Sensors and Materials, Vol. 38, No. 7 (2026) 3953–3966
MYU Tokyo

S & M 4543

Adaptive Control of Occupant Comfort in Dynamic Architecture Using Sensor Data

Shihui Wei[1] and Yanping Chen[2*]

[1]Fuyang Institute of Technology, Fuyang 236031, China
[2]School of Artificial Intelligence and Big Data, Hefei University, Hefei 230601, China

(Received August 21, 2025; accepted July 15, 2026)

Keywords: adaptive feedback control, dynamic architecture, machine learning, user comfort, smart buildings, environmental control systems

An adaptive control system with a dynamic architecture was developed and evaluated. The system integrates heterogeneous sensor networks with machine learning models to enhance occupant comfort and energy efficiency. The dynamic architecture combines edge-cloud data processing with predictive algorithms, enabling real-time monitoring of environmental and behavioral parameters. Performance evaluation results showed that the occupant comfort index was consistently maintained within a narrow band between indices 26 and 32, with a sharp peak at 29. Correlation analysis results showed a positive relationship between illuminance and comfort [Pearson correlation coefficient (r) = +0.73], and moderate and weak negative correlations with relative humidity ($r = -0.57$) and ambient temperature ($r = -0.36$). Despite high-fidelity data acquisition, predictive modeling showed prediction flattening, with random forest regression outputs compressed between 26.5 and 27.5, failing to capture dynamic fluctuations in occupant perception. This limitation underscores the need for advanced sensor technologies capable of integrating physiological signals, such as heart rate variability and localized thermal dissipation, to overcome environmental inertia. The results of this study underscore the importance of continuous model training, multimodal sensor fusion, and feedback mechanisms in advancing adaptive architecture toward personalized, occupant-centric management.

1. Introduction

Dynamic architecture offers structural flexibility and adaptation to changing environmental conditions.(1) To ensure automated adaptability, the structure of the dynamic architecture is built to detect, sense, and analyze data to adjust microclimates on the basis of occupancy patterns, localized weather variations, temporal metrics, and user profiles.(2) Environmental parameters in the conventional architecture are controlled on the basis of preset thresholds that are manually configured. In contrast, the dynamic architecture utilizes continuous data streams captured for automated decision-making.(2) The dynamic architecture necessitates the integration of advanced

*Corresponding author: e-mail: chenypo@hfuu.edu.cn
https://doi.org/10.18494/SAM5899

ISSN 0914-4935

sensors, solid-state actuators, and edge-cloud computing to handle rapid data transmission and cross-module synchronization.

The conventional architecture employs predefined control loops, which introduce deployment overhead, requiring reliable hardware infrastructures that parse massive volumes of environmental data safely and sustainably,[3] whereas the dynamic architecture relies upon the reliability and stability of environmental and physiological sensors. To address such problems, advanced metal-oxide gas-sensing materials, micro-electro-mechanical systems, and optical sensors are used to reduce latency and power constraints in continuous data acquisition.[4]. For instance, nondispersive infrared sensors for CO_2 monitoring, capacitive polymer thin films for relative humidity tracking, and photodiode-based silicon lux meters enable precise monitoring of indoor microclimates. Despite such advancements, it is a significant challenge to integrate diverse sensors for cohesive and low-latency data fusion owing to temporal misalignment, wireless packet decreases, and different transduction principles across different sensor nodes of the occupants.[5]

Thermal, visual, and acoustic comforts are important metrics for assessing building management automation.[6] Human comfort is highly subjective and is determined by complex interdependences between ambient air temperature, relative humidity, and lighting intensity. However, previous building management systems fail to accommodate individual variances.[7] Therefore, dynamic architecture is used for automated building management as it employs continuous learning loops by using accurate physical sensor data and occupant feedback modules.[8,9] In the architecture, the physical sensor network dictates overall building management system efficiency.[10,11] However, there are limitations to overcome before adopting the sensor network into the dynamic architecture.

Sensor degradation, calibration drift, and environmental fouling corrupt input signals, undermining predictive models and their automated logic in a dynamic architecture.[1] In addition to them, effective alignment between physical sensor data and human perception is essential in machine-learning algorithms.[2] Although sensor networks detect microclimate variations, converting these signals into robust metrics also poses a bottleneck.[3] A limitation in prediction flattening also exists during early deployment, preventing models from capturing environmental fluctuations and producing static, unresponsive baselines.[12] Such limitations are caused by incomplete data fusion and weak feature engineering rather than algorithmic errors.[6]

To address the limitations, sensors developed with advanced materials must be employed. Wearable polymer-based photoplethysmography sensors enable heart rate variability tracking, and pyroelectric infrared (PIR) arrays support noninvasive metabolic and localized thermal monitoring.[8] Sensors with such advanced materials present reduced tracking latency and enhanced model responsiveness. In this study, we analyzed the performance of an edge–cloud sensor network designed for the dynamic architecture for efficient building management.[9] On the basis of the result, we propose hardware, sensor configurations, and preprocessing mechanisms that prevent sensor data drift and missing values from occurring in the extended operation of the architecture.[10] The results of the performance evaluation of the sensor network are used to identify an optimization strategy of sensor fusion. The strategy can be applied to next-generation building management.

2. Methods

2.1. Dynamic architecture

The dynamic architecture for building management employs a spatially distributed, heterogeneous sensor network to collect and monitor environmental and occupant data in real time. Instead of relying on aggregate or simulated data, sensor nodes are implemented to capture localized microclimatic variations (Fig. 1).

In this study, thermal and relative humidity conditions were measured with the SHT31-DIS digital sensor (Sensirion, Switzerland), which integrates a capacitive polymer thin-film element for relative humidity and a band-gap temperature sensor on a CMOS chip. Indoor air quality was assessed using the Senseair S8 module (Senseair, Sweden), based on nondispersive IR (NDIR) technology with optical filtering to measure CO_2 concentrations up to 2000 ppm. Ambient light levels were monitored using the TSL25911FN sensor (AMS, Austria), which combines broadband and IR photodiodes to approximate human eye response. Acoustic data was collected through the ICS-43434 MEMS microphone (InvenSense/TDK, USA), featuring a silicon membrane transducer and a 24-bit inter-integrated sound (I^2S) audio output. Occupancy mapping was conducted using AMN31111 PIR sensors (Panasonic, Japan), which detect changes in infrared radiation emitted by moving bodies.

These sensors were connected to an edge-computing microcontroller on the localized bus interfaces that comprise an inter-integrated circuit (I^2C), universal asynchronous receiver-

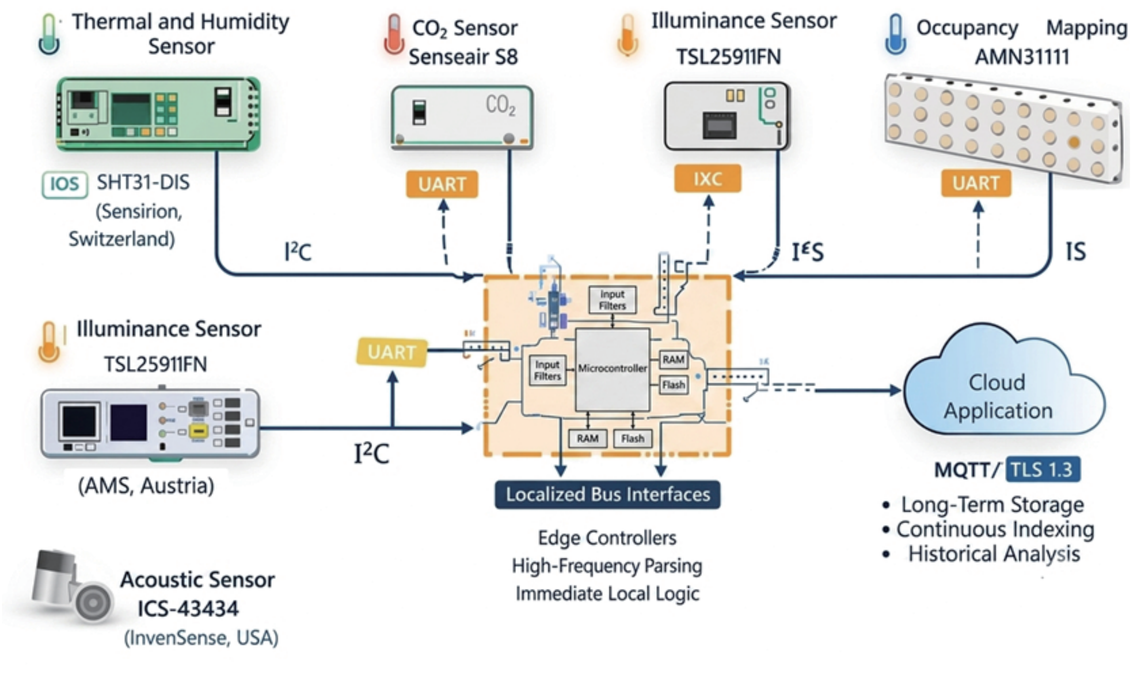

Fig. 1. (Color online) Dynamic architecture sensor network for environmental management of building (created using AI).

transmitter (UART), and inter-integrated sound (I^2S). The edge-computing microcontroller was employed for high-frequency parsing and immediate control logic to minimize latency in safety-critical tasks such as lighting adjustments. Long-term storage, feature indexing, and historical analysis were carried out in the cloud application layer through message queuing telemetry transport (MQTT) secured with transport layer security (TLS) 1.3.

2.2 Data collection and preprocessing

In this study, data were collected in a chronological sequence and sorted in accordance with their time of acquisition, with each successive observation assigned an incremental sample index. This indexing was employed to preserve the temporal dependences of the dataset, ensuring that predictive models were evaluated against occupant comfort values in the same order.

The dynamic architecture was tested in a multistory office building in Hefei, Anhui Province, China. The building was designed to meet modern green building standards.[13] For the experiment, one open-plan floor was divided into two identical sections called Zone A and Zone B. Each zone covered 120 m^2 with a ceiling height of 2.8 m. Both zones had the same window-to-wall ratio, faced west, and started with the same occupancy density (about 10 workstations each). This setup helped control outside heat effects and differences in human activity. Zone A followed standard office protocols, while Zone B was equipped with a dynamic edge-cloud sensor network.

Continuous monitoring by sensors often encounters deployment anomalies such as wireless packet failures, sensor aging, and baseline thermal drift. Therefore, data preprocessing is required to preserve data integrity before feature extraction. Sensor drift and missing values are addressed by using a multistage cleaning strategy. Transient network disconnections are resolved using localized backward filling and linear interpolation across time matrices. For structural gaps caused by sensor power cycles, missing values are reconstructed using hardware-informed imputation, cross-referencing correlated neighbor node data.[14]

Because sensor data have different units, including ppm for CO_2, lux for light intensity, and celsius (°C) for temperature, data collected were normalized using the minimum–maximum normalization method, converting all data to a uniform range of [0,1]. Long-term exposure to atmospheric contaminants degrades the oxide layers of chemiresistive arrays. To maintain performance, drift compensation was conducted to calibrate sensor baselines.[15]

2.3 Model and validation

The selection of an appropriate machine learning algorithm is vital for a dynamic architecture. Regression methods, including linear and polynomial regression, are frequently employed to optimize temperature, relative humidity, and light intensity on the basis of historical and real-time data. These methods are used to identify correlations between environmental parameters and user comfort metrics and determine optimal indoor conditions. Advanced techniques, such as support vector regression and random forest regression, are utilized to capture nonlinear relationships and multivariate interactions. Classification algorithms are used to distinguish occupant preferences among various environmental conditions to formulate actionable control strategies. Decision trees and random forests are advantageous owing to their interpretability when managing numerous input variables. Deep learning architectures, such as neural networks, are integrated to capture complex nonlinear patterns in comfort metrics. Clustering algorithms, such as k-means and hierarchical clustering, provide additional utility by grouping occupant preferences, thereby supporting individualized and adaptive control strategies. These algorithms are used in a dynamic architecture to make targeted responses to diverse occupant needs.

To unify multimodal sensor streams (CO_2, relative humidity, temperature, and illuminance) into a single metric, a machine learning model was developed. The model integrates an unsupervised clustering layer followed by a supervised regression model. For feature engineering and initial segmentation, a k-means clustering algorithm was used to group historical environmental vectors into spatiotemporal profiles. This segmentation enabled automatic categorization of distinct indoor states, such as peak occupancy versus nighttime vacancy, solely on the basis of sensor inputs. In each segment, a random forest regression model was used for predictive mapping. The random forest model comprised 100 decision trees with a maximum depth of 12, balancing nonlinear mapping capabilities with overfitting prevention. Input vectors included normalized sensor data from the SHT31-DIS, Senseair S8, and TSL25911FN devices, combined with explicit user comfort labels. The target output is a continuous occupant satisfaction score. To mitigate data drift and ensure long-term stability, an incremental online gradient descent algorithm was used with the random forest model.[16] Terminal weights were continuously adjusted in response to new sensor streams to reduce computational overhead by eliminating the need for full retraining.

Standard *k*-fold cross-validation introduces temporal leakage of data, which compromises prediction accuracy. To preserve chronological dependences, a rolling forward-chaining validation method was implemented.

- Iteration 1: Train on the first 60% of the dataset, validate on the subsequent 20%
- Iteration 2: Expand training to 80%, validate on the next 20%
- Iteration 3: Train on the full dataset, validate on the final 20% (test layer)

This approach ensures that models are consistently validated on future data relative to the training window. Model performance was assessed using the mean squared error (*MSE*), root mean squared error (*RMSE*), and Pearson correlation coefficient (r). To evaluate the effectiveness of the sensor-driven dynamic architecture, a localized testing method was conducted in two similar zones.

- In Zone A (baseline), rule-based environmental control protocols were used under a typical commercial architecture. Heating, ventilation, and air conditioning (HVAC) systems and automated blinds were controlled on the basis of fixed thresholds. Indoor temperature was maintained at 22 °C during daytime hours, and lighting was controlled during the operation hours of 08:00–18:00, without real-time adjustments.

- In Zone B, a sensor-based control network with a dynamic architecture was implemented. Microclimate variables were continuously updated through real-time predictions from the multimodal sensor loop. Fan speeds, air changes per hour, and lighting were adaptively adjusted on the basis of sensor data of illuminance and CO_2 levels, and occupant comfort metrics.

2.4 Comfort index

The comfort index refers to a unified numerical metric designed to represent occupant comfort by integrating heterogeneous sensor inputs. Raw data from temperature, relative humidity, CO_2 concentration, and illuminance sensors were normalized to eliminate scale disparities. These normalized values were aggregated through a weighted mapping procedure that accounts for established correlations between environmental parameters and subjective comfort ratings. The resulting composite score is an index value, which provides a standardized scale for evaluating comfort across diverse conditions. The use of an index is advantageous because it enables the consolidation of multimodal sensor data into a single interpretable measure. The index is used for statistical tracking, density profiling, and comparative analysis across operational windows. By expressing comfort in index form, reliance on raw sensor units, which are not directly comparable, can be avoided, and instead, a coherent framework for assessing and maintaining occupant satisfaction is provided.(17)

Each normalized data point is assigned a weight reflecting its relative importance to occupant comfort. For instance, temperature and CO_2 concentration are weighted more than illuminance, on the basis of empirical studies or user feedback. The weights are denoted as w_T, w_H, w_{CO_2}, and w_L for temperature, relative humidity, CO_2, and illuminance. The comfort index (*CI*) is computed as a weighted sum of the normalized variables.

$$CI = w_T \cdot T' + w_H \cdot H' + w_{\mathrm{CO}_2} \cdot \mathrm{CO}'_2 + w_L \cdot L' \tag{1}$$

Here, *CI* is the comfort index, and $T', H', \mathrm{CO}'_2, L'$ are the normalized sensor values. *CI* was rescaled to a convenient integer range. In this study, the comfort index was scaled to range between 1 and 40. This range represents the band of conditions most frequently associated with occupant satisfaction. Examples of the data collected and comfort index calculated in this study are presented in Table 1.

3. Results

3.1 Performance of sensor network

The performance of the deployed sensor network and its edge–cloud data processing framework was evaluated under continuous operational conditions. During this evaluation, raw

Table 1
Real-time sensor data captured using SHT31-DIS and TSL25911FN sensors.

Timestamp (hh:mm:ss)	Temperature (°C)	Relative humidity (%)	CO_2 concentration (ppm)	Illuminance (Lux)	Comfort index (Actual)
10:00:00	21.4	54.2	520	310	25.6
10:15:00	21.6	53.8	490	345	27.3
10:30:00	22.1	55.1	560	290	25.4
10:45:00	22.5	52.3	460	410	29.7
11:00:00	23	58.7	780	180	20.5
11:15:00	22.8	57.4	690	220	22.5
11:30:00	22.2	51	480	390	28.7
11:45:00	21.9	49.5	420	450	31.4
12:00:00	22.4	50.2	440	420	29.3
12:15:00	23.1	56.8	850	150	18.3
12:30:00	22.7	51.1	470	405	29.1

sensor data were systematically converted into spatiotemporal profiles to facilitate structured analysis. The hardware layer comprised the SHT31-DIS sensor, which measured temperature and relative humidity, and the TSL25911FN sensor, which measured illuminance. Data from these sensors were mapped to empirical system distributions. The SHT31-DIS sensor data corresponded to a comfort index between 26 and 32, and the TSL25911FN revealed the highest comfort index of 29.

The occupant comfort index showed that indoor microclimate parameters were consistently maintained within a structured band. The empirical distribution analysis showed that the absolute comfort tracking range was concentrated between indices 26 and 32 (Fig. 2). Furthermore, density profiling revealed a sharp and narrow peak near index 29. This result indicates that the automated control method stabilized ambient conditions, maintaining them within a steady-state range and ensuring that occupant comfort remained localized around optimal values.

To determine which variables affected the comfort index, a Pearson correlation matrix was created (Table 2). A strong positive correlation (r = 0.73) was observed between occupant satisfaction and the illuminance data. Such a strong relationship shows the importance of real-time lighting adjustments. Conversely, relative humidity exhibited a negative correlation (r = −0.57). Ambient temperature showed a lower negative correlation (r = −0.36) under the control using the dynamic architecture. The results show that the architecture prioritizes adaptive adjustments and relative humidity over standard temperature baseline changes when stabilizing user comfort index levels.

Despite maintaining high-fidelity data, the evaluation of the regression model showed a limitation in predictive accuracy. The comfort index over time tracking matrix (Fig. 3) shows a performance gap when comparing actual occupant comfort scores (blue line) against the random forest regression predictions (orange line) across a chronological 19-sample sequence. This sequence represents a continuous 4.75 h dynamic monitoring window captured at a uniform 15

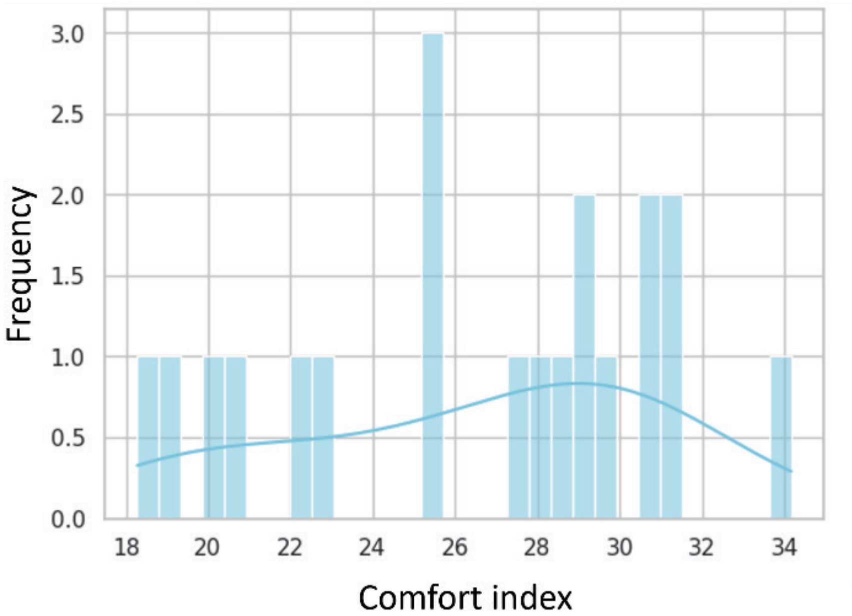

Fig. 2. (Color online) Frequency of comfort index.

Table 2
Correlation analysis between sensor components and occupant comfort metrics, showing the strength and direction of associations.

Sensor component	Physical variable	Pearson correlation (r)
TSL25911FN	Illuminance (lux)	+0.73
SHT31-DIS	Relative humidity (%)	−0.57
SHT31-DIS	Ambient temperature (°C)	−0.36

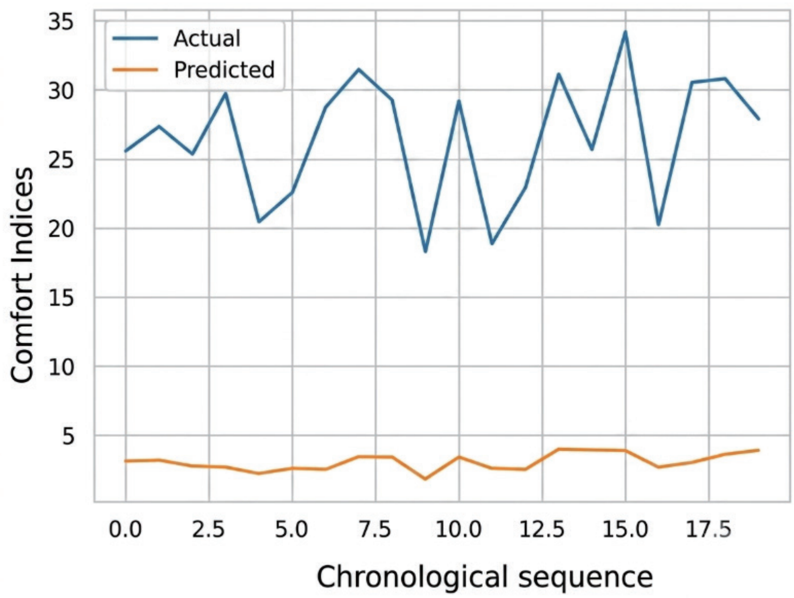

Fig. 3. (Color online) Actual and predicted occupant comfort indices across a 19-sample chronological sequence.

min sampling interval (19 samples), reflecting environmental and behavioral transitions during peak operational hours. Comfort indices fluctuated between 26 and 32 in response to immediate spatial changes, but the predictions of the random forest model showed a narrow band of the comfort index between 26.5 and 27.5. Such an inability to capture rapid fluctuations shows the phenomenon of prediction flattening.

The inability does not stem from deficiencies in the machine learning algorithm but rather from a bottleneck in sensor-to-feature engineering. Because variables such as temperature and humidity change slowly owing to thermal mass and building inertia, environmental sensors cannot capture sudden shifts in human perception or immediate metabolic responses. To overcome prediction flattening, the sensor array must be expanded to incorporate physiological and material-level sensing modalities. Examples include wearable polymer-based photoplethysmography bands for heart rate variability monitoring and noninvasive PIR matrix sensors for localized thermal dissipation tracking.[18] These modalities enable the architecture to detect rapid physiological changes and integrate them into predictive comfort modeling. Challenges of sensor network deployment in two large-scale intelligent building automation projects were compared in this study.

- Microsoft Building 125 (Redmond, USA): This facility integrates more than 600 environmental and occupancy sensors to monitor real-time thermal profiles. Mobile application interfaces provide direct occupant feedback, enabling facility engineers to balance predictive control loops with explicit human input. This approach parallels the chronological split strategies employed in our Zone B configuration, demonstrating the value of combining predictive modeling with active feedback mechanisms.[19]
- The Edge Building (Amsterdam, Netherlands): With over 28000 IoT sensor nodes, this building implements individualized workspace profiling. Occupant smartphone locations are continuously mapped against ambient illuminance and air change vectors, enabling dynamic adjustment of microclimate conditions. Reported satisfaction rates reached 89% for thermal comfort and 92% for lighting quality, underscoring the effectiveness of large-scale adaptive control systems in achieving both comfort and sustainability.[20]

The Edge Building shows high occupant satisfaction (89% thermal and 92% lighting), since they use a rigid, centralized enterprise building management system. These systems demand proprietary communication networks, costly industrial PLCs, and dedicated local servers, introducing single-point failure risks and significant processing overhead. In contrast, we adopted a decentralized hybrid edge–cloud topology. High-frequency parsing, sliding-window filtering, and immediate environmental adjustments are executed locally on edge microcontrollers, eliminating network latency bottlenecks and ensuring operational continuity even during cloud disconnections. By decoupling localized edge control from macrolevel cloud analytics, the architecture remains inherently scale-agnostic. In large commercial deployments, multiple edge nodes stream data to a centralized cloud application layer through MQTT protocols, enabling coordinated multizone management. Equally important, the modular design supports small-scale residential applications: a single edge microcontroller can serve as a standalone automation hub, interfacing directly with household appliances without the need for enterprise-grade backbones or costly software licenses.

A constraint to widespread adoption of adaptive building systems is the installation and hardware cost. Centralized commercial solutions, such as those implemented at the Edge Building, often require multimillion-dollar investments because of proprietary sensor licensing, industrial-grade wiring, and extensive professional calibration. By contrast, our decentralized approach reduces reliance on proprietary infrastructure, lowering both capital expenditure and long-term maintenance costs.

These case studies indicate that balancing heterogeneous sensor inputs with continuous drift compensation can mitigate traditional trade-offs between energy efficiency and occupant comfort. However, achieving this balance requires highly responsive, multimodal hardware layers capable of simultaneously tracking environmental conditions and human physiological metrics. The results of this study reinforce the necessity of integrating advanced sensing modalities and adaptive feedback mechanisms to enhance predictive accuracy and ensure occupant-centric control in dynamic architecture.

4. Discussion

4.1 Feedback mechanisms and control strategies

The evaluation results present the strengths and limitations of the dynamic architecture for adaptive building management. Although the dynamic architecture effectively maintained occupant comfort, the predictive model exhibited prediction flattening, failing to capture rapid fluctuations in subjective comfort. This underscores the necessity of integrating effective feedback mechanisms to supplement environmental sensing.

Direct feedback channels, such as mobile applications and interactive control panels, provide occupants with simple and immediate means of reporting comfort indices and preferences. These tools must be designed to minimize user burden and collect granular data to refine predictive models. Indirect feedback mechanisms, including behavioral observation and physiological monitoring, further enhance system responsiveness. Occupancy patterns, device interactions, and physiological signals such as heart rate variability or skin temperature can provide continuous streams of implicit feedback, complementing explicit user input. To reduce the tracking latency observed in early deployment, the deployment of wearable polymer-based photoplethysmography bands or localized pyroelectric infrared arrays is a vital pathway for capturing noninvasive metabolic and thermal metrics.[18]

Control strategies must be created for multiple objectives: occupant comfort, energy efficiency, and system stability. Predictive control, supported by machine learning models, enables proactive adjustments rather than reactive responses. Multi-objective optimization frameworks are essential to balance comfort requirements against operational costs.[21]

Algorithms for the personalization of microclimates must be developed to provide individualized comfort.(22) At the same time, override options must become available to ensure user agency when automated control does not align with immediate preferences.

4.2 Complexity of maintaining comfort in dynamic systems

It is inherently complex to maintain consistent comfort in a dynamic architectural environment because of the interdependencies among environmental systems. HVAC, lighting, shading, and air quality modules must operate synergistically, as changes in one system often cascade into others. For example, lighting adjustments influence thermal loads, while ventilation changes affect air quality distribution. Advanced predictive algorithms and high-fidelity sensor configurations are required to anticipate these interactions and maintain equilibrium across subsystems.(23) Occupancy patterns also add complexity, as they vary across time of day, week, and season. High-density occupancy requires different control strategies compared with low-density periods, and systems must remain flexible to accommodate transitions.(24) Predictive models must account for rare events, such as extreme weather or atypical occupancy, which may not be adequately represented in historical training data.

Multi-objective optimization approaches are necessary to reconcile conflicting goals and to ensure comfort while minimizing energy consumption. Equipment constraints, maintenance requirements, and safety standards restrict control possibilities. Fault detection and diagnostic tools are critical to prevent sensor degradation or hardware equipment failures from undermining comfort indices.(25) Integration of external technologies introduces additional complexity, requiring robust communication protocols and error-handling mechanisms to ensure seamless operation.

4.3 Integration with existing infrastructure

Deploying a dynamic architecture in a building management system presents technical and logistical challenges. Existing automation systems rely on communication protocols that are incompatible with modern IoT sensors and machine learning frameworks. Retrofitting large-scale sensor networks requires careful scheduling to minimize disruption and ensure adequate spatial coverage and reliability.(26) Structural, electrical, and aesthetic constraints further complicate sensor placement and system design.

Interoperability issues exist when integrating systems from multiple vendors, each with distinct data formats and control philosophies. Effective integration demands translation layers, standardized data formats, and gateway protocols to harmonize disparate systems without compromising performance.(26) In older buildings, limited connectivity and a lack of adaptive control capabilities exacerbate these challenges.

The results of this study show that the designed control system is effective in maintaining occupant comfort, particularly through adaptive adjustments to lighting and humidity. However, the predictive model requires improvement to capture dynamic fluctuations in comfort perception. Enhancing predictive accuracy will necessitate richer datasets, advanced algorithms, and integration of physiological monitoring. Robust feedback mechanisms, multi-objective optimization strategies, and seamless integration with existing infrastructures are essential for advancing adaptive control systems in dynamic architecture.

5. Conclusions

The adaptive control system with a dynamic architecture showed the capacity to maintain occupant comfort within a stable range (indices 26–32), with peak satisfaction localized near 29. Quantitative analysis revealed that illuminance exerted the strongest influence on comfort (r = +0.73), and humidity (r = −0.57) and temperature (r = −0.36) contributed negatively. These results showed the effectiveness of sensor-driven adaptive control in stabilizing microclimate conditions. However, the predictive model exhibited limitations, failing to capture rapid fluctuations in subjective comfort owing to a reliance on slowly varying environmental parameters. The results of this study underscore the necessity of integrating physiological and behavioral sensing modalities, such as wearable photoplethysmography and pyroelectric infrared arrays, into adaptive systems. Such an advancement will enable real-time detection of metabolic and perceptual changes to enhance predictive accuracy and responsiveness.

The role of data fusion and multi-objective optimization in balancing comfort, energy efficiency, and system stability is vital. Case studies, including Microsoft Building 125 and the Edge Building, show the feasibility of large-scale adaptive systems. Personalization of microclimates can be realized through granular occupant segmentation, robust communication protocols for integration with legacy infrastructures, and continuously learning algorithms by adopting a dynamic architecture into intelligent, flexible, and sustainable environments.

Acknowledgments

This study was supported by (1) the “Digitalization-Driven BIM-AI Integration: Innovative Research on Green Building Safety Assessment and Concrete Performance Prediction (Anhui Provincial Department of Education Natural Science Key Project, No. 2025AHGXZK30273)”, (2) the “Design and Development of Energy Management System (EMS) for Industrial and Commercial Energy Storage (Fuyang Institute of Technology Horizontal Research Project, No. 2025FZYHXKYPT301)”, and (3) the “Research on High-performance Computing Models and Key Technologies for Intelligent Vehicles under the Background of Big Data and AI (Fuyang Institute of Technology Achievement Cultivation and Transformation Project, No. 2024KYXM17)”.

References

1 L. A. Van Ellen, B. N. Bridgens, N. Burford, and O. Heidrich: Build. Environ. **203** (2021) 108068. https://doi.org/10.1016/j.buildenv.2021.108068
2 N. M. Matter and N. G. Gado: Eng. Res. J. **181** (2024) 1. https://doi.org/10.21608/erj.2024.344313
3 M. Almesbah and J. Wang: Designs **9** (2025) 41. https://doi.org/10.3390/designs9020041
4 Y. Ding, T. Wang, S. Gu, C. Zhao, W. Jin, F. Yang, C. Ding, M. Zhang, D. Yan, and Y. Luo: Microchem. J. **225** (2026) 118255. https://doi.org/10.1016/j.microc.2026.118255
5 C. Wang, F. Zhang, J. Wang, J. K. Dayle, P. A. Hancock, C. M. Mak, and S. Liu: Buil. Environ. **193** (2021) 5107647. https://doi.org/10.1016/j.buildenv.2021.107647
6 W. Song and J. K. Calautit: Buil. Environ. **257** (2024) 111463. https://doi.org/10.1016/j.buildenv.2024.111463
7 S. G. Anavatti, F. Santoso, and M. A. Garratt: Proc. 2015 Int. Conf. Advanced Mechatronics, Intelligent Manufacture, and Industrial Automation (ICAMIMIA, 2015) 1. https://doi.org/10.1109/ICAMIMIA.2015.7537196
8 C. Berger, A. Mahdavi, E. Ampatzi, K. Bandurski, R. TY. Hellwig, M. Schweiker, F. Topak, and M. Zgank: J. Build. Eng. **76** (2023) 107196. https://doi.org/10.1016/j.jobe.2023.107196
9 J. Wang, S. Wang, X. XU, and F. Xiao: Energy Build. **41** (2009) 570. https://doi.org/10.1016/j.enbuild.2008.12.001
10 J. Saini and M. Dutta: IJERPH **17** (2020) 4942. http://dx.doi.org/10.3390/ijerph17144942
11 Lv. Zhihan: Front. Internet Things **1** (2022) 912388. https://doi.org/10.3389/friot.2022.912388
12 S. Krishnan, J. Wang, E. Wu, M. J. Franklin, and K. Goldberg: Proc. VLDB Endow. **9** (2016) 948. https://doi.org/10.14778/2994509.2994514
13 T. Hong: Energy Build. **41** (2009) 426. https://doi.org/10.1016/j.enbuild.2008.11.003
14 R. Li, Z. Li, B. A. Kofi, J. Sun, Y. He, and M. Jiao: Chemosensors **14** (2026) 143. https://doi.org/10.3390/chemosensors14060143
15 R. Askar, L. Bragança, and H. Gervásio: Appl. Sci. **11** (2021) 4483. https://doi.org/10.3390/app11104483
16 S. Y. Tan, M. Jacoby, H. Saha, A. Florita, G. Henze, and S. Sarkar: Energy Build. **258** (2022) 111828. https://doi.org/10.1016/j.enbuild.2021.111828
17 H. Huang, G. Xue, J. Zhan, Y. Yang, B. Jia, Z. Dong, Z. Deng, and X. Zhao: Nano-Micro Lett. **18** (2026) 398. https://doi.org/10.1007/s40820-026-02233-5
18 G. Fenza, M. Gallo, V. Loia, F. Orciuoli, and E. Herrera-Viedma: Appl. Soft Comput. **106** (2021) 107366. https://doi.org/10.1016/j.asoc.2021.107366
19 Mitsubishi Electric: https://iconics.com/resources/success-stories/microsoft (accessed July 2026).
20 BRE Group: https://bregroup.com/case-studies/the-edge-amsterdam (accessed July 2026).
21 A. Latifah, S. H. Supangkat, E. Leksono, and A. Indraprastha: J. Eur. Syst. Autom. **58** (2025) 923. https://doi.org/10.18280/jesa.580506
22 T. Zhang, Y. Liu, Y. Rao, X. Li, and Q. Zhao: Build. Environ. **175** (2020) 106810. https://doi.org/10.1016/j.buildenv.2020.106810
23 Y. Tian, Y. Tian, Y. Jiang, and V. Mrzljak: Buildings **16** (2026) 2569. https://doi.org/10.3390/buildings16132569
24 C. Kanthila, A. Boodi, A. Marszal-Pomianowska, K. Beddiar, Y. Amirat, and M. Benbouzid: Energy Build. **318** (2024) 114442. https://doi.org/10.1016/j.enbuild.2024.114442
25 R. Li, Z. Li, B. A. Kofi, J. Sun, Y. He, and M. Jiao: Chemosensors **14** (2026) 143. https://doi.org/10.3390/chemosensors14060143
26 X. Li, H. Ge, and B. Huang: Sustainability **17** (2025) 11230. https://doi.org/10.3390/su172411230

About the Authors

Shihui Wei received his M.S. degree in civil engineering from Chongqing University in 2011. From 2019 to 2024, he was a lecturer at Fuyang Institute of Technology in China. Since 2025, he has been an associate professor at Fuyang Institute of Technology in China. His research interest is in building energy efficiency. (20170501@fyvtc.edu.cn)

Yanping Chen received her M.S. degree in communication and information systems from China University of Geosciences, Wuhan, China, in 2006. Since 2018, she has been an associate professor at Hefei University, China. Her research interests include computer networks, AI, and sensors.
(chenypo@hfuu.edu.cn)