaluated. This is because the Topp equation tends to underestimate the water content of certain types of soils, including volcanic, organic, and fine-textured soils.

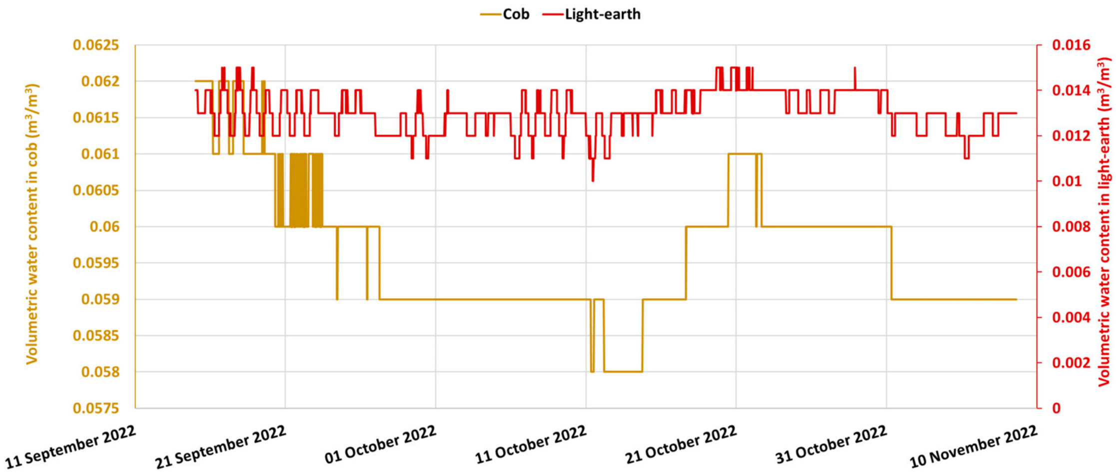


Figure 8. Evolution of water content within the light-earth and cob layers constituting the building's west wall.

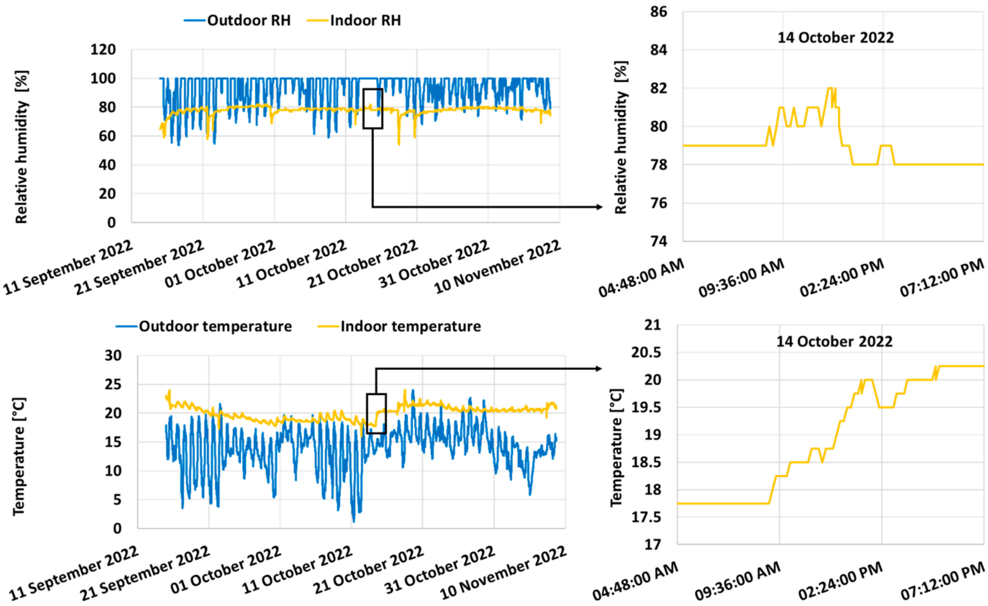


Figure 9. Indoor and outdoor temperatures and relative humidities, with the peaks generated due to heating being switched on and human presence.

4.1.2. Building Indoor Ambience

The results displayed in Figure 9 depict the variations in indoor and outdoor temperatures as well as relative humidity levels. The indoor temperature fluctuated between 17 °C and 25 °C, while the outdoor temperature ranged from 1 °C to 22 °C. The indoor relative humidity (RH) varied between 60% and 80%, whereas the outdoor RH ranged between 60% and 100%.

These findings indicate that the CobBauge building exhibits effective thermal insulation, as the indoor temperature remains relatively stable despite substantial fluctuations in the outdoor temperature. However, it is noteworthy that the variation in indoor humidity levels within an earth building should ideally be maintained between 30% to 60% for optimal indoor air quality and occupants' thermal comfort. In specific cases, such as regions with high outdoor humidity, slightly higher indoor humidity levels may be acceptable.

The results reveal indoor humidity levels ranging from 60% to 80% in the CobBauge building. This elevated level of relative humidity within the prototype building is likely due to the fact that the cob layer has not yet reached its practical water content and remains somewhat moist. Consequently, it may be advisable to monitor and control the indoor environment to ensure optimal indoor conditions, particularly when the interior of the walls is still in the process of drying out.

The results of this study hold significant implications for the design and construction of energy-efficient and sustainable buildings, especially in regions characterized by extreme temperature and humidity fluctuations. The incorporation of natural materials like cob, known for its favorable hygrothermal properties, can play a pivotal role in decreasing energy consumption, enhancing indoor air quality, and ensuring occupants' thermal comfort.

However, it is important to note that further research is warranted to fully explore the potential of earth-based and other natural building materials in diverse climatic conditions and for various types of buildings. Such ongoing investigation will not only refine our understanding but also enable the development of tailored solutions that harness the benefits of these materials across a wider spectrum of environmental challenges and architectural requirements.

4.1.3. Discussion of the Experimental Results

The prototype building in this study was meticulously designed, encompassing various aspects such as volume, orientation, envelope, doors, and windows, to faithfully replicate the behavior of a CobBauge envelope and building in real-world conditions. To the best of the authors' knowledge, this represents the first study delving into the hygrothermal behavior of an actual cob building. Consequently, finding directly comparable works is challenging due to the unique nature of this investigation.

However, when drawing parallels with other earth-based construction techniques, such as rammed earth, it becomes apparent that the behavior observed in the present study closely resembles that reported in reference [20]. This correlation underscores the potential for shared insights and lessons learned between different earth-based construction methodologies, even in the absence of directly comparable studies.

In this context, when examining the evolution of water content within the wall layers, the observed behavior in the present study bears a striking resemblance to that reported in reference [20]. Over the studied period from 15 September to 8 November 2022, an average indoor temperature of 20.07 °C, with a standard deviation of 1.16 °C, was recorded. Additionally, an average indoor relative humidity of 77.86%, with a standard deviation of 2.57%, was measured.

These values, along with the trends in water content, temperature, and relative humidity, exhibit remarkable similarity to those documented in reference [20], which focused on rammed earth construction. In that study, an average indoor temperature of 20.1 °C, with a standard deviation of 1.9, and an average relative humidity of 68.3%, with a standard deviation of 5.3, were reported. This parallel reinforces the notion that certain behaviors and patterns are consistent across different earth-based construction techniques, further contributing to our understanding of their hygrothermal dynamics.

The results of the present study confirm that, like other earth-based techniques, cob construction can ensure temperature and RH regulation and, accordingly, good hygrothermal comfort.

4.2. Numerical Results

4.2.1. Building Indoor Ambiance

The LSTM model used for simulating indoor temperature and humidity integrates the following input parameters: external temperature, outdoor humidity, solar radiation, and moisture content within the wall layers. These parameters were selected based on their potential influence on indoor conditions and were incorporated into the model to capture their impact.

In this section, we present the validation of the LSTM model for predicting indoor temperature and relative humidity. The results demonstrate strong validation, with an R^2

of 0.994, MSE of 0.0072, and RMSE of 0.85 for indoor air temperature, as well as an R^2 of 0.960, MSE of 0.313×10^{-8}, and RMSE of 0.00017 for relative humidity (Figure 10).

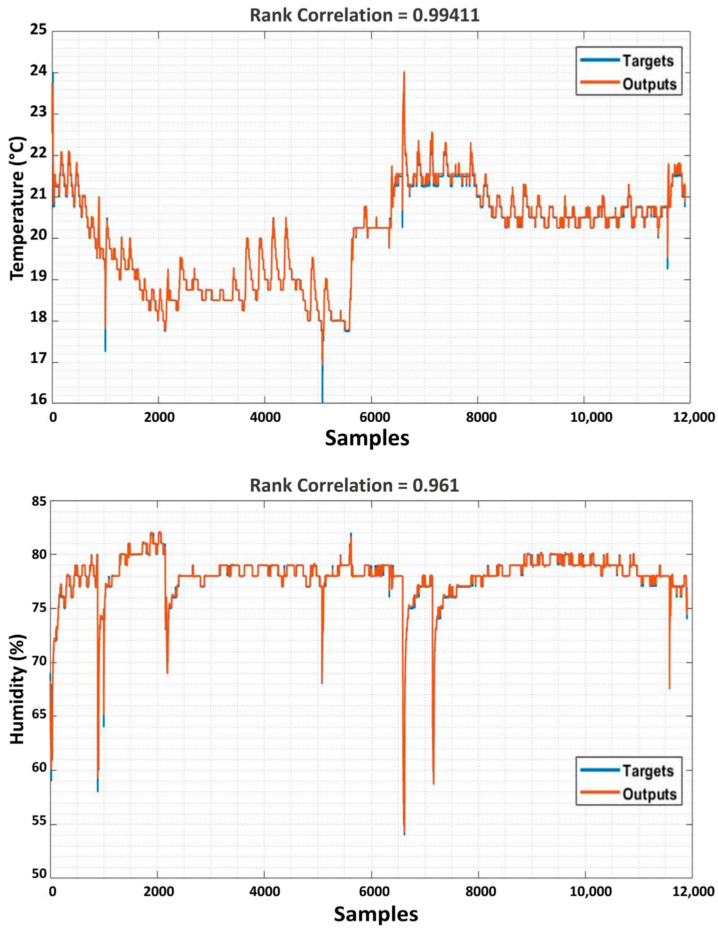


Figure 10. Validation of indoor air temperature and relative humidity.

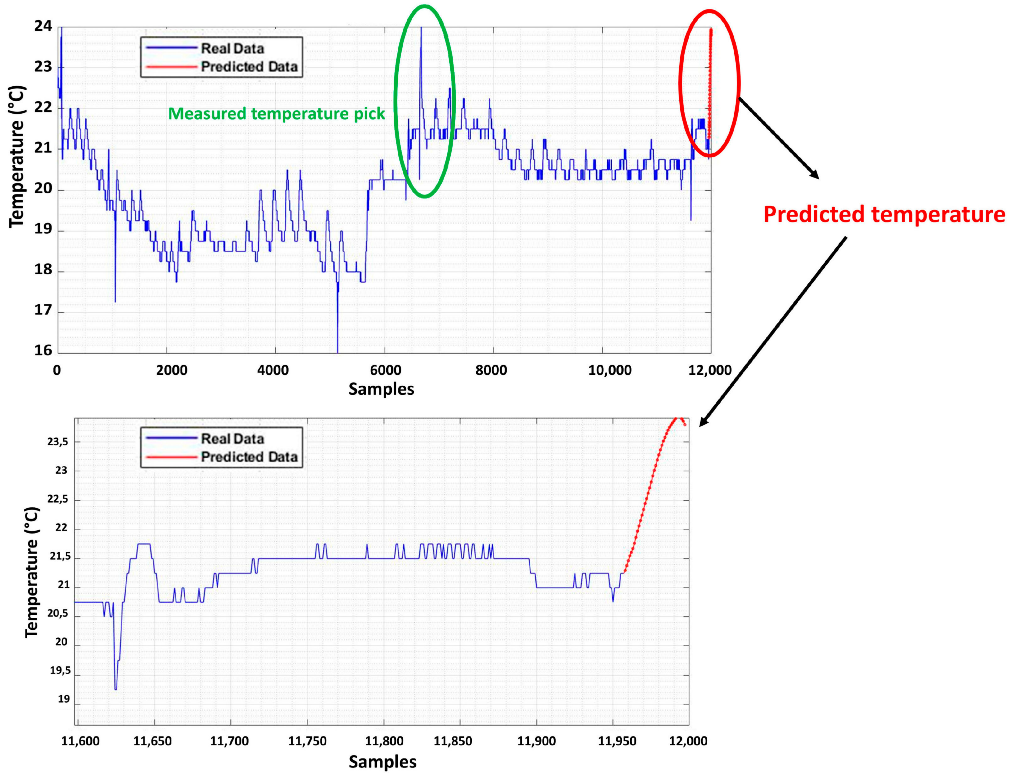
An LSTM model belongs to the family of recurrent neural networks, which are proficient in capturing intricate temporal relationships within sequential data. It emerges as an ideal candidate for modeling time-series data, like indoor temperature and humidity, owing to its inherent capacity to retain historical inputs and leverage them for accurate predictions.

Our findings indicate that the LSTM model holds promise as an effective approach for forecasting indoor temperature and relative humidity. This has significant implications for applications in fields like building automation and energy management.

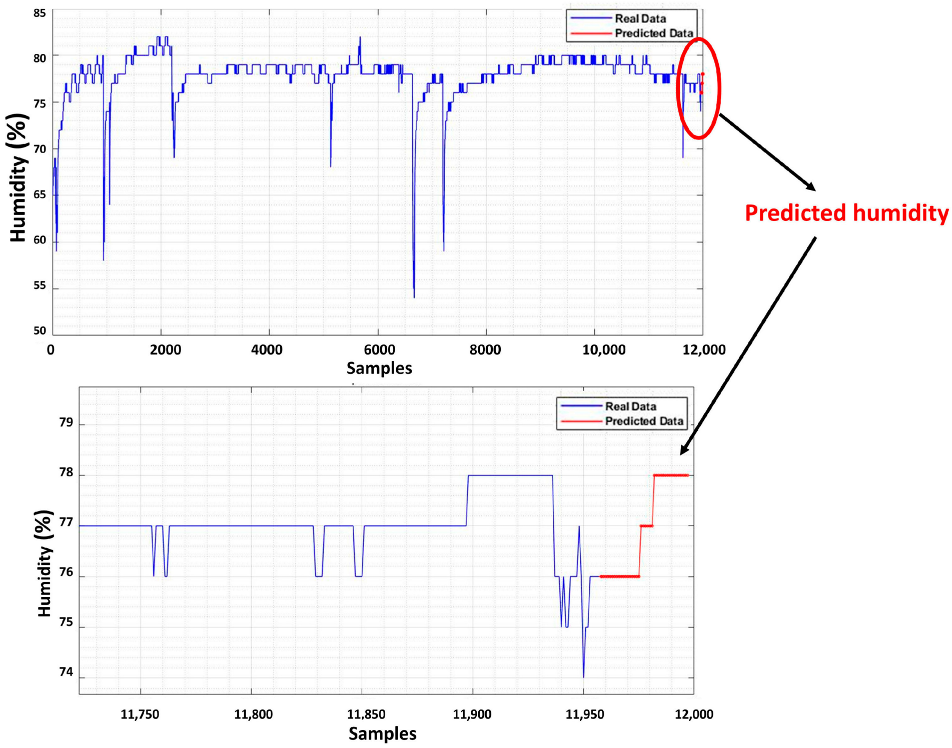
It is worth noting that the validation results reveal the LSTM model's superior performance in predicting indoor air temperature compared to relative humidity (see Figure 10). One plausible explanation for this discrepancy is that temperature typically exhibits more predictable patterns, while relative humidity can be influenced by a multitude of factors, including wall-related moisture levels, transient internal moisture sources, unpredictable precipitation, ventilation, and occupants' behavior.

Another factor that likely contributes to the superior performance of the LSTM model for indoor temperature is the inherent consistency and lower susceptibility to measurement errors or fluctuations in temperature data when compared to relative humidity data. Furthermore, the LSTM model might have been more adept at capturing the fundamental trends within the temperature data, which can be influenced by factors like outdoor temperature and time of the day.

In addition to validating the LSTM model for indoor temperature and relative humidity prediction, the model's capability to forecast future indoor air temperature and humidity data beyond the test period was investigated. As depicted in Figure 11, the LSTM model demonstrates impressive accuracy in predicting these data points beyond the measured data. This success is attributed to the model's ability to account for variables such as outdoor temperature and time of the day, which exert influence on these trends.



(**a**)



(**b**)

Figure 11. Hygrothermal behavior prediction: (**a**) indoor air temperature and (**b**) indoor relative humidity.

The LSTM model predicts future data by utilizing the past sequences of temperature and humidity values as inputs. It processes these inputs to update its internal state, enabling it to generate predictions for the next time step. This capability to capture underlying temporal patterns and dependencies in the data empowers the model to make accurate forecasts for future time steps.

To achieve this objective, the LSTM model employs a sequence of interconnected layers within the neural network architecture. These layers are purposefully designed to handle sequential data effectively. Within these layers lies a memory cell, which is capable of retaining information from previous time steps. Additionally, a set of gates controls the flow of information among cells. This mechanism equips the model with the ability to selectively retain or discard information from prior time steps, a critical element for producing precise forecasts of forthcoming values.

The LSTM model's capability to forecast future indoor temperature and relative humidity data is due to its capability to comprehend and model the fundamental patterns and dependencies inherent in the data. This enables the model to accurately predict future time steps based on past observations as a foundation.

4.2.2. Building Walls' Moisture

The LSTM model used for simulating moisture content within the walls incorporates specific input parameters, including external temperature, outdoor humidity, solar radiation, and indoor ambience. Figure 12 illustrates the validation of this LSTM model concerning moisture content at three distinct depth points within the central portion of the building's west wall. Point 1 represents the cob layer (in direct contact with the indoor ambience), point 2 corresponds to the light-earth layer (in contact with the outdoor ambience), and point 3 is located at the interface between the "cob" and "light-earth" layers.

The validation results reveal an R^2 of 0.973, MSE of 3.1312×10^{-8}, and RMSE of 0.00017 for point 1; an R^2 of 0.925, MSE of 1.016×10^{-8}, and RMSE of 0.00012 for point 2; and an R^2 of 0.938, MSE of 1.014×10^{-8}, and RMSE of 0.00010 for point 3. These outcomes demonstrate the LSTM model's ability to accurately forecast moisture content at different depth points within the building's wall.

The variations in the validation results among the three points can be attributed to the distinct characteristics of the layers in which they are located. Point 1, located in the cob layer directly in contact with the building's indoor air, may be less affected by the interior environment's temperature and relative humidity. This could be due to the favorable thermal and hygric inertia of cob. Conversely, points 2 and 3 are positioned at the interface and within a layer in contact with outdoor air, making them more susceptible to outdoor environmental conditions, such as rainfall, humidity, solar radiation, and temperature fluctuations. Additionally, light earth exhibits a more pronounced hygroscopic behavior than cob. Consequently, the LSTM model might have a greater capacity to discern the temporal patterns and dependencies in the data for point 1, resulting in a superior validation outcome compared to points 2 and 3.

4.3. Economic Discussions

For a building system to gain traction in the market, it must also demonstrate economic competitiveness. Having a low environmental impact alone is insufficient to persuade homeowners, businesses, and local authorities to adopt a new building system. Therefore, within the current project, the cost of a 1 m^2 section of a CobBauge wall with a thickness of 70 cm (40 cm of cob and 30 cm of light earth) was assessed and compared to other construction systems. To compute this cost, the relevant expense items are detailed in Table 2.

The cost of the CobBauge construction system was determined to be 617 Euro/m^2, reflecting optimization in the construction process. This cost is notably higher than that of a traditional cob wall (typically around 450 Euro/m^2 for uninsulated cob, as per Norman craftsmen's costs). For comparative purposes, the CobBauge system proves to be two to three times more expensive than conventional options like cement cinder block or timber-frame construction.

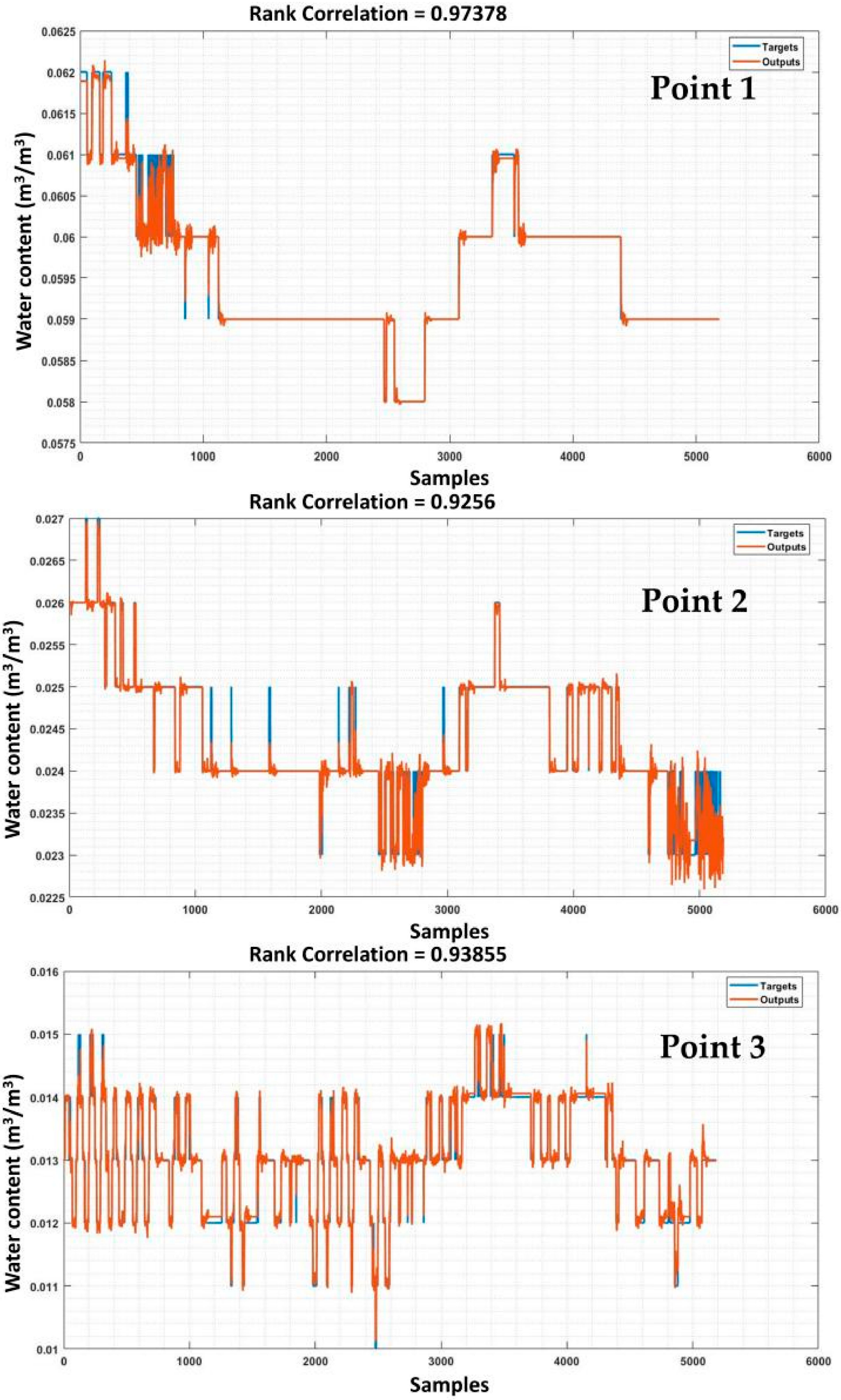


Figure 12. Water content validation at different depths.

Table 2. Expenses considered in the calculation of the CobBauge constructive system cost.

Expense	Unit	Quantity	Price/Unit [Euro]	Total [Euro]
Sifted earth supplied for slip (light earth: 30 cm wall thickness)	kg	76.40	000.15	11.45
Crushed reed (light earth: 30 cm wall thickness)	m^3	00.42	205.13	86.15
Soils (cob: 40 cm wall thickness)	ton	0.952	028.50	27.13
Flax straw (cob: 40 cm wall thickness)	kg	20.00	000.14	02.80
Workforce	hour	06.65	040.00	266.0
Concrete mixer	-	-	-	07.46
Mechanical shovel	-	-	-	83.20
Manuscopic	-	-	-	25.74
Equipment and formwork depreciation	Fixed price	01.00	008.00	08.00
Margins and risks	%	20	497.94	99.59
Total/m^2				617.52

Previous costs are based on a prototype building. For larger buildings constructed with locally sourced soils and alternative natural fibers like hemp shives or miscanthus (instead of reed), costs may be reduced to approximately 544 Euro/m^2. Reed, due to its disorganized industry, is about four times more expensive than hemp shives. Furthermore, if construction site soil is used, the cost could potentially be lowered to around 495 Euro/m^2.

These cost estimates pertain to the building wall before the application of indoor and outdoor renders. To determine the overall cost of a finished wall, an additional sum of approximately 150 Euro/m^2 should be considered. For the CobBauge process to become competitive, solutions must be explored to mitigate construction costs.

4.4. Durability and Maintenance Discussions

When developing a new construction system, it is crucial to consider long-term durability and maintenance requirements. Cob buildings are well known for their durability over time, with examples of 16th-century houses and manor houses still standing in regions like Normandy, Brittany (France), and Devon (UK). In the case of CobBauge homes, it is expected that they will endure for at least 50 years, a service life comparable to buildings constructed using conventional materials such as concrete.

To the best of our knowledge, a CobBauge building necessitates no more maintenance than a conventional structure. Except in cases of deterioration resulting from significant mechanical wear, both interior (earthen) and exterior (lime) renderings can be renovated every 20 to 50 years.

The materials used in CobBauge construction are reversible and easy to repair, with the possibility of reusing degraded materials for repairs. Moreover, the CobBauge construction system generates zero waste, as light earth can be used as compost, and cob can be extended and revegetated.

5. Conclusions

The hygrothermal behavior of full-scale earth-based buildings has garnered limited attention in the literature. To address this gap, the present study focuses on evaluating the hygrothermal performance of a CobBauge prototype building through in situ measurements and artificial neural network modeling.

To achieve this goal, the indoor environment of a CobBauge prototype building was closely monitored, and the collected measurement data are presented herein. The experimental results reveal intriguing aspects of the CobBauge prototype building's thermal insulation capabilities. Notably, the indoor temperature remains relatively stable, fluctuating between 17 °C and 25 °C, even in the face of significant outdoor temperature variations ranging from 1 °C to 22 °C.

Then, an LSTM model was developed and trained with the in situ recovered data. This latter demonstrated an excellent performance in predicting indoor temperature and relative humidity as well as moisture content at different depth points in the walls of the CobBauge prototype building. The model's ability to capture the underlying patterns and dependencies in the data, along with its ability to remember past inputs and use them to make accurate predictions, make it a promising approach for predicting indoor ambiences.

The data collected in this study will serve as a foundational resource for on-site learning and can be invaluable to various stakeholders, including researchers, local builders, practitioners, and construction experts such as engineers and architects. The data can be particularly beneficial when designing new buildings utilizing the innovative CobBauge construction method.

Furthermore, the findings of this investigation bear substantial relevance in the fields of building automation and energy management. Accurate predictions of indoor environmental conditions are paramount in these domains for optimizing energy consumption and guaranteeing the thermal comfort of occupants.

Despite its numerous advantages, CobBauge remains relatively expensive in comparison to conventional construction systems. In order for the CobBauge process to achieve competitiveness, efforts must be directed toward finding solutions to reduce construction costs. This can be accomplished by enhancing the knowledge and skills of construction professionals, ultimately reviving a long-lost traditional building technique and adapting it for the 21st century.

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