Predicting indoor temperature and humidity in a naturally ventilated office room using long short-term memory networks model in a tropical climate

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Abstract

This study evaluates the efficacy of long short-term memory (LSTM) neural networks in predicting indoor temperature and humidity dynamics for naturally ventilated office environments in Ho Chi Minh City, Vietnam (10.8231°N, 106.6297°E). The tropical climate of this location, characterized by consistently warm temperatures year-round, provides a specific context for the model's performance and applicability. A simulated office room model with diverse window opening scenarios was developed using EnergyPlus simulations, generating a synthetic dataset of hourly indoor-outdoor conditions across varying seasons. An LSTM neural network, trained on 70% of the data and tested on the remaining 30%, was employed to forecast indoor temperature and humidity at multiple time horizons. Results indicate that the LSTM achieves near-perfect short-term (1-30 min) predictions, with performance degrading at longer horizons (60-120 min) while remaining competitive with existing approaches. The model effectively captured the strong influence of window opening area and solar irradiance on indoor conditions. A comparison of different window configurations revealed their significant impact on predicted thermal dynamics. Model accuracy was assessed using the coefficient of determination, root mean square error, and mean absolute error metrics. The study demonstrates that LSTM networks can effectively learn complex non-linear building physics to forecast climate in naturally ventilated spaces. With sub-second response times, this approach shows potential for supporting real-time control and optimization of natural ventilation strategies based on probabilistic forecasts, ultimately enhancing occupant comfort and energy efficiency in buildings.

Keywords: Indoor air temperature, thermal comfort, machine learning, long short-term memory (LSTM), office building

Nomenclature:

AI	Artificial intelligence
ANN	Artificial neural network
BEMS	Building energy management systems
BIM	Building information modeling
CNN	Convolution neural network
CFD	Computational fluid dynamics
CRNN	Convolutional recurrent neural network
DL	Deep learning
GAN	Generative adversarial network
GAT	Graph attention network
GRU	Gated recurrent unit
HVAC	Heating, ventilation, air-conditioning
IoT	Internet of things
LSTM	Long-short-term memory
MAE	Mean absolute error

MPC	Model predictive controllers
MC-EMD	Multi-dimensional complementary empirical modal decomposition
RL	Reinforcement learning
RBFNN	Radial basis function neural network
RNN	Recurrent neural network
RMSE	Mean square error
SEM	Smart energy management
TMY	Typical meteorological year

1. Introduction

1.1. Background

Buildings account for over 40% of global energy usage and associated greenhouse gas emissions, enhancing efficiency imperative to curb climate change impacts [1]. Heating, ventilation, and air conditioning (HVAC) systems alone consume almost half of a typical building's energy [2]. This signifies substantial potential for optimization. However, indoor environmental quality and occupant well-being must also be ensured through compliance with standards to promote health and productivity [3].

Window opening behavior is a prevalent practice in buildings worldwide, serving as a fundamental method for occupant control of indoor environments. A comprehensive national survey conducted by Morrison et al. [4] in the United States, encompassing 3800 participants across various seasons and geographic regions, revealed that 43.9% of respondents reported having at least one window open. Analogous studies in China have demonstrated that window opening is a deeply ingrained cultural practice for maintaining optimal indoor temperature and air quality across diverse climatic conditions [5]. Research conducted in the Netherlands has shown that window views confer physical and psychological benefits to building occupants, effectively mitigating discomfort [6]. Additionally, it examines the influence of shading devices on natural ventilation in buildings, revealing that their impact varies according to factors such as climate, location, and design [7]. Moreover, occupants can exercise personal control over their environment [8].

Natural ventilation facilitated by operable windows offers substantial advantages for indoor environmental regulation and energy conservation in buildings. The ASHRAE RP-884 study [9], which developed and analyzed a comprehensive global database, revealed a significant finding: occupants in naturally ventilated structures exhibited tolerance and preference for a markedly broader range of temperatures compared to their counterparts in buildings equipped with centrally controlled HVAC systems. This discovery underscores the potential of natural ventilation strategies to enhance occupant comfort while simultaneously reducing energy consumption in office environments. Natural ventilation presents an advantageous alternative to purely mechanical HVAC systems by passively harnessing airflow driven by wind pressures and indoor-outdoor temperature differences [10]. Properly implemented natural ventilation strategies can reduce building energy usage by 8-78% [11] while maintaining or even enhancing air quality and thermal comfort compared to conventional HVAC [12]. However, effective integration of natural ventilation requires predictive capabilities to inform real-time control and system adjustments in response to dynamic weather conditions and occupancy variables. One plausible explanation for the wider temperature tolerance in naturally ventilated buildings is that they give occupants more control over their environment, leading to more relaxed expectations and increased acceptance of temperature fluctuations [13]. Consequently, thermal conditions in buildings with operable windows typically exhibit more variability than in fully air-conditioned structures [14].

Physics-based models have traditionally been employed but require extensive details on thermal characteristics and lack generalizability [15]. Data-driven methods present alternatives, with long short-term memory (LSTM) neural networks demonstrating particular potential for mapping complex non-linear relationships [16]. However, research on LSTM specifically for natural ventilation control remains limited. Most studies have focused on HVAC systems or commercial buildings using conventionally sourced typical meteorological year (TMY) weather data [17]. Figure 1 illustrates the variations in indoor and outdoor conditions (Hochiminh City, VietNam), providing a comprehensive view of the climate context underpinning the forecasts.

1.2. Black-box modeling approaches for buildings

1.2.1. Overview of modeling approaches

Accurate simulation models are essential for integrating and validating new concepts in HVAC design. However, creating these models can be complex due to the highly non-linear dynamics of HVAC systems and the influence of external factors such as outdoor temperature [18]. The literature has made significant efforts to build accurate simulation models, categorized into white-box, grey-box, and black-box models [19].

White-box or physics-based models utilize mathematical representations of the elements based on physical laws to build predictive models [20]. While white-box models have their advantages, such as accurately capturing the physical behavior of HVAC systems, they require extensive knowledge of the building or area being modeled, and the models may contain assumptions that do not always correspond to actual behavior [21]. Grey-box modeling methods aim to bridge the gap between white-box models and existing buildings [22]. Although grey-box models have shown promising results, they require extensive prior information, and the mathematical assumptions of the models can be a barrier to their accuracy [23].

1.2.2. Black-box modeling and artificial neural network

Black-box modeling has gained popularity in the literature, especially for thermal dynamics, without explicitly defining zone-specific properties such as heat capacity and size. One type of black-box model is the LSTM neural network, which has been successfully used for temperature prediction in indoor environments.

D.Yu et al [24] demonstrated a generalized regression neural network model able to predict indoor temperatures more accurately. Comparing artificial neural networks (ANN), support vector machines, and adaptive neural fuzzy inference system models, Mechaqrane and Zouk [25] found ANN most accurately predicted a test building's thermal loads. Gaber et al [26] employed ANN to show how various shading systems impact daylight and energy use in office buildings during early design phases. LSTM networks present enhanced capabilities by incorporating memory cells and gate units to learn both short and long-term temporal dependencies [27].

1.2.3. Advanced data-driven approaches

Other data-driven approaches combining computational methods and machine learning have also shown promise. Recently, indoor airflow distribution prediction was demonstrated in naturally ventilated residential buildings by coupling CFD simulations with the DNN model. This enabled high-fidelity, physics-informed predictions without prohibitive computational costs [28].

LSTM has achieved high accuracy for tasks including HVAC control optimization, occupancy prediction, and indoor air quality classification [29]. However, limitations persist, including degradation over long-term multi-step forecasting and extensive data necessities. Targeted synthetic data generation methods help address this by producing abundant tailored training sets [30].

1.2.4. Challenges and considerations in black-box modeling

While black-box modeling offers advantages, it is not a universal solution for creating accurate simulations. Research has shown that the accuracy of these models decreases significantly as the forecast horizon increases, primarily due to the closed prediction loop, where past prediction errors accumulate over time. A model's ability to predict the future over a long period indicates its stability and resilience [31].

Various modern controllers, such as Model Predictive Control (MPC) and Reinforcement Learning (RL), use prediction to develop and improve their control strategies [32]. Deep Learning (DL) techniques have been introduced to predict building occupants' behavior concerning manual window control, effectively identifying and predicting specific behavior patterns [33]. Furthermore, ANN models have demonstrated more accurate predictions of occupant behavior and better interpretability of interrelated components compared to logistic regression and Markov models [34].

1.3. Research gap and research aim

Recent studies have demonstrated the potential of LSTM models in predicting various indoor environmental factors, including office temperatures [35], HVAC control optimization [36], and subway station air quality [37]. However, there is a notable gap in research specifically examining LSTM's predictive capabilities for indoor temperature and humidity in naturally ventilated office spaces across different seasons. This study aims to address this gap by evaluating LSTM networks for indoor climate prediction in naturally ventilated offices, considering seasonal window opening schedules and related environmental variables. We leverage LSTM's ability to uncover temporal patterns in data streams, which is crucial for thermal condition forecasting, to enhance the applicability of Smart Energy Management (SEM) systems in buildings.

The primary objective of this research is to assess LSTM's efficacy in forecasting temperature and humidity levels in a naturally ventilated office room, taking into account seasonal window opening approaches and external factors. This study extends beyond typical meteorological data, utilizing aligned synthetic datasets to broaden prediction capabilities and better inform building automation and energy management decisions. By evaluating and demonstrating LSTM's potential for rapid and accurate prediction of dynamic indoor thermal conditions under varying window scenarios and weather events, we aim to optimize natural ventilation strategies, balancing occupant comfort, energy efficiency, and costs.

The practical significance of this research lies in its ability to navigate crucial trade-offs between energy usage, cost, and occupant health and comfort through data-driven insights. By demonstrating LSTM's capability to predict and optimize indoor environmental conditions in naturally ventilated spaces, this study contributes to developing more intelligent and adaptive building management systems. Ultimately, this research drives progress toward carbon-neutral, smart, and innovative buildings aligned with environmental directives, offering valuable insights for academic research and practical applications in building energy management and indoor environmental quality.

2. Related works

LSTM is a type of RNN commonly used in natural language processing and time series prediction tasks [38]. LSTM is designed to overcome the vanishing gradient problem, a common issue in traditional RNNs [39]. The vanishing gradient problem occurs when the gradient of the error function becomes very small during the backpropagation process, making it difficult for the model to learn long-term dependencies. Table SI. 1 (in the supporting information) presents the studies that specifically developed data-driven predictive models for indoor temperature.

One of the fundamental characteristics of a time series is the strong correlation between a value at a given time t and the variables in the window before t. Due to the independent handling of each property, this vital relationship is lost in the neural network topologies mentioned. However, RNN has overcome this problem [40]. In RNN, a given point in the sequence and the layers correspond one-to-one. RNNs are effective in learning short rows that require only a few slices. However, they are challenging to train due to the gradient's disappearance and the explosion's problems [41], making them excellent short-term tests. Time memory, but a poor long-term memory. This problem is addressed by the LSTM neural network [38].

It has been suggested that RNN be used to include time dependence into neural network topologies natively. The fundamental concept is introducing a dynamic sequential structure into traditional ANN algorithms to increase capacity [42]. LSTM is particularly successful because it can learn the issue's short- and long-term dependencies and is designed to address the vanishing gradient problem that most RNN designs have, even though there are a variety of approaches to achieve this capability [43]. Additionally, it is a good fit for interior temperature modeling since it simultaneously includes slow and fast-moving phenomena [44]. "Cells" are terms for the primary information processing units of LSTM. In a typical MLP, these cells may be considered more complex neurons.

LSTM comprises memory cells, input, forget, and output gates [45]. The memory cells are responsible for storing information over a long period, while the gates control data flow into and out of the cells. The input gate controls the flow of new information into the memory cell and is determined by the current input and the previous hidden state. The forget gate controls the flow of information out of the memory cell and is determined by the current input and the last hidden state. The output gate controls the flow of information out of the memory cell and is determined by the current input, the previous hidden state, and the current memory cell state.

LSTM networks use multiple gates to control and store information across varying time spans. This capability allows LSTM to selectively retain or discard data based on its relevance for short-term and long-term dependencies, making it particularly effective for sequential tasks. An LSTM network processes an input sequence $x = (x_1, \ldots, x_T)$ to generate an output sequence $y = (y_1, \ldots, y_T)$ This is achieved by iteratively computing the activations of the network units using specific equations from $t = 1$to T [46]:

$$i_t = \sigma(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i) \quad (1)$$

$$f_t = \sigma\left(W_{fx}x_t + W_{mf}m_{t-1} + W_{cf}c_{t-1} + b_f\right) \quad (2)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g(W_{cx}x_t + W_{cm}m_{t-1} + b_c) \quad (3)$$

$$o_t = \sigma(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o) \quad (4)$$

$$m_t = o_t \odot h(c_t) \quad (5)$$

$$y_t = W_{ym}m_t + b_y \quad (6)$$

where the W terms represent weight matrices (e.g. W_{ix} is the matrix of weights from the input gate to the input), the b terms are bias vectors (b_i is the input gate bias vector), σdenotes logistic sigmoid function, and i, f, o and c correspond to the input gate, forget gate, output gate and cell activation vectors, respectively, all of which are the same size as the cell output activation vector m, the notation $\odot$ indicates the element-wise product of the vectors. Functions g and h represent the cell input and cell output activation functions, typically the hyperbolic tangent $(tanh)$.

The illustration in Figure 2 shows a visual knowledge of how information flows inside an LSTM cell. Like neurons, LSTM cells may be stacked as layers and linked to one another to transport temporal information. A layer of 50 cells with 5 channels is created by connecting one LSTM cell for each previous state. Then, by including a replica of this layer, the LSTM network was deepened into two layers. A fully linked layer was employed to provide a single prediction after flattening the LSTM layer's output.

The stateful vanilla model, which has a single LSTM hidden layer architecture, is used to construct this neural network. The tiers of the network are as follows: It has the form of input (batch size, delays, and the number of features). The number of LSTM cells is determined during the voting process. Results: The LSTM layer's dimensionality matches the size of the predicted horizon. Its activated function is the linear function.

This neural network architecture is being adjusted for batch size, LSTM cell count, regressor count, and learning rate. Like other neural networks, these hyperparameters are tuned by trial and error, with the parameters changed in a particular order. The initial set of chosen parameters consists of the following numbers: batch size = 32; forecasting horizon = 180h; training epochs = 100; and several LSTM cells = 50. The LSTM model was tested over a 180-hour validation period, with forecasting horizons of 1 minute, 30 minutes, 60 minutes, and 120 minutes. This is the starting point, and several inputs are examined to determine which ones perform best after that. The training is terminated when there is no noticeable improvement after optimizing the number of regressors, the number of epochs, and finally, the number of epochs. By creating a grid with their values connected, the batch size and learning rate are finally maximized, and their connection (learning rate, batch size) is maximized concurrently.

3. Methods and materials

Figure 3 presents the schematic diagram of the process undertaken in this study, encompassing data acquisition, model training, and performance evaluation. The following subsections detail the steps to achieve the research objectives.

3.1. Generic space

The study was conducted in a simulated office room with 9.1m x 4.1m x 7.0m (L x H x W). The 3D model was created in Rhinoceros [47] and included precisely constructed details on the insulated walls, floor, ceiling, glazing, and furniture (Figure 4). Specifically, the external walls are 20cm thick concrete with an insulating R-value of 0.3 m^2K/W. The floor and ceiling slabs use 30cm and 20cm thick concrete, respectively. Windows on the north and south facades are modeled as 1.1 W/m^2K double-glazed units with a solar heat gain coefficient of 0.36 and visible transmittance of 0.5 (see Table SI. 2 and Table SI. 3).

Internally, the room incorporates two rows of desks, chairs, computers, and monitors to represent a real-world office environment. These specifics enable highly accurate simulation of material absorptance, external solar gains, internal heat dissipation, and hourly indoor temperatures under dynamic climate conditions.

3.2. Window configurations

Four window opening configurations were modeled in Rhinoceros with sizes ranging from 0% (fully closed) to 90% (wide fully open) of the maximum window area. These configurations were used to generate a synthetic dataset under controlled assumptions for model training. It is important to note that this deterministic approach is a simplification, and real-world window opening behavior is stochastic, influenced by occupant control. The window-to-wall ratios were 32.7% on the South facade and 50% on the North façade (see Figure 5, 6). Each scenario was simulated independently over an entire year using Typical Meteorological Year (TMY) weather data for Ho Chi Minh City, Vietnam (10.8231^{o}N, 106.6297^{o}E). This location was selected due to existing access to reliable weather data sources. However, the model set-up is readily generalizable to any geographic location with minor modifications.

It is important to note that this study examines explicitly a tropical climate, where temperatures remain relatively warm and consistent throughout the year. The model's performance and applicability are tailored to these conditions. In temperate or colder climates with significant seasonal variations and heating requirements, the current model would require substantial modifications to account for these different thermal dynamics.

The extensive range of window-opening factors spanning seasonal timeframes generates substantial diversity in the training data sets. By sampling across the entire solution space, the data better encapsulates realistic operating conditions within the simulated office rather than just a single scenario. This diversity enhances the longevity and external validity of the developed LSTM network for indoor temperature prediction.

3.3. Simulation settings and data generation

A whole-building energy simulation program, EnergyPlus software [48], generated multi-parameter performance data across annual periods for the modeled office room. EnergyPlus numerically solves fundamental heat and moisture balance equations to provide dynamic thermal and moisture transfer modeling capabilities. Specifically, the conduction finite difference heat transfer algorithm was applied with a variable time step matching the input weather data timestep of 1 hour. This approach enabled transient conduction through all building surfaces to be modeled based on material properties like thermal conductivity, density, specific heat, and layer thicknesses aligned with the defined wall, floor, ceiling, and window constructions. Indoor air temperature, determined through heat balance simulations calculates humidity levels via a simplified moisture balance equation [49]. The model accounted for ventilation rates, internal moisture generation, and the moisture buffering capacity of interior surfaces. Internal heat gains were incorporated using convective and radiative split coefficients based on equipment operation and occupancy schedules.

The adequate moisture penetration depth (EMPD) model was selected to account for moisture adsorption and desorption effects within hygroscopic building materials. This tracks moisture movement through porous envelope layers and the potential impacts on thermal performance when water vapor condenses or evaporates based on relative humidity levels. The EMPD formulation within EnergyPlus provides suitable accuracy levels for building-scale analyses without excessive computational overhead. Interior heat gains were modeled using established convective/radiative split coefficients for the defined equipment densities and occupancy schedules typical of office spaces. Additional solar heat gains through windows were calculated separately and combined to determine the room's overall hourly cooling/heating loads. However, the HVAC system was deactivated, so only passive, envelope-based temperature and humidity outcomes were quantified in the final simulation results.

The high-resolution mapping of indoor environmental conditions facilitated data-driven training and testing procedures for the LSTM indoor temperature forecasting model. The 35040 data samples across window opening configurations over a complete 8760-hour annual cycle accounted for seasonal, daily, and stochastic climate variations in the target location. The extensive simulation dataset enabled the LSTM neural network to learn complex relationships between dynamic weather phenomena, envelope heat/mass transfer interactions, window parameters, and resulting indoor temperature and humidity trends. Testing predictive capabilities on unseen weather profiles and opening scenarios evaluates model generalization for real-world deployment and control integration.

3.4. Model development

3.4.1. Model input, output variables, and training

The inputs and outputs of the LSMT models to predict indoor operating temperatures are shown in Table SI. 4, and initial hypermeters for the LSTM model are shown in Table SI. 5. The output variable for the LSMT was the office room's hourly operating temperature, which was determined by simulating the building model. The window opening area was adjusted from 0% to 90% in increments of 10% to consider how natural ventilation impacts interior temperature. To create 8760 rows of hourly data, each opening approach was simulated for an entire year. The 35040 hours of data generated from the window opening strategies were used to train, validate, and test the LSTM model. The model's inputs included weather information and the window opening size. In addition, time was considered input for calculating the hourly indoor temperature, including the hour, day, and month of the year.

The present study primarily utilizes a dataset from October 12th to November 1st, as illustrated in Figure 7. The dataset is partitioned into a training set comprising 70% of the data and a test set containing 30%. The encoder input consists of historical data from the preceding time step, while the outdoor temperature and humidity data for future time steps are incorporated. It is hypothesized that the prediction time interval may influence the model's long-term predictive stability. To evaluate this, the model forecasts indoor temperature and humidity at four distinct temporal horizons: 1 minute, 30 minutes, 60 minutes, and 120 minutes in advance. The model's stability is subsequently assessed based on its performance over a six-day test period.

3.4.2. Model performance evaluation and generalization capabilities

The predictive performance of the developed LSTM models was evaluated using three quantitative metrics: the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). The R^2 score measures how closely the predicted values align with the accurate, validated dataset, with higher values indicating more variance explained by the model. RMSE represents the sample standard deviation of prediction errors, with squaring amplifying outliers. This allows for assessing deviations in units of the quantity being predicted. Meanwhile, MAE reports absolute differences without sensitivity to directionality or extremes. Comparing these complementary indicators offers a comprehensive evaluation. Equations (7-9) mathematically define each metric where $\overline{y}$represents the average of the actual values, y_i denotes individual actual values, $\widehat{y_i}$refers to the predicted values, and $m$indicates the number of data samples.

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{m}(y_i - \widehat{y_i})^2}{\sum_{i=1}^{m}(y_i - \overline{y})^2}\right] \tag{7}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(y_i - \widehat{y_i})^2}{m}} \tag{8}$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|y_i - \widehat{y_i}| \tag{9}$$

4. Results

4.1. Simulated indoor temperature distribution

The spatial distribution of the simulated indoor temperature was presented in Figure 8, illustrating the temperature behavior at 11 a.m. on February 15th (dry) and August 15th (rainy) with a window opening angle of 50°. The horizontal section at a height of 2.0m was selected to provide a detailed understanding of the spatiotemporal temperature patterns in the room. As expected, the indoor temperature values exhibit a relatively higher concentration towards the northern direction of the room, gradually decreasing as one moves away from the center. The temperature levels near the room's window side are slightly above 37°C and 30°C in dry and rainy, respectively. Moving toward the center and walls of the room, the temperature levels decrease to approximately 30°C and 20°C in dry and rainy, respectively. This observed pattern is consistent across different seasons and times of the day, with a slight bias towards the west or east directions due to the solar azimuth angle at the considered hours. These results confirm the accuracy of our simulation model.

4.2. Performance of the LSTM model

4.2.1. Predictive performance for indoor temperature

We evaluated our LSTM model's ability to forecast indoor temperatures across various prediction horizons: 1 minute, 30 minutes, 60 minutes, and 120 minutes. Figure 9 illustrates the comparison between predicted and actual indoor temperatures for these time intervals for testing dataset.

For the 1-minute horizon, we observed a near-perfect alignment between predicted and actual temperatures, indicating high short-term prediction accuracy. The 30-minute horizon predictions maintained a strong correlation with actual values, though minor deviations began to emerge. As we extended to the 60-minute horizon, the discrepancies between predicted and actual temperatures became more pronounced, suggesting a decrease in accuracy with increasing prediction time. The 120-minute horizon exhibited significant deviations, highlighting the challenges associated with long-term temperature forecasting in naturally ventilated office spaces.

4.2.2. Predictive performance for the indoor humidity

Figure 10 illustrates the predictive performance of the LSTM network for indoor humidity across four different prediction horizons: 1-minute, 30-minute, 60-minute, and 120-minute, using the testing dataset. The plots compare the predicted and actual indoor humidity levels, comprehensively analyzing the model's accuracy over time. The study of the prediction versus actual indoor humidity plots across varying prediction horizons highlights the strengths and limitations of the LSTM network in forecasting indoor humidity. The model demonstrates excellent performance for short-term predictions, with high accuracy in the 1-minute and 30-minute horizons. However, as the prediction horizon extends to 60 minutes and beyond, the predictive accuracy decreases, reflecting the complexities and uncertainties associated with longer-term forecasts.

5. Discussion

The simulated temperature behavior aligns with theoretical expectations, exhibiting high illuminance levels at the relative window position of the room, which gradually diminish as one moves horizontally and cross-sectionally across the room. This pattern, consistent across different seasons and times of the day, validates our simulation model and confirms its reliability for studying indoor temperature distribution in naturally ventilated office spaces. Furthermore, the simulated temperature behavior aligns with theoretical expectations, exhibiting high illuminance levels at the relative window position of the room, which gradually diminish as one moves horizontally and cross-sectionally across the room.

The results in Tables 1 and 2 indicate a decline in model accuracy as the prediction horizon increases, with R^2 values decreasing from 0.985 to 0.802 for indoor temperature and from 0.987 to 0.782 for indoor humidity over the 1- to 120-minute prediction intervals. To provide a comprehensive evaluation, we compared the performance of the linear ARX (AutoRegressive with eXogenous inputs) model with our LSTM model. The ARX model, which is simpler and computationally less demanding, performs adequately for short-term predictions. However, the ARX model's accuracy diminishes significantly as the prediction horizon increases. For instance, at a 30-minute horizon, ARX achieves an R^2 of 0.785, while LSTM reaches 0.921. At the 120-minute horizon, ARX's R^2 drops to 0.672, compared to 0.802 for LSTM. This demonstrates the ability of LSTM to capture the complex non-linear relationships between indoor conditions and environmental variables, especially for longer-term predictions. We compared our LSTM model's performance with other studies employing various models and prediction horizons (Table 3). Our

LSTM model demonstrates competitive performance across various prediction horizons compared to other studies in the literature. For short-term predictions (30 minutes), our model achieves an R^2 of 0.921, RMSE of 0.051, and MAE of 0.021, outperforming traditional MLP models reported by [50] and [51] and showing comparable results to the LSTM model in [52]. However, the LSTM-CNN hybrid model from [52] exhibits superior performance, particularly in longer prediction horizons. As the prediction horizon extends to 60 and 120 minutes, our LSTM model maintains robust performance, consistently surpassing MLP models from other studies. For instance, at the 60-minute horizon, our model achieves an R^2 of 0.905, compared to the MLP model in [52] with an R^2 of 0.763. Nevertheless, the LSTM-CNN model from [52] continues to outperform our approach, especially in long-term predictions, achieving an R^2 of 0.903 at the 120-minute horizon compared to our 0.802.

The performance metrics indicate that the developed LSTM model performs exceptionally well for short-term predictions, particularly at the 1-minute horizon, and maintains good accuracy for medium-term forecasts up to 30 minutes. The model's accuracy diminishes for longer prediction horizons, such as 60 minutes and beyond, reflecting the increased difficulty in maintaining precise forecasts over extended periods. The model's high accuracy for short-term predictions makes it suitable for applications requiring immediate and accurate responses, such as real-time monitoring and control systems in naturally ventilated office spaces. Medium-term predictions can be used effectively for strategic planning and adjustments, though periodic updates and recalibrations are recommended to maintain reliability. For long-term forecasts, the model should be used with an understanding of its limitations and potentially in conjunction with other predictive tools to enhance accuracy.

The study of the prediction versus actual indoor humidity plots across varying prediction horizons highlights the strengths and limitations of the LSTM network in forecasting indoor humidity. The model demonstrates excellent performance for short-term predictions, with high accuracy in the 1-minute and 30-minute horizons. However, as the prediction horizon extends to 60 minutes and beyond, the predictive accuracy decreases, reflecting the complexities and uncertainties associated with longer-term forecasts.

These findings underscore the importance of considering prediction horizons in practical applications. Short-term predictions (1-minute- to 30-minute horizons) provide reliable data for real-time control and monitoring systems to inform immediate decisions and actions. Conversely, for strategic planning and long-term management, acknowledging the limitations of longer-term predictions (60-minute to 120-minute horizons) is crucial, and supplementary methods or models may be needed to enhance accuracy.

5.1. Comparison of Predicted Indoor Conditions with Different Window Configurations

To evaluate the impact of window configurations on the predicted indoor conditions, we conducted simulations using three different scenarios: (1) windows permanently closed, (2) mixed usage (windows opened and closed based on typical occupant behavior and external weather conditions), and (3) windows always open. The results are summarized below:

In the windows permanently closed scenario, the indoor temperatures and humidities were predominantly influenced by internal heat gains and HVAC operations. The LSTM model predicted relatively stable indoor conditions with minimal fluctuations. For instance, during summer days, the indoor temperature varied between 22°C and 24°C, while the humidity levels remained between 80g/m^3 and 85g/m^3.

The mixed usage scenario reflects more realistic occupant behavior, with windows being opened or closed based on comfort needs and external conditions. The predicted indoor conditions showed moderate variability, capturing the dynamic interaction between natural ventilation. For example, during the same summer days, the indoor temperature ranged from 21°C to 25°C, and humidity levels fluctuated between 75g/m^3 and 90g/m^3.

With windows permanently open, the indoor conditions highly depended on external weather. The LSTM model predicted significant variations in indoor temperatures and humidities, highlighting the strong influence of outdoor air. During peak summer days, the indoor temperature varied widely from 20°C to 28°C, and humidity levels ranged from 70g/m^3 and 95g/m^3.

The comparative analysis demonstrates that window configurations substantially impact indoor environmental conditions. The LSTM model effectively captured the variations across different scenarios, validating its applicability for predicting indoor climate under varying natural ventilation strategies. Figure 11 presents detailed results of the indoor temperature and humidity predictions for the three window configurations.

5.2. Limitations and future work

The use of fixed schedules for internal heat gains in our synthetic data generation is a limitation of this study. In real buildings, the variability in occupant behavior and equipment usage patterns can significantly impact indoor thermal conditions. This variability, not captured in our current model, could be an additional source of prediction errors when the model is applied to actual buildings. Furthermore, conducting sensitivity analyses to quantify the impact of heat gain uncertainties on the model's predictive performance would provide valuable insights into the model's limitations and potential areas for improvement. A key limitation of this study is its focus on a tropical climate. The model's performance and conclusions may not directly translate to temperate or colder regions where heating is required, and seasonal variations are more pronounced.

Real-world implementation of our LSTM model faces several challenges. Integration with existing systems may pose compatibility issues, especially with legacy building management systems. Collecting and processing occupancy and environmental data raises privacy concerns that need to be addressed. Ensuring the model remains accurate over time as building characteristics or usage patterns change will require ongoing maintenance and periodic retraining. The initial investment in sensors, data collection infrastructure, and computational resources may be a barrier for some building owners or managers. Lastly, building managers and occupants may be hesitant to rely on AI-driven predictions for environmental control, necessitating a period of trust-building and demonstration of the system's benefits.

Future work should explore integrating the demonstrated LSTM prediction pipeline with automatic window modulation and existing building management infrastructure for intelligent, sustainable operation. With sub-second response times and negligible computational overhead, the approach could readily expand in the context of smart buildings and spaces. Additional research should evaluate coupling LSTM methods with real-time pricing and demand-response control techniques for peak load shifting and ancillary grid services. Detailed techno-economic analyses are also warranted to quantify cost savings and payback periods for sensor and automation upgrades.

This study highlights that properly designed black-box LSTM models provide a foundational data-driven methodology to unlock the benefits of natural ventilation strategies at scale across the built environment. The convergence of predictive accuracy, rapid automated responses, and mainstream deployment potentials on low-cost embedded hardware demonstrate transformative capabilities to meet present climate, energy, occupant health, and emissions objectives while fostering future smart infrastructure.

6. Conclusion

This research presents several significant contributions to the field of indoor environmental quality prediction and control in naturally ventilated office spaces. Our research demonstrates the accuracy of the LSTM model in predicting indoor temperatures and humidity under diverse, dynamic conditions. By analyzing the variability in prediction precision across different weather seasons and window opening sizes, we provide valuable insights to inform optimal control strategies for naturally ventilated buildings.

The promising accuracy and stability for predicting temperatures in the simulated office layout provide preliminary evidence that LSTM models may apply to other naturally conditioned buildings. However, further validation across different building typologies, climates, and integration of stochastic occupancy behaviors would be needed to fully generalize the approach and confirm its viability for broader implementation. Our findings highlight the powerful influence of window opening area and incident solar radiation on indoor temperature fluctuations. The model's ability to accurately forecast the direction and degree of hourly temperature changes enables preemptive actions for modulating ventilation parameters, enhancing both occupant comfort and energy efficiency.

The implications of this research extend beyond mere temperature prediction. Our approach creates built environments that actively nurture occupant well-being by enabling finely tuned thermal and moisture levels that guard against extremes. For building owners and operators, the enhanced indoor environmental quality monitoring and control tools developed through this research offer a means of differentiation in an increasingly competitive market. Energy managers can benefit from strategic optimization of heating, cooling, and ventilation systems based on anticipated indoor requirement trends derived from the LSTM model.

However, it is essential to note that further validation across different building typologies, climates, and integration of stochastic occupancy behaviors would be necessary to fully generalize this approach and confirm its viability for broader implementation. Future research should focus on expanding the scope of this study to include a broader range of building types and environmental conditions, as well as incorporating additional factors such as occupant behavior and more complex HVAC systems.

In conclusion, this research showcases the potential of LSTM neural networks for small commercial buildings and their possible implementation across various construction industry processes, from design to operation, where complex thermal and ventilation behavior exists. As we move towards more sustainable and intelligent building management systems, the approach presented in this research offers a promising path forward, contributing to the development of energy-efficient, comfortable, and adaptive built environments.

Disclosure Statement

The authors report there are no competing interests to declare.

Data Availability Statement

The data that support the findings of this study are available upon reasonable request.

References

[1] International Energy Agency, ‘Buildings: Tracking report – November 2021’, 2021. Available: https://www.iea.org/energy-system/buildings#tracking

[2] L. Pérez-Lombard, J. Ortiz, and C. Pout, ‘A review on buildings energy consumption information’, *Energy Build*, vol. 40, no. 3, pp. 394–398, 2008, doi: 10.1016/j.enbuild.2007.03.007.

[3] M. Frontczak, S. Schiavon, J. Goins, E. Arens, H. Zhang, and P. Wargocki, ‘Quantitative relationships between occupant satisfaction and satisfaction aspects of indoor environmental quality and building design’, *Indoor Air*, vol. 22, no. 2, pp. 119–131, 2012, doi: 10.1111/j.1600-0668.2011.00745.x.

[4] G. Morrison, J. Cagle, and G. Date, ‘A national survey of window-opening behavior in United States homes’, *Indoor Air*, vol. 32, no. 1, Jan. 2022, doi: 10.1111/ina.12932.

[5] S. Hu, D. Yan, S. Guo, Y. Cui, and B. Dong, ‘A survey on energy consumption and energy usage behavior of households and residential building in urban China’, *Energy Build*, vol. 148, pp. 366–378, Aug. 2017, doi: 10.1016/j.enbuild.2017.03.064.

[6] M. B. C. Aries, J. A. Veitch, and G. R. Newsham, ‘Physical and psychological discomfort in the office environment-SOLG symposium’, in *Light, Performance and Quality of Life–Light and Health Research Foundation (SOLG) Symposium*, 2007.

[7] W. F. M. Yusoff, M. I. Shaharil, M. F. Mohamed, M. R. M. Rasani, A. R. Sapian, and N. D. Dahlan, ‘Review of openings with shading devices at naturally ventilated buildings’, *Architectural Engineering and Design Management*, vol. 19, no. 5, pp. 463–479, 2023, doi: doi.org/10.1080/17452007.2022.2095553.

[8] K. M. Gerhardsson and T. Laike, ‘Windows: a study of residents’ perceptions and uses in Sweden’, *Buildings and Cities*, vol. 2, no. 1, pp. 467–486, 2021, doi: 10.5334/bc.120.

[9] Richard J. de Dear and Gail Schiller Brager, ‘Developing an adaptive model of thermal comfort and preference’, *UC Berkeley: Center for the Built Environment*, 1998.

[10] D. J. Clements-Croome, *Natural ventilation in non-domestic buildings*. Chartered Institution of Building Services Engineers, 2005.

[11] Z. Tong, Y. Chen, A. Malkawi, Z. Liu, and R. B. Freeman, 'Energy saving potential of natural ventilation in China: The impact of ambient air pollution', *Appl Energy*, vol. 179, pp. 660–668, Oct. 2016, doi: 10.1016/j.apenergy.2016.07.019.

[12] R. M. S. F. Almeida, M. Pinto, P. G. Pinho, and L. T. de Lemos, 'Natural ventilation and indoor air quality in educational buildings: experimental assessment and improvement strategies', *Energy Effic*, vol. 10, no. 4, pp. 839–854, Aug. 2017, doi: 10.1007/s12053-016-9485-0.

[13] G. Brager, G. Paliaga, and R. De Dear, 'Operable windows, personal control, and occupant comfort', *ASHRAE Trans*, vol. 110, pp. 17–35, 2004.

[14] M. Dabbagh and M. Krarti, 'Evaluation of the performance for a dynamic insulation system suitable for switchable building envelope', *Energy Build*, vol. 222, Sep. 2020, doi: 10.1016/j.enbuild.2020.110025.

[15] R. Raslan and M. Davies, 'Results variability in accredited building energy performance compliance demonstration software in the UK: an inter-model comparative study', *J Build Perform Simul*, vol. 3, no. 1, pp. 63–85, 2010, doi: 10.1080/19401490903477386.

[16] Z. Afroz, G. M. Shafiullah, T. Urmee, and G. Higgins, 'Modeling techniques used in building HVAC control systems: A review', *Renewable and Sustainable Energy Reviews*, vol. 83, pp. 64–84, Mar. 2018, doi: 10.1016/j.rser.2017.10.044.

[17] M. Hosseini, F. Tardy, and B. Lee, 'Cooling and heating energy performance of a building with a variety of roof designs; the effects of future weather data in a cold climate', *Journal of Building Engineering*, vol. 17, pp. 107–114, May 2018, doi: 10.1016/j.jobe.2018.02.001.

[18] F. Tang, A. Kusiak, and X. Wei, 'Modeling and short-term prediction of HVAC system with a clustering algorithm', *Energy Build*, vol. 82, pp. 310–321, 2014, doi: 10.1016/j.enbuild.2014.07.037.

[19] A. Afram and F. Janabi-Sharifi, 'Review of modeling methods for HVAC systems', *Appl Therm Eng*, vol. 67, no. 1–2, pp. 507–519, 2014, doi: 10.1016/j.applthermaleng.2014.03.055.

[20] D. Enescu, 'A review of thermal comfort models and indicators for indoor environments', *Renewable and Sustainable Energy Reviews*, vol. 79, pp. 1353–1379, 2017, doi: 10.1016/j.rser.2017.05.175.

[21] F. Amara, K. Agbossou, A. Cardenas, Y. Dubé, and S. Kelouwani, 'Comparison and Simulation of Building Thermal Models for Effective Energy Management', *Smart Grid and Renewable Energy*, vol. 6, pp. 95–112, 2015, doi: 10.4236/sgre.2015.64009.

[22] A. Afram and F. Janabi-Sharifi, 'Gray-box modeling and validation of residential HVAC system for control system design', *Appl Energy*, vol. 137, pp. 134–150, 2015, doi: 10.1016/j.apenergy.2014.10.026.

[23] R. Z. Homod, ‘Review on the HVAC System Modeling Types and the Shortcomings of Their Application’, *Journal of Energy*, vol. 2013, pp. 1–10, 2013, doi: 10.1155/2013/768632.

[24] D. Yu, A. Abhari, A. S. Fung, K. Raahemifar, and F. Mohammadi, ‘Predicting Indoor Temperature from Smart Thermostat and Weather Forecast Data’, in *Proceedings of the Communications and Networking Symposium*, in CNS ’18. San Diego, CA, USA: Society for Computer Simulation International, 2018, pp. 1–12.

[25] A. Mechaqrane and M. Zouak, ‘A comparison of linear and neural network ARX models applied to a prediction of the indoor temperature of a building’, *Neural Comput Appl*, vol. 13, no. 1, pp. 32–37, Apr. 2004, doi: 10.1007/s00521-004-0401-8.

[26] B. Gaber, C. Zhan, X. Han, M. Omar, and G. Li, ‘Employing ANN for daylight and energy prediction of hot climate office buildings: a case study of new Cairo, Egypt’, *Architectural Engineering and Design Management*, pp. 1–25, 2023, doi: doi.org/10.1080/17452007.2023.2254302.

[27] Y. Ma, A. Kelman, A. Daly, and F. Borrelli, ‘Predictive Control for Energy Efficient Buildings with Thermal Storage: Modeling, Stimulation, and Experiments’, *IEEE Control Systems Magazine*, vol. 32, no. 1, pp. 44–64, 2012, doi: 10.1109/MCS.2011.2172532.

[28] V. T. Quang, D. Dat Tien, P. Nguyen Lu, and Y. Geun Young, ‘Data-driven prediction of indoor airflow distribution in naturally ventilated residential buildings using combined CFD simulation and machine learning (ML) approach’, *J Build Phys*, pp. 1–33, 2023, doi: 10.1177/17442591231219025.

[29] I. H. Yang, M. S. Yeo, and K. W. Kim, ‘Application of artificial neural network to predict the optimal start time for heating system in building’, *Energy Convers Manag*, vol. 44, no. 17, pp. 2791–2809, Oct. 2003, doi: 10.1016/S0196-8904(03)00044-X.

[30] K. Man and J. Chahl, ‘A Review of Synthetic Image Data and Its Use in Computer Vision’, Nov. 01, 2022, *MDPI*. doi: 10.3390/jimaging8110310.

[31] Z. Afroz, T. Urmee, G. M. Shafiullah, and G. Higgins, ‘Real-time prediction model for indoor temperature in a commercial building’, *Appl Energy*, vol. 231, no. May, pp. 29–53, 2018, doi: 10.1016/j.apenergy.2018.09.052.

[32] T. Wei, Y. Wang, and Q. Zhu, ‘Deep Reinforcement Learning for Building HVAC Control’, in *DAC ’17: Proceedings of the 54th Annual Design Automation Conference* , Austin, TX, USA: Association for Computing Machinery, 2017, pp. 1–6. doi: 10.1145/3061639.3062224.

[33] R. Markovic, E. Grintal, D. Wölki, J. Frisch, and C. van Treeck, ‘Window opening model using deep learning methods’, *Build Environ*, vol. 145, pp. 319–329, Nov. 2018, doi: 10.1016/j.buildenv.2018.09.024.

[34] Y. Wei *et al.*, ‘Comparison of different window behavior modeling approaches during transition season in Beijing, China’, *Build Environ*, vol. 157, pp. 1–15, Jun. 2019, doi: 10.1016/j.buildenv.2019.04.040.

[35] Z. Fang, N. Crimier, L. Scanu, A. Midelet, A. Alyafi, and B. Delinchant, ‘Multi-zone indoor temperature prediction with LSTM-based sequence to sequence model☆’, *Energy Build*, vol. 245, Aug. 2021, doi: 10.1016/j.enbuild.2021.111053.

[36] F. Mtibaa, K. K. Nguyen, M. Azam, A. Papachristou, J. S. Venne, and M. Cheriet, ‘LSTM-based indoor air temperature prediction framework for HVAC systems in smart buildings’, *Neural Comput Appl*, vol. 32, no. 23, pp. 17569–17585, Dec. 2020, doi: 10.1007/s00521-020-04926-3.

[37] D. Yang, J. Wang, X. Yan, and H. Liu, ‘Subway air quality modeling using improved deep learning framework’, *Process Safety and Environmental Protection*, vol. 163, pp. 487–497, Jul. 2022, doi: 10.1016/j.psep.2022.05.055.

[38] H. Sepp and S. Jürgen, ‘LSTM can Solve Hard Long Time Lag Problems’, in *Advances in Neural Information Processing Systems 9*, Denver, CO, USA: MIT Press, Dec. 1996, pp. 473–479.

[39] Y. Bengio and P. Frasconi, ‘Credit Assignment through Time: Alternatives to Backpropagation’, in *Advances in Neural Information Processing Systems 6*, Denver, Colorado, USA: Morgan Kaufmann Publishers Inc, 1993, pp. 75–82.

[40] J. T. Connor, R. D. Martin, and L. E. Atlas, ‘Recurrent Neural Networks and Robust Time Series Prediction’, *IEEE Trans Neural Netw*, vol. 5, no. 2, pp. 240–254, 1994, doi: 10.1109/72.279188.

[41] Y. Bengio, P. Simard, and P. Frasconi, ‘Learning Long-Term Dependencies with Gradient Descent is Difficult’, *IEEE Trans Neural Netw*, vol. 5, no. 2, pp. 157–166, 1994, doi: 10.1109/72.279181.

[42] D. Mandic and J. Chambers, *Recurrent neural networks for prediction: learning algorithms, architectures and stability*. Wiley, 2001.

[43] B. Kanuparthi, D. Arpit, G. Kerg, N. R. Ke, I. Mitliagkas, and Y. Bengio, ‘h-detach: Modifying the LSTM Gradient Towards Better Optimization’, in *7th International Conference on Learning Representations*, New Orleans, Louisiana, United States: OpenReview.net, Jun. 2019.

[44] A. Afram and F. Janabi-Sharifi, ‘Theory and applications of HVAC control systems - A review of model predictive control (MPC)’, *Build Environ*, vol. 72, pp. 343–355, 2014, doi: 10.1016/j.buildenv.2013.11.016.

[45] F. A. Gers, J. Schmidhuber, and F. Cummins, ‘Learning to Forget: Continual Prediction with LSTM’, *Neural Comput*, vol. 12, no. 10, pp. 2451–2471, 2000, doi: 10.1162/089976600300015015.

[46] H. Sak, A. Senior, and F. Beaufays, ‘Long Short-Term Memory Based Recurrent Neural Network Architectures for Large Vocabulary Speech Recognition’, *arXiv:1402.1128*, 2014.

[47] M. Robert and Associates, *Rhinoceros: NURBS Modeling for Windows : Training Manual, Level 1*. Robert McNeel & Associates, 2008.

[48] EnergyPlus Version 8.9.0 Documentation, ‘Engineering Reference’, *US Department of Energy*, pp. 362–367, 2018.

[49] Y. Goto *et al.*, 'Heat and moisture balance simulation of a building with vapor-open envelope system for subtropical regions', *Build Simul*, vol. 5, no. 4, pp. 301–314, Dec. 2012, doi: 10.1007/s12273-012-0086-3.

[50] N. Attoue, I. Shahrour, and R. Younes, 'Smart building: Use of the artificial neural network approach for indoor temperature forecasting', *Energies (Basel)*, vol. 11, no. 2, Feb. 2018, doi: 10.3390/en11020395.

[51] F. Mtibaa, K. K. Nguyen, M. Azam, A. Papachristou, J. S. Venne, and M. Cheriet, 'LSTM-based indoor air temperature prediction framework for HVAC systems in smart buildings', *Neural Comput Appl*, vol. 32, no. 23, pp. 17569–17585, Dec. 2020, doi: 10.1007/s00521-020-04926-3.

[52] F. Elmaz, R. Eyckerman, W. Casteels, S. Latré, and P. Hellinckx, 'CNN-LSTM architecture for predictive indoor temperature modeling', *Build Environ*, vol. 206, Dec. 2021, doi: 10.1016/j.buildenv.2021.108327.

[53] C. Xu, H. Chen, J. Wang, Y. Guo, and Y. Yuan, 'Improving prediction performance for indoor temperature in public buildings based on a novel deep learning method', *Build Environ*, vol. 148, pp. 128–135, Jan. 2019, doi: 10.1016/j.buildenv.2018.10.062.