

LSTM FORECASTING OF UCL CENTRAL HOUSE'S OFFICE TEMPERATURE USING REAL-TIME BMS DATA UNDER FUTURE CLIMATE CONDITIONS

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Abstract: This research tackles the challenge of evaluating and forecasting thermal resilience in ageing non-domestic buildings under climate change, where physics-based models are often impractical. It applies multivariate Long Short-Term Memory (LSTM) neural networks, trained on Building Management System (BMS) data from 2023–2025, to assess UCL Central House. Despite a major retrofit in 2010, recent summer peaks up to 31 °C reveal overheating risks and limitations in current setpoint policies. The proposed multivariate LSTM model, using inputs such as indoor temperature, HVAC operation, occupancy, and weather, achieved high predictive accuracy ($R^2 = 0.88$, MAPE = 1.14%). Projections for 2030 indicate frequent indoor temperature exceedances above 27–30 °C, with heatwaves reaching 34 °C and cooling demand rising by up to 60%. Although adaptive occupant behaviour offers some resilience, dependence on mechanical cooling poses risks to energy use, carbon emissions, and well-being. The study highlights the potential of data-driven methods to support retrofit strategies, operational planning, and climate resilience.

Keywords: Building Management System (BMS), Indoor Thermal Performance Forecasting, Multivariate LSTM, Overheating Risk and occupant well-being, Future Climate

1. Introduction

The performance of non-domestic buildings is increasingly critical for energy use, occupant wellbeing, and climate resilience. Office buildings, particularly in London where 62% of stock is over 30 years old and a quarter predates 1950 (Porterfield, 2023), contribute heavily to HVAC energy demand and affect productivity and health. European heatwaves have highlighted the need for retrofitting as a sustainable strategy (Evans et al., 2023; Dragonetti et al., 2025), yet older buildings often lack sufficient physics data for reliable performance prediction (Verticchio et al., n.d.; Lewry, 2015; Salvia et al., 2020; Berg & Mahdavi, 2024). UCL Central House, built in the 1940s and retrofitted in 2010, demonstrates this gap: although physical design predictions in 2010 and 2017 suggested stable comfort (Jain, 2020), recent BMS data (2023–2025) show summer peaks up to 30 °C. To address this, LSTM neural networks are applied to BMS data, integrating weather, HVAC, and occupancy. By incorporating multivariate inputs, lag features, and temporal encoding, the model forecasts conditions during both HVAC operation and free-running periods, supporting retrofit planning, 2030 worst-case comfort risk assessment, and understanding of occupant and HVAC responses both in current and future condition, highlighting the value of data-driven modelling for resilient management of ageing office stock.

2. Literature Review

Machine learning (ML) better captures real building complexities than physics-based models, which rely on simplifying assumptions (Triadji, Berawi & Sari, 2022). LSTMs excel in indoor temperature forecasting by handling temporal dependencies, seasonality, and noise (Hochreiter & Schmidhuber, 1997; Okut, 2021). Gaps include coarse data, limited BMS integration, heterogeneous dataset challenges, and lack of robust benchmarking.

BMS centrally control HVAC, lighting, and other systems to enhance efficiency and comfort (Digitemie & Ekemezie, 2024). Future systems will integrate ML/AI for energy and occupant optimization, but current use is limited by simplified occupancy assumptions and underutilization of real-time operational data for long-term comfort forecasting.

Indoor temperature is influenced by HVAC, occupancy, design, and thermal mass (Ding et al., 2023). Accurate forecasting supports proactive HVAC control, reducing energy and emissions while maintaining comfort, with potential savings of ~ 20 kWh/m²/year. It also aids heatwave preparedness and sustainability compliance.

Rising temperatures and urban heat will increase overheating risks in London offices (Kolokotroni et al., 2012). Cooling demand could rise up to 55% by 2050 (Morshed & Mourshed, 2022), with passive measures insufficient. Forecasting with climate projections is crucial for resilient and efficient building management. Despite UCL having a BMS, no practical framework exists for integrating building data to predict future temperatures efficiently. Most studies use limited features, select algorithms based on popularity, lack preprocessing details, and focus on short-term horizons (1h–1d), leaving longer-term forecasting gaps.

3. Methodology

3.1 Case Study – Central House

4,500 m² office building in central London, refurbished in 2010 with improved insulation and double glazing. The study focuses on the northwest third-floor open-plan office of Central House, which is prone to summer overheating and solar heat gain. BMS data show that the cooling system is often inactive despite high occupancy and temperatures, making it ideal for analyzing temperature thresholds during free-running conditions under future climate scenarios. The selected space uses VRF multi-split system with heat recovery; mixed-mode operation (heating and cooling) with free-running periods. The data of Hourly BMS records from May 2023 to July 2025 (18,693 hours), including outdoor weather, HVAC status, and occupancy patterns.

3.2 Data & Model Setup

- **Input:** Multivariate (continuous and discrete) features, including outdoor temperature, humidity, HVAC modes, building closures, and historical indoor temperature.
- **Output:** Single variable (indoor temperature)
- **Prediction:** Single-step forecast, enabling the prediction of both HVAC-controlled and free-running periods.

3.3 Preprocessing

Missing values in the dataset were addressed using linear interpolation, ensuring continuity in the time series. Temporal features such as month and hour were extracted and transformed using cyclical encoding to capture their periodic nature. The dataset was then split into 80% training and 20% testing sets. All continuous features were normalized using StandardScaler, while discrete variables were preserved in their original form. To embed temporal dependencies for the LSTM model, lag features ranging from T_1 to T_24 were created, allowing the network to learn patterns across previous time steps.

3.4 LSTM Model

The architecture used LSTM layer (500 units), two dense layers (100 units each), and output layer (1 unit). The model was trained using Mean Absolute Error (MAE) as the loss function and optimized with the Adam optimizer. Training was conducted over 150 epochs with a batch size of 300, incorporating early stopping with a patience of 30 to prevent overfitting. Input data were structured in the 3D shape (samples, timesteps, features), with the previously created lag features enabling single-step forecasting for the LSTM model.

3.5 2030 Forecast

Future weather and occupancy data were preprocessed using the same procedures as the training dataset to ensure consistency. Recursive predictions were performed, where the model's outputs were fed back as inputs for subsequent timesteps, allowing multi-step forecasting. Finally, the predicted indoor temperatures were inverse-transformed to restore them to their original scale, enabling direct comparison with realistic indoor conditions.

4. Results and Analysis

4.1 Outdoor Temperature

The analysis of outdoor temperatures in London from 2023 to 2030 in Figure 1 shows a clear warming trend. While minimum temperatures remain relatively stable, maximum temperatures increase each year, reaching approximately 34.8 °C in 2030. Median temperatures rise gradually, and the overall variability widens, particularly in 2030, indicating more frequent and extreme heat days.

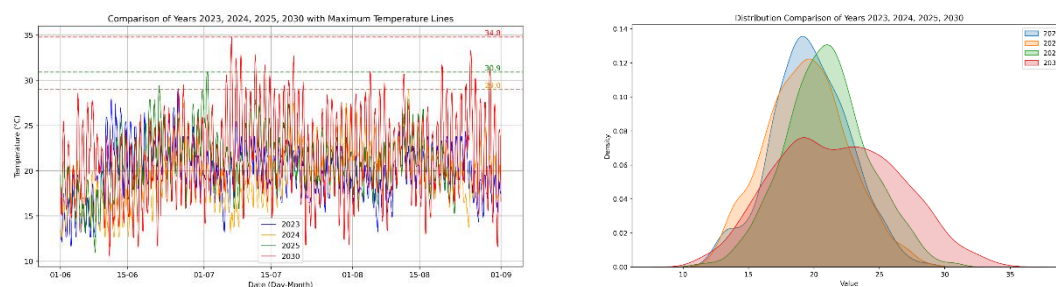


Figure 1. Comparison of 2023, 2024, 2025, and 2030 Outdoor Temperature

4.2 Office Space Temperature

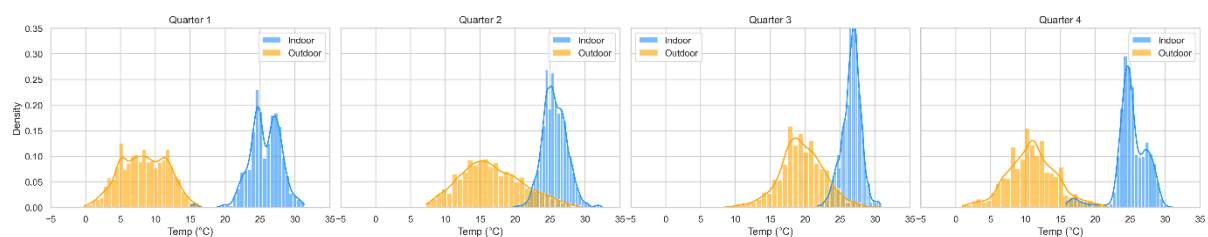


Figure 2. Histogram Analysis of Outdoor and Indoor Temperature by Quarter

Despite significant fluctuations in outdoor temperature, indoor temperatures in the Central House third-floor open-plan office remain relatively stable between 20–28 °C throughout the year in Figure 2. Heating systems maintain higher winter temperatures, while free-running conditions in summer contribute to consistent indoor thermal conditions.

4.3 Relationship Between Outdoor Temperature, User Behaviour, and Space Temperature

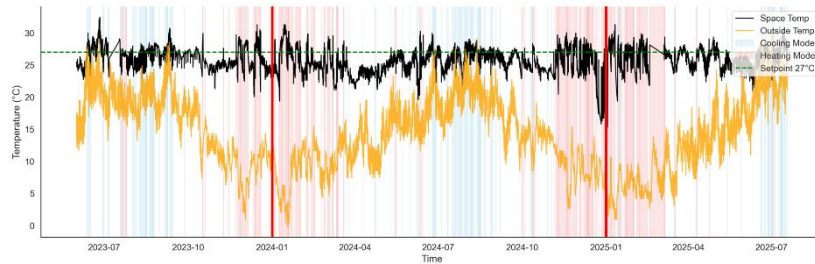


Figure 3. Indoor and Outdoor Temperature Trends with Cooling and Heating Operation (2023–2025)

Cooling systems are typically activated when indoor temperatures reach 26–27 °C as shown in figure 3 and table 1, reflecting occupant comfort thresholds. Analysis of BMS data from 2023–2025 indicates an increasing reliance on cooling systems, particularly during peak summer months. Indoor temperatures around 27 °C can arise from heating in winter, free-running conditions in summer, or cooling operation, showing the interplay between occupant behaviour, HVAC use, and outdoor conditions.

Table1. Analysis of user behaviour relationship with cooling system and space temperature setpoint (2023–2025)

Total Cooling On Day (unit : day)			User Behavior: Minimum Temperatures Triggering AC Use			
Year	01/06-31/08	01/06 – 17/07	Time		Outside Temp (°C)	Space Temp (°C)
2023	42	9	08/03/2023	08.00	14.92	26.82
2024	52	13	06/07/2024	08.00	14.52	26.38
2025	No data yet	21	04/07/2025	08.00	19.15	27.70

4.4 Outdoor Heat Days and Heatwaves

McCarthy et al. (2019) define a “heatwave” as three or more consecutive days with daily maximum temperatures at or above 28 °C. Accordingly, in this study, any day exceeding 28 °C that does not occur for three consecutive days is classified as a “heat day.” Records from 2023–2025 show that 2023 and 2024 has 1 heat day in the case study area, 2025 has 3 heat days, while projections for 2030 indicate a sharp increase, with about 40 heat days and 8 heatwaves.

4.5 Multivariate LSTM Model and Performance Comparison

The multivariate LSTM model achieves an R^2 of 0.88, RMSE of 0.25, MAE of 0.29, and MAPE of 1.14%, demonstrating its ability to model complex temporal and nonlinear relationships in indoor temperature data. In comparison, Linear Regression achieves $R^2 = 0.87$, RMSE = 0.245, MAE = 0.15, and MAPE = 35.45%, while Random Forest records $R^2 = 0.553$, RMSE = 0.961, MAE = 0.809, and MAPE = 3.076%.

Testing with different input scenarios (adding and eliminating Mode_Cooling features) highlights the importance of including operational variables. Including them improves

accuracy and allows the model to simulate realistic indoor temperature patterns under varying HVAC operation and free-running condition, enabling prediction flexibility.

4.6 2030 Forecasted Indoor Temperatures

The 2030 projection in Figure 4 and 5 under free-running conditions indicates that indoor temperatures will closely follow outdoor trends, often exceeding 28 °C during peak summer periods. The distribution of indoor temperatures shifts towards 30–35 °C compared to 2023–2025, implying increased thermal stress and cooling demand.

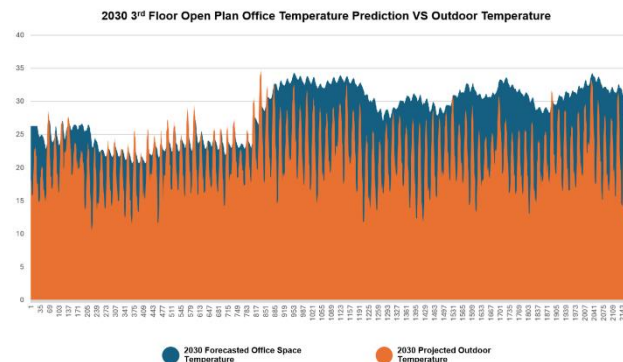


Figure 4. 2030 3rd floor Open Plan Office Temperature Prediction vs Outdoor Temperature

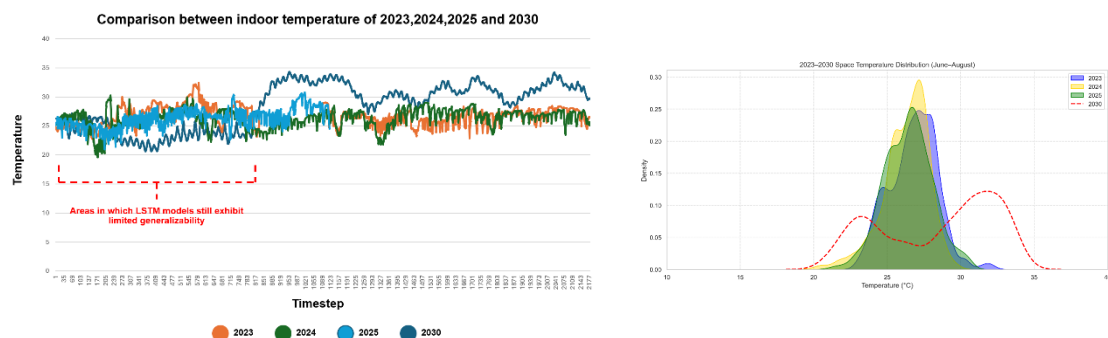


Figure 5. Comparison of Office Indoor Temperatures in 2023, 2024, 2025, and Projected 2030

5. Discussion

Using BMS data from UCL Central House, the research reveals that office indoor conditions in 2030 can potentially range 23–29 °C, with exceedances frequently above 30–34 °C during summer free-running periods. Cooling system in this open plan office is usually activated at 26–27 °C. Exceedance analysis showed that weekday during June–August temperatures surpassed AC setpoint of 26.3 °C up to 75 times, 27 °C up to 67 times, and exceeded 30 °C on 35 occasions. Cooling demand corresponded accordingly: extrapolating to 2030, continuous high cooling demand (36–60%, or 1,600–1,900 kWh above the normal baseline of ~1,200 kWh) in June–August is anticipated if no retrofit measures are implemented. Findings underscore that rising outdoor temperatures will increase reliance on mechanical cooling, elevate energy demand, and threaten occupant comfort, emphasizing the need for passive retrofit measures such as shading, thermal mass enhancement, and ventilation to improve resilience.

Key limitations include incomplete BMS data (missing occupancy, solar irradiance, wind, and sub-metered energy), a short two-year dataset, and LSTM’s opacity, which can underestimate extreme temperatures. Future work should improve BMS coverage (include

sub-metering and occupancy sensors), extend temporal data, integrate energy use, and explore hybrid or explainable AI models. Embedding predictive models into smart building systems could enable proactive, climate-resilient management.

6. Conclusion

This study applied multivariate LSTM networks on BMS data to forecast UCL Central House's 2030 indoor temperatures under future climate scenarios. The multivariate LSTM model effectively captures dynamic patterns in indoor temperature, closely matching observed values in both training and testing datasets, while accounting for the influence of free-running periods and mechanical control. The model achieved high accuracy ($R^2 = 0.88$, MAPE = 1.14%). Forecasts for June–August 2030 indicate temperatures mainly 23–29 °C, with peaks above 30–34 °C, up to 40 heat days and 8 heatwaves. Key benefits include predicting AC usage, assessing occupant impacts if cooling fails, and modelling alternative operational modes. Findings highlight BMS data's value for scenario testing and the need for passive retrofits, while hybrid approaches could enhance robustness and interpretability, supporting thermal resilience, occupant wellbeing, and net-zero goals.

7. References

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