Data-Driven Zone-Level Temperature Prediction for Energy-Efficient and Demand-Responsive HVAC Control in Smart Buildings

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Abstract. The main objective of this study is to develop an accurate and scalable data-driven methodology for predicting zone-level indoor air temperature (IAT) to support sustainable HVAC operation in smart buildings. These objectives were achieved by collecting IoT-enabled time-series thermal data from multiple air handling unit-based zones within an educational building. A rule-based zone grouping strategy based on floor level, orientation, solar exposure and usage characteristics was implemented to address spatial variability. Three deep learning architectures, namely Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Recurrent Neural Network (RNN), were developed and evaluated using real operational data. The models were used to capture temporal thermal dynamics and to assess prediction accuracy and computational efficiency under both normal and demand response (DR) operating conditions. The most important results indicated that the LSTM model achieved the best prediction performance, with a Mean Absolute Error (MAE) of approximately 0.1°C and coefficient of determination (R^2) values of up to 95%. The developed models also showed fast prediction times of approximately 4–5 seconds, making them suitable for real-time HVAC applications. In addition, the prediction performance remained stable during DR events, confirming the robustness of the developed models under dynamic operating conditions. The significance of the obtained results lies in showing that zone-level data-driven thermal prediction combined with intelligent zone grouping can provide reliable short-term IAT forecasting for sustainable and responsive HVAC operation in smart buildings.
***Keywords*:** building energy management, demand response, indoor thermal modeling, real-time prediction, time-series forecasting, zone grouping.

DOI: https://doi.org/10.52254/1857-0070.2026.3-71.04
UDC: 697.7

Previziunea temperaturii la nivel de zonă, bazată pe date, pentru un control al sistemelor HVAC eficient din punct de vedere energetic și în funcție de cerere în clădirile inteligente

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Rezumat. Obiectivul principal al acestui studiu este dezvoltarea unei metodologii precise și scalabile, bazate pe date, pentru prezicerea temperaturii aerului interior (IAT) la nivel de zonă, în vederea susținerii funcționării durabile a sistemelor HVAC în clădirile inteligente. Acest obiectiv a fost atins prin colectarea de date termice în serii temporale, bazate pe IoT, din mai multe zone deservite de unități de tratare a aerului dintr-o clădire educațională. A fost implementată o strategie de grupare a zonelor bazată pe reguli, utilizând nivelul etajului, orientarea, expunerea solară și caracteristicile de utilizare, pentru a aborda variabilitatea spațială. Trei arhitecturi de învățare profundă, și anume Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) și Rețeaua Neuronală Recurentă (RNN), au fost dezvoltate și evaluate utilizând date operaționale reale. Modelele au fost folosite pentru a capta dinamica termică temporală și pentru a evalua acuratețea predicției și eficiența computațională atât în condiții normale de funcționare, cât și în condiții de răspuns la cerere (DR). Rezultatele au indicat că modelul LSTM a obținut cea mai bună performanță de predicție, cu o Eroare Absolută Medie (MAE) de aproximativ 0.1 °C și valori ale coeficientului de determinare (R^2) de până la 95%. Modelele dezvoltate au demonstrat, de asemenea, timpi de predicție reduși, de aproximativ 4–5 secunde, ceea ce le face potrivite pentru aplicații HVAC în timp real. În plus, performanța de predicție a rămas stabilă în timpul evenimentelor DR, confirmând robustețea modelelor dezvoltate în condiții dinamice de funcționare. Semnificația rezultatelor obținute constă în demonstrarea faptului că predicția termică bazată pe date la nivel de zonă, combinată cu gruparea inteligentă a zonelor, poate furniza prognoze IAT fiabile pe termen scurt pentru o funcționare sustenabilă și adaptivă a sistemelor HVAC în clădirile inteligente.
***Cuvinter-cheie*:** gestionarea energetică a clădirilor, răspunsul la cerere, modelarea termică interioară, predicția în timp real, prognozarea seriilor temporale, gruparea pe zone.

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Прогнозирование температуры на уровне зон на основе данных для энергоэффективного и адаптивного к спросу управления системами отопления, вентиляции и кондиционирования воздуха в «умных» зданиях

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Аннотация. Основная цель данного исследования — разработка точной и масштабируемой методологии, основанной на данных, для прогнозирования температуры воздуха в помещении (IAT) на уровне зон, что позволит обеспечить устойчивую работу систем отопления, вентиляции и кондиционирования воздуха (HVAC) в интеллектуальных зданиях. Эти цели были достигнуты путем сбора временных рядов тепловых данных с использованием IoT-технологий из нескольких зон обработки воздуха в учебном здании. Для учета пространственной изменчивости была реализована стратегия группировки зон на основе правил, учитывающая уровень этажа, ориентацию, солнечное излучение и характеристики использования. Были разработаны и оценены три архитектуры глубокого обучения: долговременная кратковременная память (LSTM), вентилируемый рекуррентный блок (GRU) и рекуррентная нейронная сеть (RNN), с использованием реальных эксплуатационных данных. Модели использовались для учета временной динамики температуры и оценки точности прогнозирования и вычислительной эффективности как в нормальных условиях, так и в условиях реагирования на спрос (DR). Наиболее важные результаты показали, что модель LSTM продемонстрировала наилучшие показатели прогнозирования со средней абсолютной ошибкой (MAE) приблизительно 0.1 °C и коэффициентом детерминации (R^2), достигающим 95%. Разработанные модели также продемонстрировали быстрое время прогнозирования, составляющее приблизительно 4–5 секунд, что делает их пригодными для применения в системах отопления, вентиляции и кондиционирования воздуха (ОВК) в режиме реального времени. Кроме того, точность прогнозирования оставалась стабильной во время событий динамического регулирования, подтверждая надежность разработанных моделей в динамических условиях эксплуатации. Значимость полученных результатов заключается в демонстрации того, что основанное на данных прогнозирование температуры на уровне зон в сочетании с интеллектуальной группировкой зон может обеспечить надежное краткосрочное прогнозирование температуры внутри помещений для устойчивой и быстрой работы систем ОВК в интеллектуальных зданиях.

***Ключевые слова*:** управление энергопотреблением зданий, реагирование на спрос, моделирование внутреннего теплоснабжения, прогнозирование в реальном времени, прогнозирование временных рядов, группировка зон.

INTRODUCTION

Rapid urbanization, economic growth and rising temperatures driven by global climate change have not only increased overall electricity consumption but also triggered more frequent peak-load events.

As the intensity and variability of electricity demand continue to rise, utilities face growing challenges in maintaining grid stability, managing peak load conditions and ensuring reliable supply. Among all end-use sectors, buildings account for a substantial share of global energy consumption with Heating, Ventilation, and Air Conditioning (HVAC) systems representing the largest and most flexible loads due to their thermal inertia [1]. Consequently, efforts to reduce energy demand in the building sector have increasingly focused on improving the operational control and energy efficiency of HVAC systems [2].

This is especially relevant in tropical cities such as Bengaluru during the summer, where increased outdoor temperature significantly increases cooling requirements [3]. However, realizing HVAC flexibility in real time requires an accurate understanding of indoor thermal behavior and accurate prediction of IAT under varying operating conditions.

Several physics-based modelling tools can be used for building simulation, including EnergyPlus [4][5], TRNSYS [6][7], DOE-2 [8], ESP-r [9] etc.

These tools compute zone-level thermal behavior using detailed heat-balance equations and are widely used for thermal simulation, HVAC performance evaluation and building energy analysis.

Data-driven models developed using machine learning (ML) techniques offer scalable, adaptive and computationally efficient alternatives [10]. These models leverage historical data such as indoor/outdoor temperatures, indoor/outdoor humidity, occupancy, HVAC power consumption, thermostat setpoints etc., to learn patterns and predict system behaviour.

With the increasing availability of building automation system data and Internet of Things

(IoT) sensors, data-driven approaches have gained prominence in HVAC control. A range of ML techniques have been explored for HVAC applications, including regression models [11], support vector machines [12], ensemble learning methods (e.g., random forest [13], XGBoost [14]), neural network (NN) [15][16][17], reinforcement learning [18], clustering [19], classification [20] etc.

Physics-based simulation tools are often time-consuming to calibrate and lack adaptability for real-time operation.

However, for fast and improved HVAC responsiveness, ML-enabled data driven approaches are more effective, as they learn complex nonlinear thermal dynamics directly from IoT based sensor data [21][22][23][24]. Accurate, real-time prediction of zone-level IAT is essential not only for maintaining occupant comfort but also for optimizing HVAC energy use and enabling intelligent, grid-interactive building operations [25].

Load forecasting in building energy systems is generally classified into long-term, medium-term, and short-term forecasting based on the prediction horizon and application objectives.

Long-term forecasting supports infrastructure planning, policy development, and future energy demand assessment, while medium-term forecasting aids operational planning and energy management. Short-term forecasting, ranging from a few minutes to several hours ahead, is particularly important for real-time HVAC control, DR participation, and intelligent energy management.

Due to the thermal inertia of buildings, indoor thermal conditions change gradually over time, making short-term forecasting most relevant for predictive HVAC control and adaptive operation under varying occupancy, weather, and cooling demand conditions [26][27].

Most existing studies on short-term indoor air temperature forecasting focus either on single-zone prediction [28][29][30][31]. or building-level environment prediction approaches [32][33][34][35].

Limited research has addressed scalable zone-grouped prediction using real operational data under dynamic HVAC conditions, particularly during DR events.

In addition, many studies rely on low-resolution data that may not capture rapid indoor thermal variations required for real-time HVAC control. To address these limitations, this work focuses on short-term indoor air temperature forecasting using high-resolution 5-minute operational data to improve prediction accuracy and model robustness.

The proposed framework aims to develop a reliable, data-driven approach for real-time zone-level IAT prediction suitable for predictive, energy-efficient, and demand-responsive HVAC operation.

The main contributions of this work are summarized as follows:

(i) Development of a data-driven ML framework for zone-level IAT prediction in an educational building located in Bengaluru, India.

(ii) Utilization of IoT-enabled building thermal data and weather data for real-time predictive modelling.

(iii) Introduction of a rule-based zone grouping strategy to group zones with similar thermal characteristics and enable shared predictive modelling.

(iv) Evaluation and comparison of neural network models, namely LSTM, GRU and RNN for capturing nonlinear thermal dynamics and temporal dependencies.

(v) Validation of accurate short-term IAT forecasting using real-time operational data and assessment of its suitability for predictive, energy-efficient and demand-responsive HVAC operation.

I. METHODOLOGY

The building considered in the work is an educational building situated in Bengaluru, India. It is an 8-storey building (ground floor + 7 floors above ground) with a total built-up area of 46.041 m^2. Approximately 37.000 m^2 of the total built-up area is air-conditioned. The air conditioning extends from the ground floor to the seventh floor, with the distribution of air handling units (AHUs) as follows: i) ground floor - 2 AHUs ii) 1st floor- 3 AHUs iii) 2nd floor to 7th floor- 4 AHUs on each floor. Thus, there are a total of 29 AHUs with capacities ranging from 2.2 kW to 7.5 kW.

The building operates on a conventional water-cooled, centralized constant air volume (CAV) HVAC system.

The building's cooling plant comprises two chillers, four cooling towers, and associated pump systems whose details are given in Table 1.

At any given time, only one of the chillers is operational to handle the building’s cooling needs. The chiller compressor is equipped with a 250 kW variable frequency drive.

The methodology comprised several key steps to develop accurate IAT prediction models. The steps were: A) Data collection B) Data preparation and Model inputs C) Zone grouping for predictive model development D) Data split, ML algorithms and Evaluation metrics E) Hyperparameter setting.

Table 1

Details of Pumps, Cooling tower fan and Chiller system.

Primary pump	11 kW (two in number)
Secondary pump	60 kW (two in number)
Condenser pump	30 kW (two in number)
Cooling tower fan	11 kW (four in number)
Two identical sets of chillers 400TR (250 kW) For each chiller:	
Nominal cooling capacity	1406.8 kW
Rated power input	238.8 kW
Voltage-Phase-Frequency	415 V-3phase-50 Hz
Chilled water leaving temperature	6.7°C
Cooling water entering temperature	29.4°C
Refrigerant	R134a
Refrigerant weight	483kg

A. Data collection

In this study, real-time weather data and indoor zone thermal data were considered for analysis.

The data were collected during the summer months of March and April 2024. Weather data were recorded for a total of 60 days.

The indoor zone thermal data were collected for 50 days, excluding weekends and holidays when the HVAC system was not in operation. Daily HVAC functioning typically followed operating hours from 08:00 to 18:00, and hence data within this operational window were used for model development

1) Weather data collection

The weather parameters comprised outdoor ambient temperature (T_o) in °C and relative humidity (H_o) in % were collected at 1-minute intervals through two Arduino-based IoT measurement systems.

This 1-minute data was averaged and converted into data with 5-minute time step for further analysis.

Each measurement system consisted of Arduino Uno boards, DHT11 humidity sensors, DS18B20 temperature sensors, Wi-Fi connectivity for data transmission, power supplies, breadboards, jumper wires and USB-B type cables as shown in Fig. 1(i) and Fig. 1(ii).

The data processing was managed through the Arduino Integrated Development Environment (IDE).

To enhance measurement accuracy, the Arduino IoT measurement systems were strategically positioned in the south-west and north-east orientations, thereby capturing variations in solar exposure during morning and afternoon periods.

The average data of these two locations were considered for more reliable estimation of outside ambient data.

Time series of weather data, namely T_0 and H_0 collected over two months using the Arduino IoT systems are shown in Fig. 2 (left side), along with average daily T_o and H_o. trends (right side).

The T_o during the 60-day period varied approximately between 26°C and 38°C.

A diurnal pattern was observed, with cooler temperatures in the early morning, followed by a steady increase through late morning, reaching a peak between hour 13:00 and 15:00. After around 16:00, T_o gradually began to decrease toward evening.

The H_o ranged from about 10% to 60%. H_o was highest during the early morning hours (around 08:00–09:00), typically reaching 50–60%. As the day progresses, H_o decreased to 20–30% by midday. In the late afternoon (around 16:00), a slight increase in H_o was observed, corresponding to the cooling of air toward evening.

2) Indoor zone thermal data collection

Indoor thermal parameters which included indoor temperature (T_{in}) and indoor humidity (H_{in}) were collected at the zone level using the Arduino IoT measurement system.

For each AHU, sensors were positioned at the AHU's inlet where outside air and return air were mixed as shown in Fig. 1(iii).

Monitoring the mixed air temperature offered insights into the overall temperature conditions entering the AHU zone.

To ensure accuracy, the Arduino IoT-based sensor data were cross-verified against the AHU thermostat measurements which confirmed a temperature sensing accuracy of ±0.1°C.

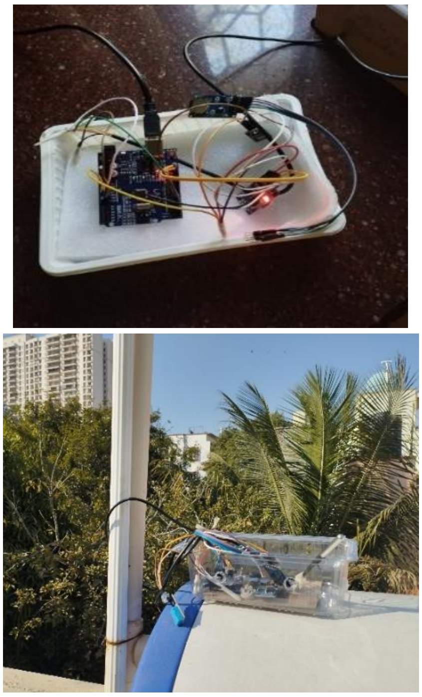

Fig. 1. Data acquisition using an Arduino-based IoT measurement system (i) Hardware setup (ii) Hardware setup for weather data collection (iii) Hardware setup for indoor zone thermal data collection.

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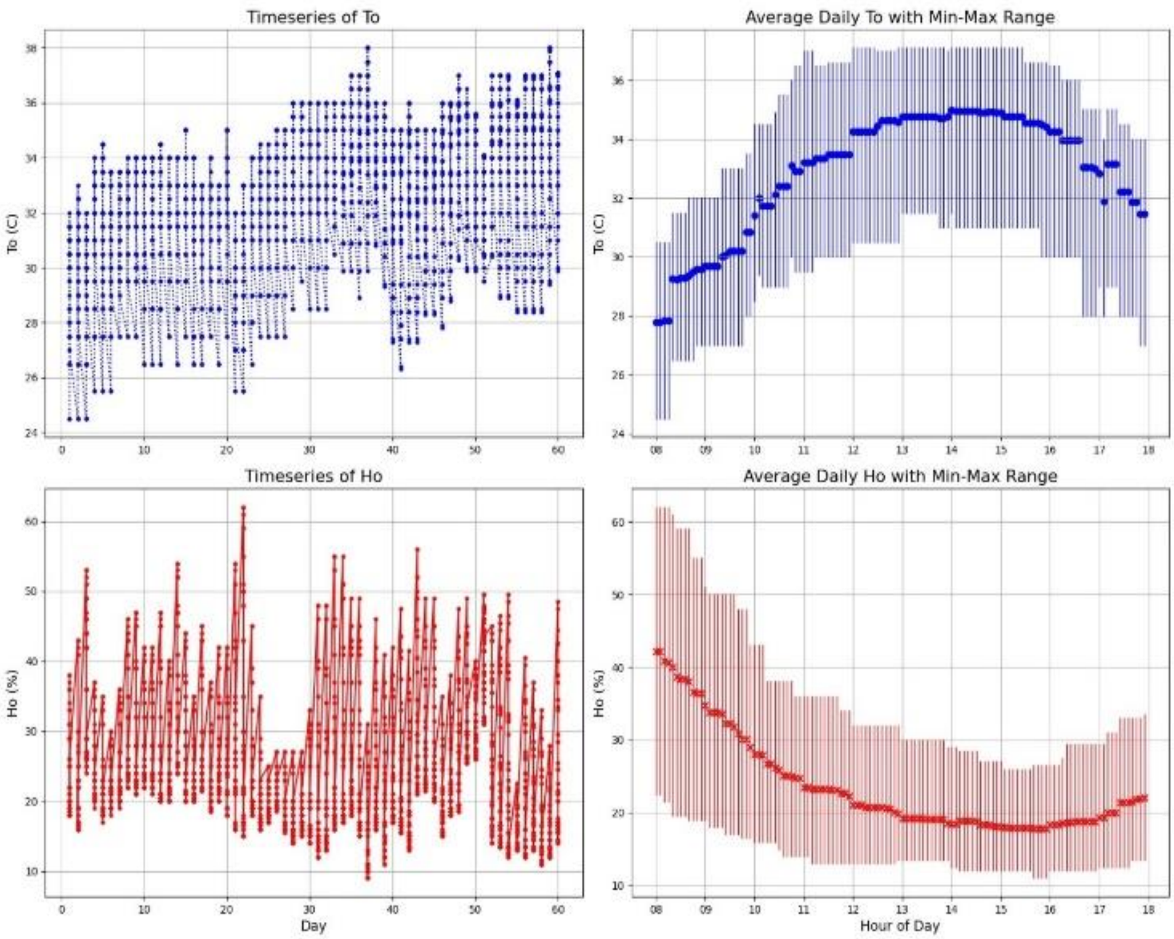

Fig. 2. Time series of weather data T_o, H_o (left side) and average daily weather T_o, H_o trends (right side).

Out of the 29 AHUs present in the building, 27 were included in this study and the 2 AHUs were excluded owing to their distinct operational schedules and stringent environmental control requirements.

During routine building operation, the thermostat set-temperature (T_{set}) for all AHU zones was maintained at 25°C, resulting in T_{in} typically ranging between 23.5°C and 25.5°C. To support sustainable load-curtailment/load-shifting strategies within the broader smart energy management framework, the building occasionally participated in DR events. During these DR periods, T_{set} was temporarily increased to 26.5°C to reduce cooling demand while maintaining acceptable comfort conditions.

Indoor thermal data for four representative AHUs (AHU1, AHU2, AHU3, AHU4) are shown in Fig. 3. For each representative AHU zone, the plots show the mean indoor temperature and relative humidity profiles together with their corresponding minimum–maximum ranges (vertical bars), computed at 5-minute intervals for a typical operating day. The vertical bars indicate that each zone experienced different levels of thermal variability throughout the day.

AHU1 was located on the 7th floor with a south-west orientation, which represented a high-exposure zone due to its upper-floor placement and strong afternoon solar gains. AHU2 was situated on the 4th floor with a north-east orientation, which corresponds to a moderate-exposure condition. AHU3 served the library on the 3rd floor which represented a large space and relatively high thermal inertia. AHU4 was a small and near-chiller zone located on the 1st floor, characterized by low thermal inertia and fast temperature response.

Across all zones, the T_{in} remained within the conditioned comfort band of approximately 23.5–25.5 °C. AHU1 exhibited relatively larger fluctuations, particularly during the afternoon period, likely influenced by its solar exposure. AHU2 showed moderate variability with a comparatively smoother profile, reflecting a stable thermal response. AHU3 showed the most stable behavior, which could be associated with the larger space and higher thermal inertia. AHU4 displayed the widest spread between minimum and maximum temperatures, indicating higher sensitivity to short-term variations due to its small volume and low thermal inertia.

B. Data preparation and Model inputs

After data collection, the first step was data preparation. This was a crucial step as the quality and reliability of the results depended directly on the quality of the input data. In this work, abnormal or inconsistent readings were processed using horizontal and vertical filtering techniques implemented through Python libraries such as Pandas and NumPy. Missing values were treated using Pandas' linear interpolation method, ensuring smooth and continuous time-series data suitable for accurate and robust modelling.

Table 2 shows the summary of inputs and target variables used in the models. The inputs included the Time of Day (ToD) in HH:MM format, T_o, H_o, T_{set} and the lagged indoor temperature (T_{in_lag}), which represented the lagged observation obtained from averaging the previous 15-minute indoor temperature values. The target variable was the indoor air temperature at the next time step (T_{in_next}).

C. Zone grouping for predictive model development

The selected 27 AHUs were categorized into four groups using a rule-based approach. Table 3 shows the rule-based criterion for zone grouping.

Based on the criteria in Table 3, the four groups considered in this study were defined as follows:

(i) Group 1 (High-exposure zones): AHUs located on top floors, characterized by strong afternoon solar gains (included all 7th floor zones and south-west-oriented zones from 6th to 4th floors).

(ii) Group 2 (Moderate-exposure zones): AHUs on top or mid-floors, experiencing moderate solar gains primarily during morning hours (north–east oriented zones from 6th to 2nd floor).

(iii) Group 3 (High-inertia zones): AHUs serving large-volume library and reading spaces, exhibiting slow thermal response due to high thermal inertia (located on the 3rd floor).

(iv) Group 4 (Low-inertia zones): AHUs serving smaller or near-chiller spaces characterized by fast temperature response dynamics (primarily on the ground and 1st floors).

D. The four representative AHUs described earlier (AHU1, AHU2, AHU3 and AHU4) corresponded to group 1 to 4 respectively, each representing its group's thermal characteristics Data split, ML algorithms and Evaluation metrics

The final dataset was split into training (80% of the data) and testing (20% of the data) sets. The training dataset was used for model learning, while the testing dataset was used to evaluate the generalization capability of the models.

Subsequently, real-time validation was performed using operational data to assess model performance under practical scenarios.

Early stopping based on validation loss monitoring was employed to reduce overfitting during training. Due to the sequential nature of the time-series data and the real-time prediction objective, a train–test split approach was adopted. The training termination criterion was based on the predefined number of training epochs selected through the random search hyperparameter tuning process.

NN techniques were adopted for IAT prediction due to their capability to effectively capture nonlinear relationships and temporal dependencies in time-series data. Accordingly, three NN architectures, namely LSTM, GRU and RNN were implemented to model short-term IAT fluctuations at finer temporal granularities.

To gauge the performance and predictive accuracy of the models, a range of evaluation metrics were employed. These metrics included MAE in °C, Root mean squared error (RMSE) in °C and R^2 in %. The models for real-time predictions were considered with the following set criterion: MAE≤0.1°C, RMSE≤0.2°C and R^2≥70%.

E. Hyperparameter setting

Hyperparameter tuning was performed using a random search strategy implemented through Keras and TensorFlow libraries. The search process explored multiple combinations of sequence length, hidden units, dense units, activation functions, batch size, learning rate, training epochs and optimizers. Table 4 shows the hyperparameter search space considered during tuning, while Table 5 shows the final hyperparameters selected for the LSTM, GRU and RNN models.

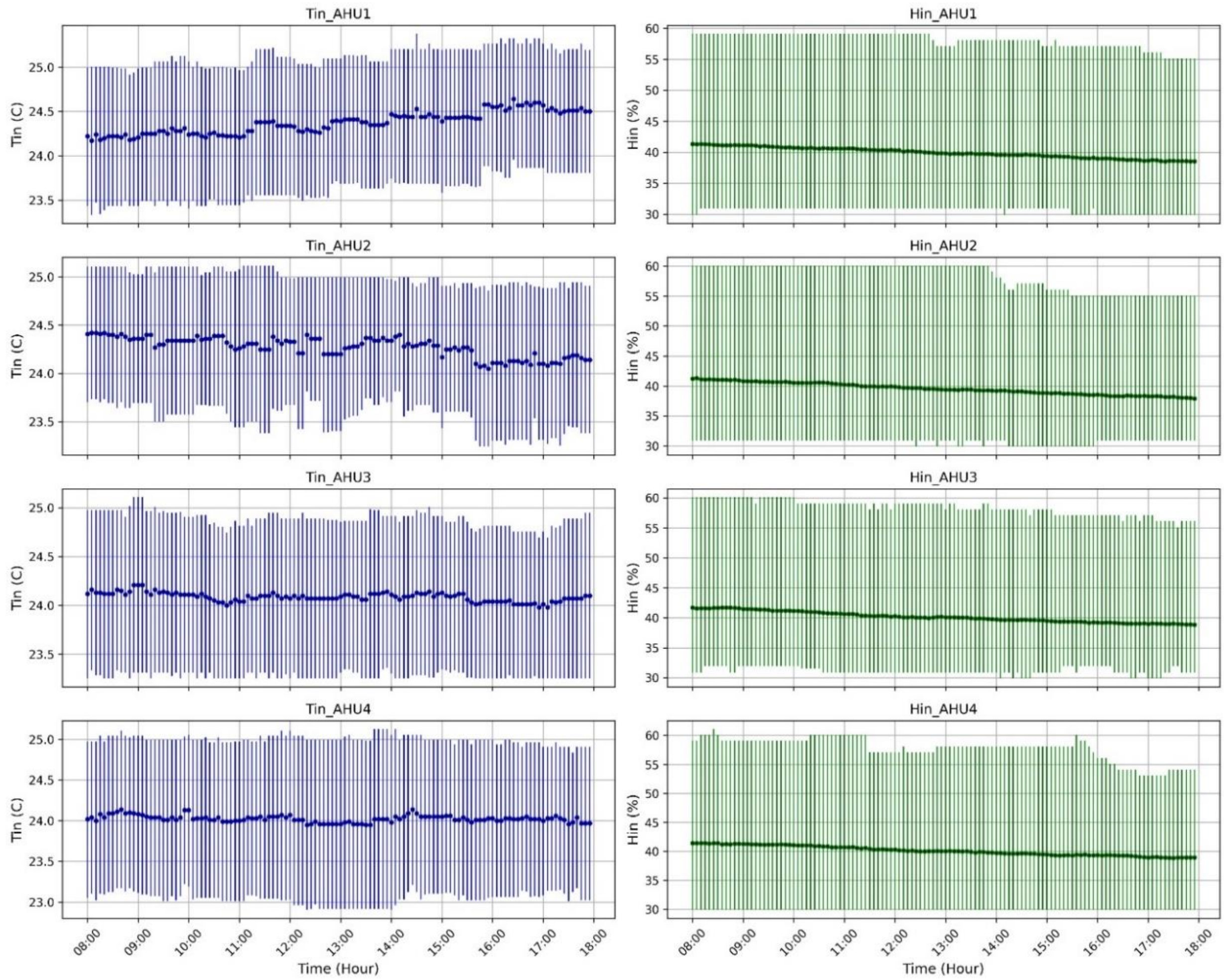

Fig. 3. Mean temperature and relative humidity trends across representative AHU zones.

Table 2

Inputs and Target variables for ML model.

Input data	Target variable
ToD T_o and H_o T_{set} T_{in_lag}	T_{in_next} (°C)

.

Table 3

Rule-based criteria for AHU zone grouping.

Criterion	Group 1	Group 2	Group 3	Group 4
Floor level	Top floors	Top/Mid floors	Mid floors	Lower floors
Orientation	South-west	North-east	Mixed	Mixed
Solar exposure (dominant period)	High(afternoon)	Medium(morning)	Moderate(variable)	Low(negligible)
Zone size	Medium	Medium	Large	Small
Thermal inertia	Medium	Medium	High	Low
Temperature response	Moderate	Moderate	Slow	Fast
No. of AHUs considered	10	10	2	5

Table 4

Hyperparameter search space and tuning strategy for NN models.

Hyperparameter	Search space
Sequence length	(2, 3, 6)
Hidden units	(32, 64, 128)
Dense units	(16, 32, 64)
Activation function	(ReLU, tanh)
Batch size	(16,32)
Learning rate	(0.0001, 0.001)
Epochs	(100, 150)
Optimizer	(Adam, RMSprop)

Table 5

Final hyperparameters selected for NN models.

Hyperparameter	LSTM	GRU	RNN
Number of recurrent layers	1	1	1
Recurrent layer type	LSTM	GRU	SimpleRNN
Sequence length	6	6	6
Hidden units	64	128	128
Dense units	32	32	64
Activation function	ReLu	ReLu	tanh
Batch size	16	16	16
Learning rate	0.001	0.0001	0.001
Epochs	100	150	150
Optimizer	RMSprop	RMSprop	Adam

II. RESULTS AND DISCUSSION

This section consists of two parts. First, the prediction performance of the developed NN models is evaluated using the test dataset. Subsequently, real-time validation is carried out to assess the applicability and robustness of the models under real-world operating conditions.

Table 6

Evaluation metrics for indoor air temperature prediction models on the test dataset.

AHU	Model	MAE (°C)	RMSE (°C)	R^2 (%)	Train time (seconds)
AHU1	LSTM	0.079	0.122	85.74	31.82
	GRU	0.080	0.125	85.56	29.02
	RNN	0.086	0.126	85.46	32.21
AHU2	LSTM	0.078	0.094	95.61	33.70
	GRU	0.082	0.098	90.60	29.26
	RNN	0.088	0.098	90.32	35.67
AHU3	LSTM	0.087	0.116	76.61	50.52
	GRU	0.089	0.124	75.63	26.72
	RNN	0.090	0.130	75.17	51.95
AHU4	LSTM	0.083	0.125	79.22	30.79
	GRU	0.086	0.125	77.65	26.67
	RNN	0.093	0.131	77.56	32.83

Table 7

Evaluation metrics for Indoor air temperature model on real-time dataset.

AHU	Model	MAE (°C)	RMSE (°C)	R^2 (%)	Prediction time (seconds)

AHU1	LSTM	0.068	0.089	85	4.24
	GRU	0.072	0.094	83	4.59
	RNN	0.078	0.101	82	4.36
AHU2	LSTM	0.060	0.082	95	4.34
	GRU	0.065	0.086	93	4.36
	RNN	0.07	0.092	91	4.50
AHU3	LSTM	0.089	0.114	75	4.41
	GRU	0.100	0.130	73	4.35
	RNN	0.105	0.135	71	4.20
AHU4	LSTM	0.070	0.095	79	4.36
	GRU	0.076	0.102	77	4.58
	RNN	0.082	0.110	74	4.29

A. Test dataset performance

The performance of the developed NN models was first evaluated using the test dataset. Table 6 shows the evaluation metrics obtained for the LSTM, GRU and RNN models across the four representative AHUs. The results indicate that all three models achieved satisfactory prediction accuracy, with MAE values below 0.1 °C, RMSE values below 0.15 °C and R^2 values above 75%.

B. Real-time validation performance

The prediction was carried out for 30th April 2024, which consisted of a total of 120 data points.

Data from 30th April were not included in the training or testing phases of the ML model development.

The models performed 5-minute ahead IAT forecasting.

Table 7 shows the prediction performance of three NN models, evaluated for AHU1 to AHU4 using MAE, RMSE and R^2 metrics.

Prediction times were also considered to assess computational efficiency.

Across all zones, the LSTM model consistently delivered the best prediction accuracy, achieving the lowest MAE and RMSE values.

For example, LSTM achieved MAE values of 0.060°C for AHU2 and 0.068°C for AHU1, indicating accurate forecasting with errors well below 0.1°C.

Similarly, R^2 values reached up to 95% for AHU2, showing agreement between predicted and actual temperatures.

Slightly lower prediction accuracy was observed in AHU3 and AHU4, which could be attributed to their distinct thermal characteristics, particularly high thermal inertia and rapid response dynamics, respectively.

The LSTM models produced reliable forecasts with prediction times around 4–5 seconds, which made them suitable for real-time HVAC control applications.

The performance of GRU and RNN models was comparable to that of the LSTM.

Overall, the results showed that LSTM provided the most accurate and reliable short-term IAT predictions across diverse zones, while maintaining computational efficiency suitable for real-time HVAC control.

The superior performance of LSTM could be attributed to its ability to capture long-term temporal dependencies and nonlinear thermal dynamics more effectively than GRU and RNN.

Fig. 4 shows a comprehensive visualization of outdoor weather conditions, zone-level IAT predictions and the building's HVAC power consumption profile during a day that includes a midday DR event.

The top plot showed that T_o increased steadily from morning to afternoon, reaching close to 38°C, while H_o gradually decreased, indicating a hot and dry daytime.

The next four plots compare the predicted IAT (using LSTM) with the actual measured values. In all cases, the predicted and actual temperature curves were closely aligned, showing the model's ability to capture fluctuations in zone-level thermal conditions.

Around midday, each AHU exhibited a noticeable rise in T_{in} due to the DR event, during which building power consumption was reduced.

During this period, the prediction model accurately followed the temperature trajectory, successfully capturing both the increase and the subsequent recovery.

The bottom plot showed the building's HVAC power consumption, where HVAC_DR represented consumption during the DR event and

HVAC_base represented consumption under normal operation without DR.

The HVAC_DR curve dipped below the HVAC_base curve, confirming a reduction in cooling energy and hence reduction in power consumption.

Overall, Fig. 4 indicated the model's ability to provide accurate short-term IAT forecasts, thereby supporting energy-efficient and demand-responsive HVAC operation.

The model also captured the transient thermal response during the DR period which indicated its robustness and effectiveness under dynamic operating conditions.

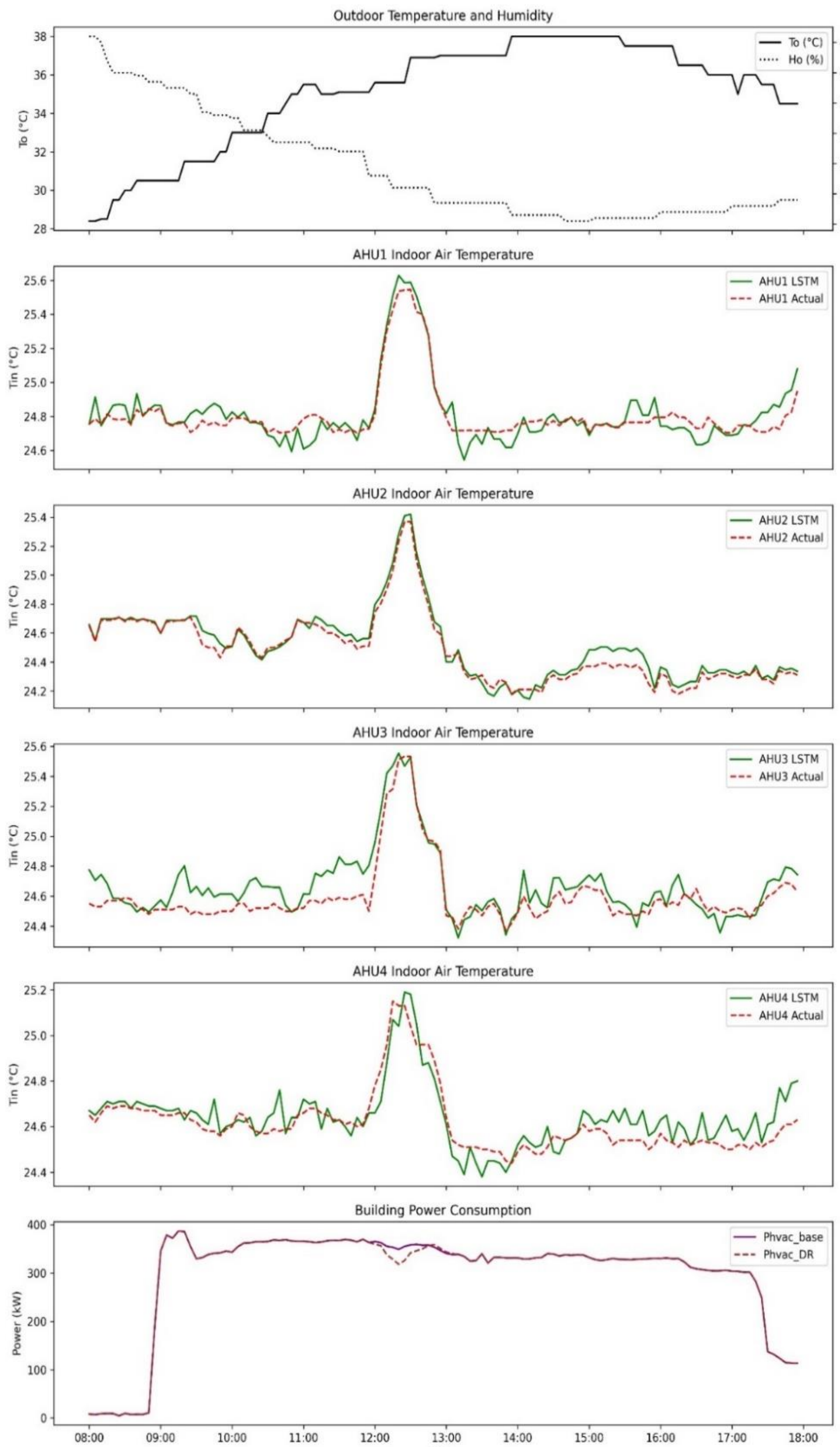

Fig. 4. Outdoor weather conditions, Zone level IAT predictions and Building power response during a Demand Response event.

The developed models demonstrated accurate and computationally efficient short-term IAT prediction suitable for real-time HVAC supervisory control and demand-responsive operation.

The proposed models successfully tracked transient variations while maintaining low prediction error and fast computational performance.

Though the framework was developed using operational data from a single building under summer climatic conditions, the proposed methodology is not restricted to a specific building type or HVAC configuration.

With appropriate training using local operational and indoor thermal datasets, the framework can be adapted to other smart buildings and HVAC systems.

Further validation using multi-season datasets and different climatic regions would strengthen the generalizability of the proposed approach.

CONCLUSION

This work presents a sustainable, data-driven approach for predicting zone-level indoor air temperature to enable intelligent, energy-efficient and responsive HVAC control in smart buildings. By integrating IoT-based data acquisition with neural network models (LSTM, GRU and RNN), the proposed approach effectively captures complex thermal dynamics across heterogeneous zones.

A rule-based zone grouping strategy was introduced to cluster zones with similar thermal behavior, improving model generalization and reducing computational complexity.

Among the evaluated models, LSTM consistently showed superior performance, achieving MAE below 0.1°C, RMSE below 0.15°C and R^2 values up to 95%, while maintaining fast prediction times of approximately 4 to 5 seconds, suitable for real-time applications.

The model performance remained robust under DR conditions, accurately capturing transient thermal variations and supporting adaptive load management.

The results showed the potential of the proposed approach for deployment in real-world smart buildings, contributing to energy-efficient, demand-responsive and climate-resilient infrastructure.

The results were satisfactory indicating the possible implementation of this data-driven model in any similar buildings.

ACKNOWLEDGMENT

Authors are grateful to the Management, B.M.S. Educational Trust, Principal and Vice-Principal, B.M.S. College of Engineering.

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