



## Full length article

# AI-optimized energy and comfort control for carbon-neutral tropical buildings

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## ARTICLE INFO

## Keywords:

AI-driven optimization  
Energy efficiency strategies  
Indoor comfort enhancement  
Carbon emission reduction  
Climate-adaptive buildings  
Sustainable building performance  
Real-time energy data  
Predictive models for energy consumption  
Hot and humid climates  
Environmental sustainability

## ABSTRACT

Cooling energy consumption constitutes a significant portion of total energy use in buildings located in hot and humid climates. This paper presents an AI-driven integrated strategy to optimize energy efficiency and indoor comfort while reducing carbon emissions in Kuala Lumpur, Malaysia. The key innovation differentiating this approach from existing studies lies in the integration of Multi-Input Bottleneck Architecture (MIBA)-based Long Short-Term Memory models, 5 min high-resolution real-time data processing, and Model Predictive Control systems incorporating adaptive comfort models. Unlike existing AI-based HVAC research that relies on hourly control or simple neural networks, this study utilizes environmental, control, and energy data sampled at 5 min intervals to forecast indoor conditions and optimize Air Conditioning and Mechanical Ventilation control strategies. Through Walk-Forward Validation across 21 stages, the energy consumption prediction model achieves high accuracy ( $R^2 > 0.88$ ). The optimization algorithm reduces daily energy consumption from 10,306 kWh to 9,864 kWh and peak usage from 84 kWh to 82 kWh. Over one-month simulation, total energy savings reached 12,871 kWh, CO<sub>2</sub> emissions decreased by 5,913 kg, and cost savings amounted to, RM 6,304. Twenty-four-hour empirical validation confirmed simulation accuracy, demonstrating consistency between theoretical modeling and actual implementation. This study provides a practical solution addressing the comfort-efficiency trade-off problem and offers innovative building management approaches for achieving sustainable energy usage and contributing to long-term environmental sustainability in hot and humid climates.

## 1. Introduction

Building energy consumption accounts for approximately 37% of global energy use [1], with cooling demands representing a significant share in hot and humid regions. In countries such as Malaysia, air conditioning alone is responsible for more than 48% of the total energy consumption of buildings [2]. Given the high dependence on cooling systems in these climates, improving air conditioning efficiency is crucial for reducing energy consumption and achieving sustainable building operations. Developing and optimizing cooling technologies tailored to these conditions is, therefore, a critical challenge.

Achieving carbon neutrality through the efficient use of energy is a key objective in strategies for addressing climate change, both now and in the future [3]. Optimizing energy consumption in hot and humid regions can help reduce greenhouse gas emissions

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<https://doi.org/10.1016/j.job.2025.113415>

Received 6 March 2025; Received in revised form 17 June 2025; Accepted 6 July 2025

Available online 21 July 2025

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## Nomenclature

|                                      |                                                                           |
|--------------------------------------|---------------------------------------------------------------------------|
| $\Delta E_R, \Delta E_S, \Delta E_T$ | Energy used in each phase during interval (kWh)                           |
| $\Delta E_{total}$                   | Total energy used during interval (kWh)                                   |
| $\Delta T_{max}$                     | Maximum allowable temperature deviation (°C)                              |
| $\hat{u}(t)$                         | Optimal control input at time $t$                                         |
| $\lambda_1, \lambda_2$               | Weighting coefficients for energy and comfort in optimization             |
| $\underline{u}(t), \bar{u}(t)$       | Minimum and maximum allowable control input at time $t$                   |
| $A, B, C, D, E, F, G$                | Coefficients for environmental response functions                         |
| $E_t$                                | Energy consumption at time $t$ (kWh)                                      |
| $E_{msbk}(t)$                        | Energy consumption of MSB $k$ at time $t$ (kWh)                           |
| $f(\cdot)$                           | LSTM prediction function                                                  |
| $i$                                  | Floor or zone index                                                       |
| $I(t)$                               | Indoor environmental function at time $t$                                 |
| $J$                                  | Objective function for MPC optimization                                   |
| $k$                                  | MSB number identifier                                                     |
| $N$                                  | Number of floors or zones                                                 |
| $n$                                  | Number of previous days for prediction                                    |
| $P_R(t), P_S(t), P_T(t)$             | Instantaneous power at time $t$ for R, S, T phases (W)                    |
| $S_{schedule}(t)$                    | Scheduling data at time $t$                                               |
| $S_{T,i}(t)$                         | Temperature satisfaction at floor $i$ and time $t$                        |
| $S_{total}(t)$                       | Overall indoor environmental satisfaction at time $t$                     |
| $T_{set,i}$                          | Set temperature at floor $i$ (°C)                                         |
| $T_{env}(t)$                         | Predicted indoor environmental value at time $t$                          |
| $T_{final}$                          | Target final temperature (°C)                                             |
| $T_{initial}$                        | Initial temperature (°C)                                                  |
| $T_{outdoor}(t)$                     | Outdoor temperature at time $t$ (°C)                                      |
| $T_i(t)$                             | Actual temperature at floor $i$ and time $t$ (°C)                         |
| $u(t)$                               | Control input at time $t$                                                 |
| $w_{T,i}$                            | Weight for temperature satisfaction at floor $i$                          |
| $X_t$                                | Historical energy consumption data at time $t$                            |
| $Y_t$                                | Predicted energy consumption at time $t$                                  |
| ACMV                                 | Air Conditioning and Mechanical Ventilation                               |
| AI                                   | Artificial Intelligence                                                   |
| ANN                                  | Artificial Neural Network                                                 |
| ARIMA                                | Autoregressive Integrated Moving Average                                  |
| ASHRAE                               | American Society of Heating, Refrigerating and Air-Conditioning Engineers |
| BAS                                  | Building Automation System                                                |
| BEMS                                 | Building Energy Management System                                         |
| CI                                   | Confidence Interval                                                       |
| CO <sub>2</sub>                      | Carbon Dioxide                                                            |
| DL                                   | Deep Learning                                                             |
| EMS                                  | Energy Management System                                                  |
| ESS                                  | Energy Storage System                                                     |
| HVAC                                 | Heating, Ventilation, and Air Conditioning                                |
| IoT                                  | Internet of Things                                                        |
| LSTM                                 | Long Short-Term Memory (neural network)                                   |
| MAE                                  | Mean Absolute Error                                                       |
| MIBA                                 | Multi-Input Bottleneck Architecture                                       |
| ML                                   | Machine Learning                                                          |
| MPC                                  | Model Predictive Control                                                  |
| MSB                                  | Main SwitchBoard                                                          |
| PMV                                  | Predicted Mean Vote                                                       |

|                |                                                      |
|----------------|------------------------------------------------------|
| PPD            | Predicted Percentage of Dissatisfied                 |
| PV             | Photovoltaic                                         |
| R <sup>2</sup> | Coefficient of determination (model accuracy metric) |
| RM             | Ringgit Malaysia (currency unit)                     |
| RMSE           | Root Mean Square Error                               |
| RNN            | Recurrent Neural Network                             |
| TR             | Ton of Refrigeration                                 |

by lowering the power demand of air-conditioning systems, which represents an important step toward a carbon-neutral society. However, in such climates, reducing reliance on air conditioning is nearly impossible, which makes it essential to enhance system performance while maintaining the effectiveness of existing systems. High temperatures and humidity necessitate the continuous operation of air-conditioning systems, which leads to a sharp increase in energy consumption. Therefore, advanced optimization technologies are required to maintain system performance while minimizing energy use.

One way to solve this problem is to introduce a smart cooling system [4]. A smart cooling system includes technology that monitors indoor temperature and humidity in real-time, and it controls cooling in an energy-efficient way. For example, pre-cooling [5] is a method that predicts a building's cooling demand in advance and reduces peak demand by pre-cooling during periods of low power usage. This approach allows for the efficient distribution of cooling energy. However, in hot and humid regions, a general pre-cooling strategy is often insufficient and may even increase energy consumption. Therefore, a control method tailored to these conditions is necessary.

In addition, implementing an Energy Management System(EMS) is essential for effective energy optimization in such climates [6]. An EMS enhances building efficiency through real-time data collection, analysis, and automated control [7]. In particular, efficient operation of the air-conditioning system is key in hot and humid environments, and the EMS is an important tool for this. However, to date, no customized EMS has been commercially used that fully accounts for the characteristics of such conditions. Existing EMS are mainly designed based on temperate climates, which limits their ability to effectively manage these unique climate conditions and energy consumption patterns. Therefore, it is necessary to develop specialized EMSs that take into account the characteristics of hot and humid regions such as Southeast Asia.

EMS combined with Artificial Intelligence(AI) enables more sophisticated energy optimizations [8]. Such systems dynamically adjust the operation of the air-conditioning system by taking into account key variables, including weather data, building usage patterns, and indoor environmental conditions. For example, a predictive control algorithm can be used to predict future air conditioning demand and proactively adjust and prepare the system.

This technological advancement has the potential to be applied to energy management in hot and humid regions. However, the commercialization of systems specifically designed for high-temperature, high-humidity environments has yet to be achieved. Therefore, this paper proposes a cooling strategy for a customized energy management system that considers the unique characteristics of these climates and leverages the latest technologies. This approach aims to improve energy efficiency, enhance indoor comfort, and ultimately contribute to sustainable building energy management.

### 1.1. Related work

Research on air-conditioning strategies in hot and humid regions is being conducted from various perspectives. In particular, the rapid increase in air-conditioning demand and its associated energy consumption and environmental impact have become major concerns. As of 2018, electricity use for household air conditioning in Southeast Asia was about 50 TWh, but it is projected to rise to 200 TWh by 2040, which accounts for about 30% of total electricity consumption [9,10]. In response, improving energy efficiency, developing innovative cooling technologies, and designing sustainable buildings have become key research priorities [11].

#### 1.1.1. Features of air-conditioning-control technology that depends on the environment

Air-conditioning-control technology has been continuously developed, and recently, smart air-conditioning systems [12–14] using artificial intelligence and the Internet of Things [15–17] have been in the spotlight. Smart energy systems enable optimized heating and cooling by taking into account both indoor and outdoor temperatures, the presence of residents, the number of people, and lifestyle [18]. These systems use the outdoor temperature as a compensation value to improve heating efficiency and enable temperature and humidity control while considering the comfort index of the residents [19].

Air-conditioning-control technology is optimized based on environmental conditions, taking into account local climate characteristics. In hot and humid regions, humidity control is especially important, and air-conditioning systems with enhanced dehumidification functions have proven effective [20]. In addition, research is exploring ways to reduce energy consumption by incorporating passive cooling [21,22], such as night ventilation in tropical climates.

#### 1.1.2. Energy-consumption patterns in buildings

The characteristics of energy consumption in buildings vary depending on the purpose, scale, and region. In commercial buildings, cooling accounts for a significant portion of overall energy consumption, which makes it an important target for energy

efficiency [23]. Factors that affect a building's energy consumption include the regional climate, the design of the building, the systems used in the building, and the way the building is operated [24]. In particular, high temperatures and high humidity tend to increase energy consumption because cooling systems need to be kept running continuously [25]. Technology is also being developed to efficiently manage buildings designed for various environments by integrating digital twin technology [26].

#### 1.1.3. Energy Management System (EMS)

Many topics have been explored in the field of energy management [27]. Energy management systems play an important role in optimizing the energy use of buildings. An EMS efficiently manages energy consumption through real-time monitoring, data collection and analysis, automatic control/optimization, and predictive management [28]. Recently, an AI-based EMS has been developed, which enables more sophisticated energy optimization. The introduction of an EMS has multiple effects, including reduction of energy costs, protection of the environment, improvement of operational efficiency, compliance with regulations, and facilitation of certification [29]. In addition, research is conducted to reduce carbon emissions in conjunction with renewable energy such as solar power [30,31].

#### 1.1.4. Pre-cooling

Pre-cooling is a method of reducing energy consumption during peak hours by cooling buildings in advance during times of low power demand [32]. This approach distributes the cooling load by using the building's heat capacity. However, the effect of pre-cooling may be small in hot and humid regions, so optimization is required to suit regional characteristics. Advanced technologies such as smart thermostats can be used to help implement pre-cooling strategies more effectively [33].

#### 1.1.5. Analysis of energy consumption data

Recently, research has been conducted to analyze building energy consumption using big data. These studies analyze more accurate and detailed energy consumption patterns using regional energy-consumption data and the city's sensor data [34]. This approach helps contribute to establishing more sophisticated energy management strategies, such as building data that is close to the actual perceived temperature by people and predicting the relationship with building energy consumption [35]. The data analysis helps understand the relationship between how a building is operated and its energy consumption patterns, which is key to developing more efficient energy-management strategies [36].

#### 1.1.6. Building engineering

Building engineering research focuses on maximizing energy efficiency and reducing carbon emissions through passive and active strategies. While existing studies have demonstrated the energy-saving effects of passive elements such as building envelope improvements, enhanced insulation, natural ventilation, and shading design [37], applying these strategies to existing buildings (retrofitting) faces limitations due to high initial costs and structural constraints.

Consequently, the integrated application of active elements has emerged as a promising alternative. Smart HVAC systems, predictive control algorithms, and building automation systems (BAS) are being actively studied to achieve additional energy savings and carbon reduction by analyzing and optimizing energy consumption patterns in real time [38]. Notably, AI-based active systems complement the physical limitations of passive elements and demonstrate potential to overcome economic and technical barriers in retrofitting existing buildings.

#### 1.1.7. AI-based energy management frameworks

Recent studies in AI-based HVAC control and carbon emission reduction have focused on fault diagnosis and predictive maintenance strategies to enhance system efficiency [39]. However, these works predominantly emphasize fault detection and maintenance optimization, with limited integration of real-time environmental variables (e.g., temperature, humidity) and occupancy fluctuations into comprehensive energy management frameworks. Furthermore, while data-driven AI algorithms have demonstrated potential in reducing HVAC energy consumption while maintaining thermal comfort [40], their validation in hot and humid climates remains insufficient.

Most existing research has focused on either fault diagnostics or temperate-climate applications, which leaves a significant gap in truly integrated energy-management frameworks capable of synchronizing occupancy patterns, environmental dynamics, and comfort metrics for efficient operation in tropical climates. Although data-driven AI techniques such as predictive maintenance have proven effective at improving system reliability and reducing downtime, only a handful of studies incorporate real-time occupancy information alongside predictive control to jointly optimize both energy consumption and user comfort under hot, humid conditions.

### 1.2. Purpose of the study and contributions

This study aims to present a building-energy-management strategy that is specific to the hot and humid climate of Southeast Asia to address the rapidly increasing energy consumption and the resulting environmental problems. In particular, we aim to develop an ACMV (Air Conditioning and Mechanical Ventilation) optimization control strategy that can maximize energy efficiency while maintaining indoor comfort in buildings with high cooling energy consumption.

Research on building energy management in tropical climates remains fragmented, as most studies examine either passive design strategies or AI-based energy prediction models without integrating real-time environmental data and occupant comfort metrics into a unified framework. Many prior works also depend on temperate climate datasets or simplified simulations, limiting their

applicability in tropical regions with significant latent heat challenges. Energy-efficiency and thermal comfort are often set as trade-offs, hindering holistic solutions for practical retrofitting scenarios. To address these gaps, this study proposes an AI-driven ACMV optimization strategy that simultaneously balances energy savings and indoor comfort, validated in a Southeast Asian case study. Additionally, we develop a retrofit-compatible, hardware-agnostic control framework, offering a scalable solution for existing buildings that yields measurable improvements in energy efficiency, carbon reduction, and sustainable operation in hot and humid environments.

1. **AI-based Real-time Energy Consumption Pattern Analysis and Optimization:** This paper presents a novel AI-driven approach that utilizes artificial intelligence and optimization techniques to analyze real-time energy consumption patterns at 5-min intervals and develop a data-driven cooling control algorithm, maximizing energy efficiency and minimizing carbon emissions.
2. **Development of an Optimization Framework for Simultaneously Predicting Indoor Environment and Energy Efficiency:** Unlike existing studies that focus on energy consumption prediction or indoor environment analysis separately, this research develops a framework that simultaneously predicts both factors, quantitatively evaluating and optimizing indoor comfort. This approach achieves both energy savings and indoor environmental improvements.
3. **Optimization and Performance Verification of the ACMV System in Hot and Humid Environments:** An ACMV control algorithm is developed to minimize energy consumption while maintaining indoor comfort in hot and humid climates. The algorithm's performance is verified through simulation, offering a more efficient control solution compared to existing systems, thus providing a climate-optimized solution.
4. **Analysis of Energy Savings, Carbon Emission Reduction, Economic Impact, and Sustainable Building Management:** By applying the optimized ACMV control strategy to an actual building, this study quantitatively analyzes energy savings, carbon emissions reduction, and cost-saving effects. It also proposes a sustainable building energy management approach utilizing smart control technologies, considering not only economic factors but also environmental sustainability.

This paper is expected to contribute academically, technically, and socially in the following ways: First, this study provides practical guidelines for building an energy management system specific to hot and humid climates, which can also contribute to the formulation of energy policies in Southeast Asia. Second, the ACMV-control algorithm developed in this study can be easily integrated into existing systems and can contribute to reducing energy management costs, reducing carbon emissions, and improving indoor comfort. Third, this study suggests the possibility of using AI in the field of building energy management and that it can contribute to the development of core technologies to build smart cities in the future. In addition, the data set constructed in this study will be used as important data for future research on building energy management in hot and humid climates.

## 2. Methods

This section describes the collection environment for data analysis in a hot and humid environment and the design of a simulator for optimizing the ACMV system [41]. First, real-time energy and environmental data were collected to analyze energy consumption patterns and indoor environmental patterns in hot and humid regions. Then, based on this, a control strategy for the air-conditioning system is developed. Subsequently, a simulator was built to evaluate and verify the optimized control plan and to derive the optimal control scenario for ACMV in such environments.

### 2.1. Data-collection environment and analysis

In order to collect data on air-conditioning energy use in the hot and humid regions of Southeast Asia, energy meters and environmental sensors (temperature, humidity, motion detection, fine dust) were installed in a building in Kuala Lumpur, Malaysia. In addition, external environmental data (temperature, humidity) were collected to analyze regional characteristics.

Fig. 1 shows a schematic of sensor and energy meter installations for data collection in a building located in Kuala Lumpur, Malaysia, a hot and humid environment. The building has 28 levels above and one floor below ground. Because installing sensors on all levels was impractical, sensors were placed in key locations to collect environmental data: the lobby (which has high foot traffic), the second level (lower part of the building), the 13th floor (middle of the building), the 28th level (upper part of the building), and the rooftop. In order to maximize the efficiency and convenience of sensor installation, communication with the gateway was established using wireless communication (Zigbee) [42], while wired communication (RJ45) was used for data transmission from the gateway to the database for storage and management [43]. As shown in the Level 1 layout in Fig. 1, two groups of sensors are installed on each level, with Group 1 positioned on the left side of the building and Group 2 on the right. In addition, one sensor group is installed on the rooftop to collect outdoor environmental data. Each indoor environmental sensor group collected temperature, humidity, motion detection, fine dust, and ultrafine dust. In this study, the indoor environment was analyzed using temperature and humidity. For the outdoor environment, temperature, humidity, and solar radiation were collected. In this study, the outdoor environment was analyzed using external temperature and humidity. The control status was collected every five minutes through the ACMV control panel located at Level 1 to collect the ACMV control data. Energy data were collected by installing meters in each of the building's four main switchboards (MSBs).

#### 2.1.1. Data collection and pattern analysis

Based on the installation environment shown in Fig. 1, data were collected in 5-min intervals from June 2024 to January 2025. The collected data were divided into environmental data, control data, and energy data. Environmental data were collected from

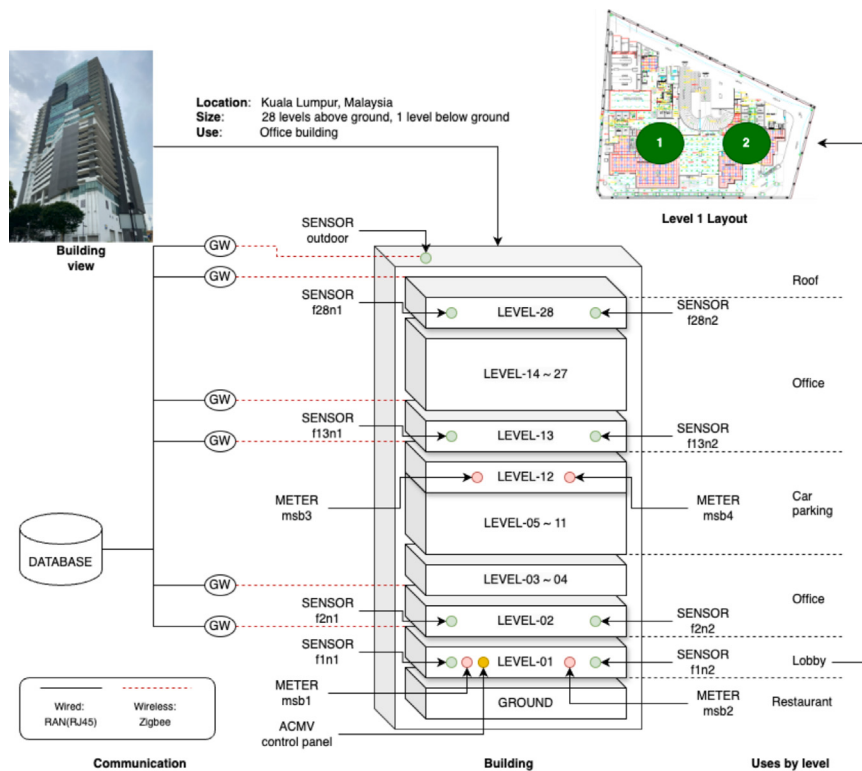


Fig. 1. Schematic of the installation environment of the studied building.

eight different groups and used to analyze the indoor environment: two groups, each from the upper levels (Level 28), middle levels (Level 13), lower levels (Level 2), and lobby (Level 1) of the building. Control data were collected through the ACMV Control Panel installed at Level 1, which allows the operational status of the ACMV installed in all spaces in the building to be monitored and controlled. Energy data could also be analyzed for various energy sources (water, gas, etc.), but this study focused on power data directly related to the air-conditioning system. To this end, data were collected and analyzed based on the building's main switchboard.

**Environmental data.** Environmental data were collected for indoor/outdoor temperature and humidity. There are eight collection points for the indoor and one collection point for the outdoor environment.

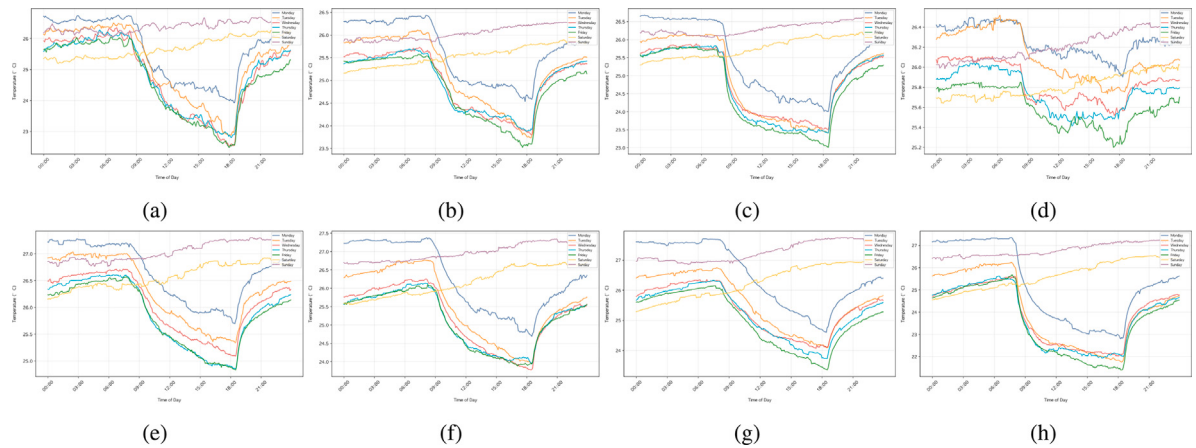
Fig. 2 shows the weekly profiles of temperature data by sensing point, averaged for each day of the week. The colors in the graph represent the days of the week: Monday (deep blue), Tuesday (orange), Wednesday (red), Thursday (cyan), Friday (dark green), Saturday (gold), and Sunday (purple). In the graph below, the colors for each day of the week are represented in the same way. (a) and (b) denote the lobby, (c) and (d) represent low-rise, (e) and (f) middle-rise, while (g) and (h) represent high-rise data. The sensor at (d) was installed in a part that was directly connected to the passageway to the next train station. Consequently, the temperature change was minimal, and the sensing point at (h) on the top floor shows the highest daily temperature difference.

Fig. 3 shows the weekly profiles of humidity data, averaged for each day of the week, collected from sensing points inside the building. The colors of the graph indicating the day of the week are the same as in Fig. 2. Data from lobby (a) and (b), low-rise (c) and (d), middle-rise (e) and (f), and high-rise (g) and (h) are shown. The difference in humidity is mainly dependent on the presence or absence of ACMV, and high humidity is maintained outside of operating hours.

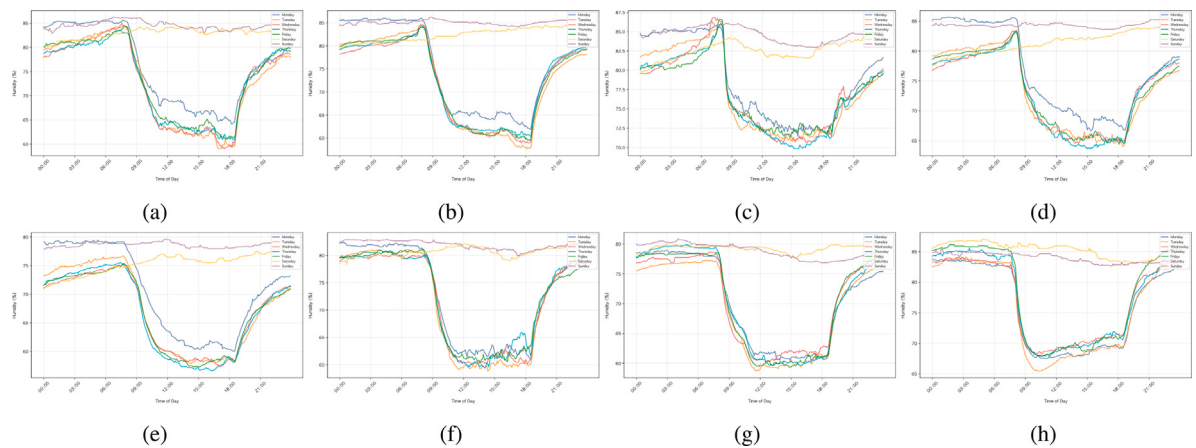
Fig. 4 presents a graph showing the weekly profiles of external environment data collected from sensor points installed on the rooftop, averaged for each day of the week. The data are represented by temperature and humidity, with colors for each day of the week matching those in Fig. 2. (a) represents the outside temperature, and (b) represents the outside humidity. The temperature gradually decreases over time while the humidity remains relatively constant.

The statistics of each collection point, as shown in Table 1, indicate that the Middle-rise (Level 13) had the most stable fluctuation range. In addition, the rooftop data confirm that the external environment is characterized by high temperature and humidity.

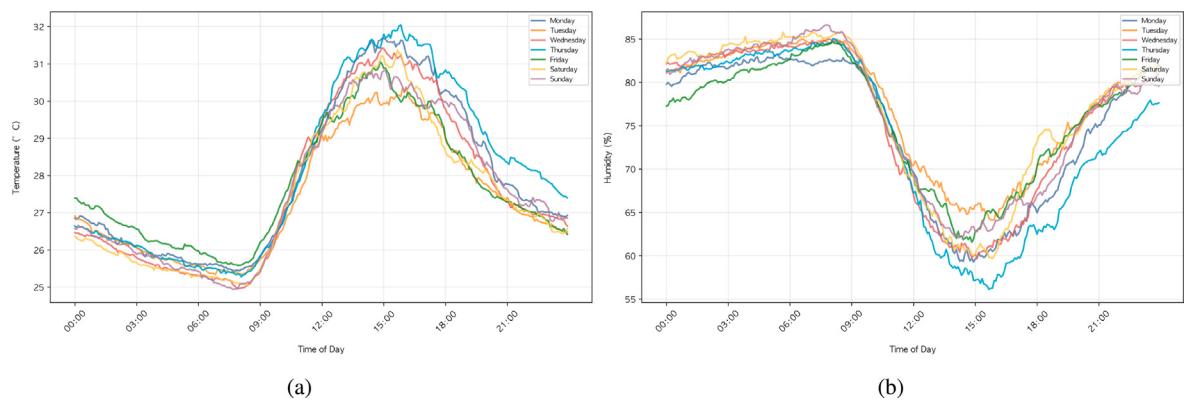
**Control data.** A total of 60 controllers control the ACMV, and data on each control status are collected at 5-min intervals. Of these, 54 controllers are installed on each floor (Levels 3–4, Level 13 to Level 28), with the exception of the parking lot (Levels 5–12), Ground, Level 1, and Level 2. Two controllers are installed on each of the Ground, Level 1, and Level 2 floors, totaling six controllers. No ACMV facilities are installed in the parking lot (Levels 5–12).



**Fig. 2.** The following graphs show the weekly profiles of temperature data by sensing point, averaged for each day of the week: (a) Lobby Point 1, (b) Lobby Point 2, (c) Low-rise Point 1, (d) Low-rise Point 2, (e) Middle-rise Point 1, (f) Middle-rise Point 2, (g) High-rise Point 1, (h) High-rise Point 2. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



**Fig. 3.** The following graphs show the weekly profiles of humidity data by sensing point, averaged for each day of the week: (a) Lobby Point 1, (b) Lobby Point 2, (c) Low-rise Point 1, (d) Low-rise Point 2, (e) Middle-rise Point 1, (f) Middle-rise Point 2, (g) High-rise Point 1, (h) High-rise Point 2. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



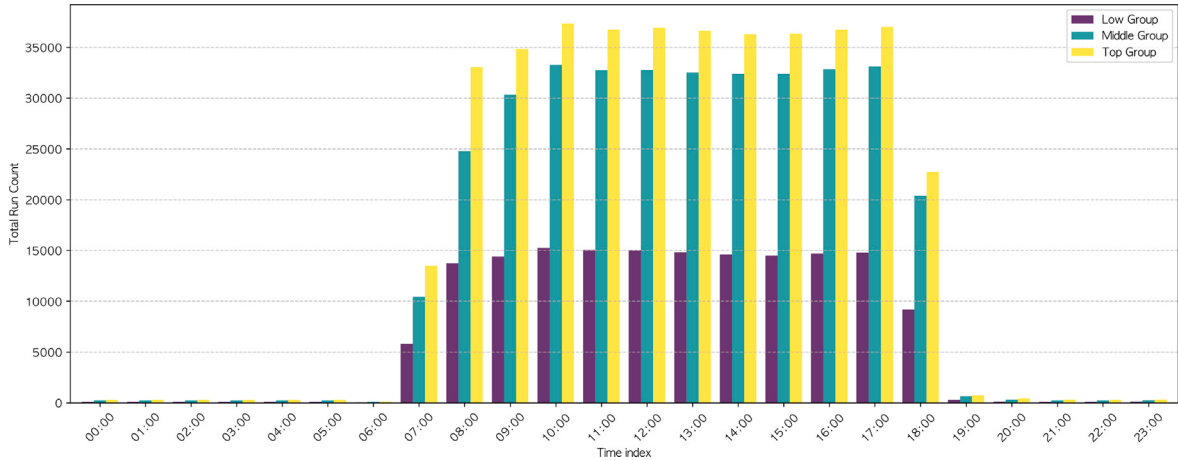
**Fig. 4.** The following graph shows the weekly profile of rooftop external environmental data, averaged by day of the week. (a) Outdoor temperature, (b) Outdoor humidity. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 1**  
Summary of sensor data (Minimum ~Maximum (Average)).

| Floor                 | Temperature (°C)                                               | Humidity (%)                                                  |
|-----------------------|----------------------------------------------------------------|---------------------------------------------------------------|
| Lobby(Level-1)        | 29.4~19.5 (25.3) <sup>a</sup> , 27.7 ~21.3 (25.3) <sup>b</sup> | 97.7~49.2 (76.4) <sup>a</sup> , 95.6~49.4 (75.9) <sup>b</sup> |
| Low-rise(Level-2)     | 28.1~20.6 (25.2) <sup>a</sup> , 27.8 ~23.5 (26.0) <sup>b</sup> | 98.8~60.6 (79.0) <sup>a</sup> , 94.0~53.7 (76.3) <sup>b</sup> |
| Middle-rise(Level-13) | 28.8~23.2 (26.3) <sup>a</sup> , 28.7 ~22.0 (25.8) <sup>b</sup> | 86.2~47.0 (70.0) <sup>a</sup> , 96.5~50.6 (74.6) <sup>b</sup> |
| High-rise(Level-28)   | 29.6~20.5 (25.9) <sup>a</sup> , 29.5 ~19.2 (24.7) <sup>b</sup> | 90.5~47.5 (72.7) <sup>a</sup> , 96.7~57.6 (78.9) <sup>b</sup> |
| Roof                  | 36.1~21.6 (27.7)                                               | 99.3~38.5 (75.6)                                              |

<sup>a</sup> Sensing point 1.

<sup>b</sup> Sensing point 2.



**Fig. 5.** ACMV Group-specific operation graph.

**Fig. 5** shows a graph illustrating the total usage of time slots for each group of ACMV facilities. Twelve controllers manage the lower floors in the Low (Bottom) Group, 24 controllers manage the middle floors in the Middle Group, and 24 controllers manage the upper floors in the Top Group. Usage is highest between 07:00 and 18:00 and lowest at 10:00.

**Energy data.** Energy data is were collected at 5-min intervals via a three-phase meter that measures the energy entering the building. The installation environment is capable of monitoring all energy usage within the building through four primary switchboards, with data collected by a meter in each MSB. The meter collects instantaneous power (W) in 5-min intervals and calculates the energy usage based on the accumulated energy value (kWh). The following formula is employed used to calculate determine energy usage ( $E_t$ ):  $E_t = (P_R(t), P_S(t), P_T(t))$ , where  $P_R(t)$ ,  $P_S(t)$ ,  $P_T(t)$  are the instantaneous power values collected measured at time  $t$  from the three-phase meter ( $R_{phase}$ ,  $S_{phase}$ ,  $T_{phase}$ ).

$$\Delta E_R = \left( P_R(t) \times \frac{5}{60} \right) \times 0.001$$

$$\Delta E_S = \left( P_S(t) \times \frac{5}{60} \right) \times 0.001$$

$$\Delta E_T = \left( P_T(t) \times \frac{5}{60} \right) \times 0.001$$
(1)

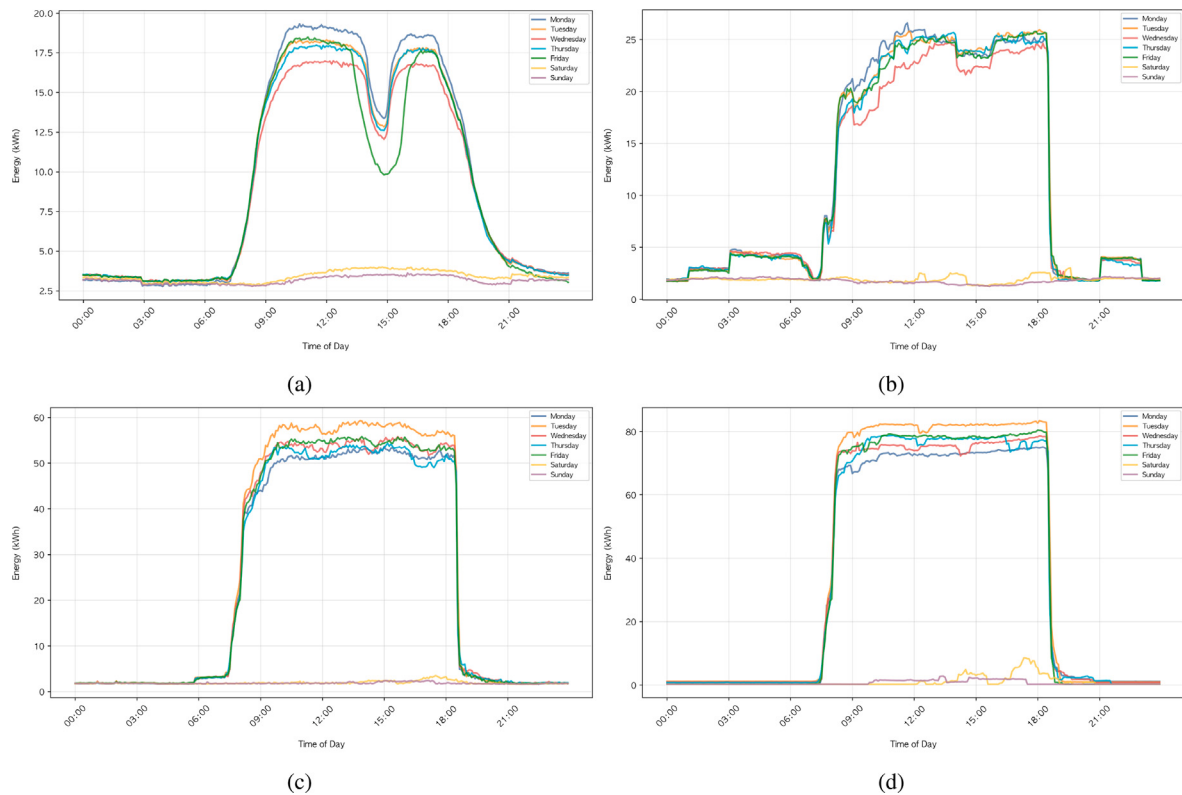
$$\Delta E_{total} = \Delta E_R + \Delta E_S + \Delta E_T$$
(2)

The above equation summarizes the energy usage of each MSB's t-hour as follows:

$$E_{msbk}(t) = \frac{5}{60} \cdot (P_{R, msbk}(t) + P_{S, msbk}(t) + P_{T, msbk}(t)) \times 0.001$$
(3)

Here,  $k$  is the MSB number, and the above formula can be used to calculate the energy consumption (kWh) of each MSB.

**Fig. 6** shows the weekly average profiles of energy consumption data collected from each MSB of the building, averaged for each day of the week. The colors in the graph correspond to the days of the week, following the same scheme as in **Fig. 2**. The graph for (a) MSB1 shows energy consumption patterns, revealing two distinct groups during lunchtime on weekdays. From Monday to Thursday, the grouping aligns with Zuhr, the general Islamic prayer time, while Friday's prayer time is longer due to the inclusion of Juma prayer time [44]. (b) MSB2 represents energy usage and is displayed in the graph using hollow circles during the afternoon period (11:00 a.m. to 5:00 p.m.). This is a phenomenon where energy usage temporarily decreases because the solar panels are connected to the meter. In addition, energy is used for ESS charging in the early morning (3:00 a.m. to 5:00 a.m.) and late evening (9:00 p.m. to 11:00 p.m.), while discharging helps maintain low energy use during the morning hours. The graph for (c) MSB3



**Fig. 6.** The following graph presents the weekly average profiles of energy usage by meter, averaged for each day of the week. (a) MSB1, (b) MSB2, (c) MSB3, (d) MSB4. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 2**  
Summary of energy consumption patterns by MSB.

| Meter | Maximum value at peak (kWh) | Maximum daily usage (kWh) | Baseline energy (kWh) <sup>a</sup> |
|-------|-----------------------------|---------------------------|------------------------------------|
| MSB1  | 24.5                        | 3479.5                    | 4                                  |
| MSB2  | 38.2                        | 4894.8                    | 2                                  |
| MSB3  | 70.8                        | 8180.3                    | 2                                  |
| MSB4  | 89.0                        | 13 547.3                  | 1                                  |

<sup>a</sup> The average value used when there is no energy use.

shows a consistent pattern by day of the week. The graph for (d) MSB4 shows a consistent energy-usage pattern throughout the week.

Table 2 provides a summary of the meter data measured at each MSB, including the peak maximum value in 5-min intervals, the daily maximum usage, and the 5-min interval base power. MSB4 recorded the highest energy usage of all meters, while MSB1 showed relatively low energy usage. In terms of baseline power, MSB4 showed the lowest value, which represents the average when energy usage is relatively low compared to other meters.

As a result of analyzing the energy-consumption patterns according to the four MSBs, each MSB showed different characteristics depending on the connected energy-consumption sources. The number of connections of the ACMV the primary connected energy-consumption source is summarized in Table 3.

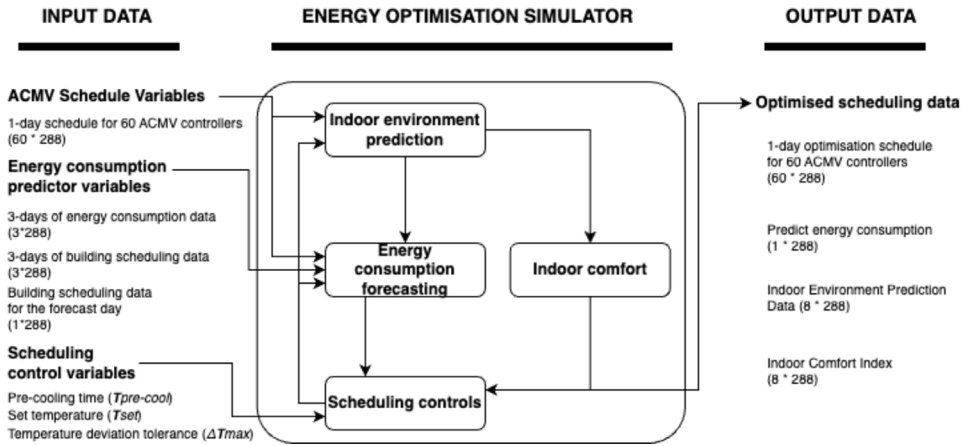
**High temperature, high humidity, and energy consumption** Hot and humid environments are characterized by a combination of high temperatures and humidity, which directly impact energy consumption. These conditions can increase discomfort, which can lead to higher cooling demand. While energy consumption generally varies depending on the season or time of day, energy consumption in hot and humid areas remains consistently high because modifications are required continuously. In particular, the use of air conditioning and humidity control equipment such as air conditioners and dehumidifiers is increasing, and buildings with collected data can optimize their indoor environments via the ACMV system.

Therefore, energy management here requires optimal operation of the air-conditioning system, efficient temperature and humidity control, and adaption of energy use to changes in the external environment. Optimization is required to efficiently reduce energy while maintaining indoor environmental conditions.

**Table 3**

Status of major devices and ACMV connections for the different MSBs.

| Meter | Primary devices                            | ACMV                       |
|-------|--------------------------------------------|----------------------------|
| MSB1  | Office equipment, lighting, etc.           | –                          |
| MSB2  | ESS, PV, ACMV (Low-rise group), water pump | 12 (E1 to 12) <sup>a</sup> |
| MSB3  | ACMV (Middle-rise group), elevator         | 24 (13 to 36) <sup>b</sup> |
| MSB4  | ACMV (High-rise group), cooling tower      | 24 (37 to 60) <sup>c</sup> |

<sup>a</sup> ACMV: E1, E2, E3, E4, E5, E6, E7, E8, E9, 10, 11, 12.<sup>b</sup> ACMV: 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36.<sup>c</sup> ACMV: 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60.**Fig. 7.** Schematic illustrating the entire simulation process.

## 2.2. Simulation

A simulator was designed to efficiently reduce energy consumption while maintaining indoor conditions in a hot and humid environment. This simulator is designed to predict indoor environments as well as energy consumption according to the ACMV schedule, analyze the indoor comfort level accordingly, and derive an optimized ACMV schedule. Fig. 7 illustrates the entire simulation process. The energy optimization simulator takes in the ACMV scheduling variables, energy consumption prediction variables, and scheduling control variables. It then outputs the optimized prediction results based on these inputs. This simulator consists of four major components: indoor environment prediction, indoor comfort analysis, energy consumption prediction, and scheduling control.

### 2.2.1. Predicting the indoor environment

The analysis of data related to the indoor environment in a building with a hot and humid environment confirms that the patterns of changes in temperature and humidity can be described by different mathematical models [45] depending on whether the ACMV is in operates or not.

Specifically, when the ACMV is active, both indoor temperature and humidity change in a logistic function form [45,46]. This form reveals a pattern of gradually converging to the target temperature over time. On the other hand, when the ACMV is stopped, changes in temperature and humidity tend to follow a logarithmic function form [45,47].

Based on these analysis results, the indoor environmental function  $I(t)$  can be defined as follows:

$$I(t) = \begin{cases} T_{\text{final}} - \frac{A}{1 + e^{-B(t-C)}}, & \text{if ACMV is ON; } B > 0 \\ C \cdot \ln(D \cdot t + E) + F \cdot e^{-G \cdot t}, & \text{if ACMV is OFF} \end{cases} \quad (4)$$

The set target temperature  $T_{\text{final}}$ , represents the desired final temperature to be maintained in the indoor environment.  $A$  denotes the difference between the initial temperature and the target temperature and indicates the time required for the system to reach the set temperature.  $B$  is a coefficient that affects the rate of temperature change, which determines how quickly the temperature changes in the logistic function.  $C$  denotes the central point of the logistic function, which plays an important role in setting the point where the target temperature is reached or where a rapid change occurs.

In addition,  $D$ ,  $E$ ,  $F$ , and  $G$  are coefficients that are determined by the impact of the external environment and the structural characteristics of the interior. These are important factors in defining the pattern of changes for both temperature and humidity

when the ACMV is turned off. These coefficients are the values needed to accurately model the patterns of changes in temperature and humidity over time. They can vary depending on various variables, such as the location, structure, and external climate of/near the building.

This paper only considers the prediction of indoor environmental changes in terms of temperature. This function is used to model changes in temperature and humidity according to the ACMV's operating status (ON/OFF). When the ACMV is operating, the indoor temperature gradually converges to the target temperature according to a logistic function. In addition, when the ACMV is stopped, it quickly follows the outdoor temperature according to a logarithmic change pattern.

In the simulator, the scheduling data of the ACMV for one day was input, and the indoor environment was predicted using a model tailored to the characteristics of each space.

### 2.2.2. Indoor-comfort index

In a hot and humid environment, indoor comfort is a very important factor, and it is an indicator that is directly linked to energy efficiency and user satisfaction. Several metrics exist to measure comfort, as well as various environmental factors. These include temperature, humidity, and air quality, which generally have an impact [48]. Existing methods for measuring comfort are usually evaluated based on a standard set based on standard environmental conditions, typically PMV (Predicted Mean Vote), PPD (Predicted Percentage of Dissatisfied) [49], or questionnaire responses based on the responses of occupants [50]. While these methods are useful to account for the satisfaction and comfort of building occupants, they are suboptimal when it comes to reflecting real-time indoor changes that may depend on changes outside the building or the time of day.

In this paper, we use a method that calculates the satisfaction level of indoor comfort based on existing environmental conditions (temperature) and predicts it based on the PMV. The relevant formula is:

$$S_{\text{total}}(t) = \sum_{i=1}^N w_{T,i} S_{T,i}(t) \quad (5)$$

Here,  $S_{\text{total}}(t)$  denotes the indoor environmental satisfaction of the entire building at time  $t$ . It is defined as the weighted sum of the temperature satisfaction for each floor  $S_{T,i}(t)$ . Here,  $w_{T,i}$  represents the weight for temperature satisfaction, which can be adjusted according to the environmental conditions of the building. In this study, the analysis is conducted by applying the same weight to all floors because the experiment was conducted at high temperatures and high humidity.

Indoor temperature satisfaction is defined based on the difference between the set temperature and the temperature. The temperature satisfaction  $S_{T,i}(t)$  at a certain floor  $i$  can be calculated as follows:

$$S_{T,i}(t) = 1 - \frac{|T_i(t) - T_{\text{set}}|}{\Delta T_{\text{max}}} \quad (6)$$

Here,  $T_i(t)$  denotes the actual temperature (unit: °C) of layer  $i$ , which is the temperature value of the corresponding layer measured in real-time.  $T_{\text{set},i}$  represents the set temperature of layer  $i$  (unit: °C), which is the target temperature that the system is trying to maintain. In addition,  $\Delta T_{\text{max}}$  is the maximum allowable temperature deviation. If the difference between the set temperature and the actual temperature exceeds this value, the satisfaction decreases rapidly.

At this time,  $\Delta T_{\text{max}}$  may vary depending on the sensitivity of the occupant to the indoor environment. For example, a person who is sensitive to temperature changes may be significantly less satisfied with even smaller temperature differences, while a less sensitive person may be able to tolerate larger temperature differences. Moreover, this sensitivity difference may vary depending on the individual, activity level, and clothing, and it is more pronounced in hot and humid environments.

This satisfaction function is structured so that as the difference between the set temperature and the actual temperature increases, satisfaction decreases. When there is no temperature difference, satisfaction is one, indicating a comfortable state. If the satisfaction level is below one or negative, it represents a very uncomfortable condition. On the other hand, if the satisfaction level exceeds one, it indicates a condition that is below the set temperature. This represents a comfortable condition in a hot and humid environment.

The simulator receives a daily temperature input, then calculates the comfort level in 5-min increments and outputs the comfort index pattern for the day using the data.

### 2.2.3. Prediction of the energy consumption

Building energy consumption forecasts depend on each Main SwitchBoard (MSB) operating schedule. To accurately predict this, an effective time series prediction model based on Long Short-Term Memory (LSTM) networks [51] is employed.

The evolution of machine learning models for building energy consumption prediction has progressed from traditional statistical approaches, such as linear regression and ARIMA, to advanced machine learning (ML) and deep learning (DL) algorithms. Early statistical models faced limitations in capturing nonlinear relationships and long-term dependencies inherent in energy consumption data. The introduction of artificial neural networks (ANNs) enabled the modeling of complex nonlinear patterns. Subsequently, recurrent neural networks (RNNs) and their specialized variant, Long Short-Term Memory (LSTM) networks, effectively addressed the challenge of learning long-term temporal dependencies, which are critical in energy consumption forecasting.

In this study, the LSTM-based model was adopted for its proven capability to process sequential data and maintain memory of temporal relationships over extended periods, thereby overcoming the constraints of conventional methods. This approach enables precise modeling of dynamic energy consumption behaviors influenced by factors such as occupancy schedules, weather conditions, and equipment operational cycles [52].

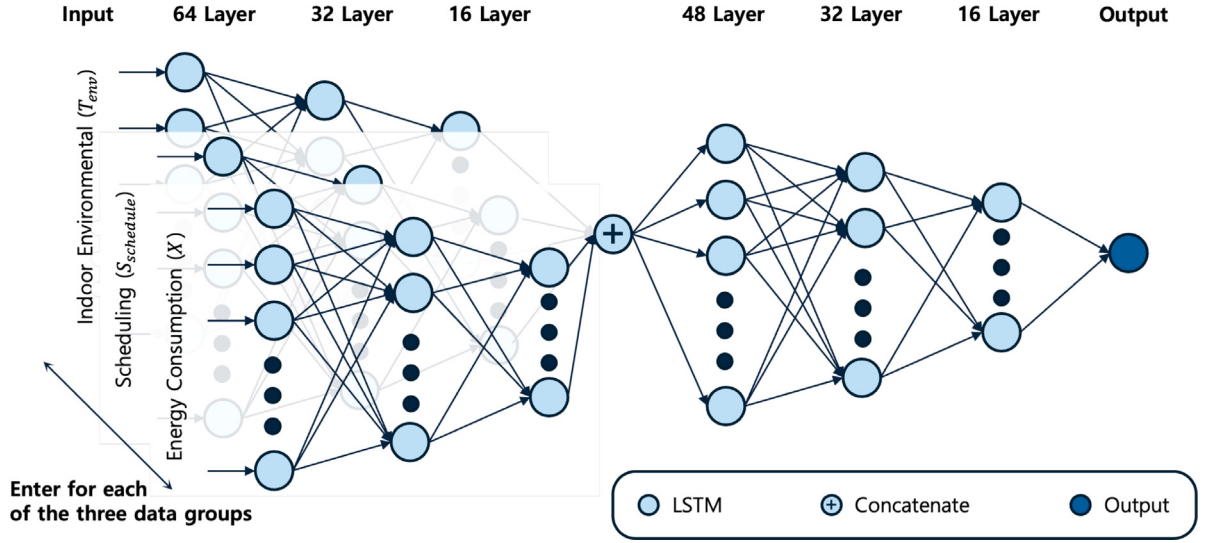


Fig. 8. Hierarchical multi-input processing and bottleneck optimization structure of MIBA-based LSTM.

Specifically, the model predicts energy consumption by taking as input the scheduling data and energy consumption records of the previous three days, as well as the scheduling data for the target prediction day. Additionally, the training data includes predicted values for temperature and humidity obtained from indoor environment forecasting, further improving the accuracy of energy consumption predictions. The configuration of the LSTM model used in this study is as follows:

$$Y_t = f \left( X_t, X_{t+1}, \dots, X_{t+n}, \right. \\ \left. S_{schedule}(t), S_{schedule}(t+1), \dots, S_{schedule}(t+n), \right. \\ \left. T_{env}(t), T_{env}(t+1), \dots, T_{env}(t+n) \right) \quad (7)$$

Here,  $Y_t$  denotes the energy consumption at the predicted time  $t$ , and  $X_t, X_{t+1}, \dots, X_{t+n}$  represent the energy consumption over the past  $n$  days. Moreover,  $S_{schedule}(t), S_{schedule}(t+1), \dots, S_{schedule}(t+n)$  represent the scheduling data for each time zone, and  $T_{env}(t), T_{env}(t+1), \dots, T_{env}(t+n)$  are the indoor environmental prediction values (temperatures). Based on this, the LSTM model learns the energy consumption pattern over time and predicts a pattern for the future.

The LSTM model used in this research consists of the following main components for each cell:

1. Input gate: Evaluates the importance of new information and decides whether to add it to the cell state. It considers the current energy consumption  $X_t$ , scheduling data  $S_{schedule}(t)$ , and indoor environment prediction values  $T_{env}(t)$ .
2. Forget gate: Assesses the relevance of existing information and decides whether to retain or remove it. This filters out unnecessary information from past energy consumption patterns for the current prediction.
3. Cell state: Stores the model's long-term memory. It maintains important patterns from the past  $n$  days of energy consumption, scheduling data, and indoor environment data, learning long-term dependencies.
4. Output gate: Determines which information from the current cell state should be output. This ultimately predicts the energy consumption  $Y_t$  at time  $t$ .

Through the interaction of these components, the LSTM model can effectively learn and predict complex energy consumption patterns over time.

The AI model used in this research is based on a basic LSTM structure. The simulator uses this model to predict the day's energy consumption by inputting energy data from three days prior, building scheduling data (including weekdays and holidays), and indoor environment prediction data. While this model has certain limitations in predicting absolute energy consumption values, it is effective in identifying energy consumption increase and decrease patterns and overall trends when coupled with scheduling data.

This approach provides sufficient performance for more accurately understanding and predicting building energy usage patterns, particularly useful in grasping the overall trends of consumption increases and decreases. These characteristics of the LSTM model are suitable for capturing and predicting the dynamic changes in complex building energy systems.

#### 2.2.4. Scheduling control

In order to optimize the operation of the air-conditioning system, the ACMV scheduling optimization part of the simulator based on model predictive control (MPC) [53] was designed. MPC uses a dynamic model of the system to calculate the optimal control

input within a given prediction interval, thereby generating an optimized operation schedule that considers both energy consumption and indoor comfort.

The MPC predicts the system status at 5-min intervals and calculates the optimal control input. This allows the ACMV system to maintain a constant indoor environment while minimizing energy consumption. The key objectives of scheduling optimization are twofold: First, the aim is to operate the system efficiently by minimizing energy consumption, and second, an environment needs to be provided that makes users feel comfortable by maintaining a comfortable indoor environment.

The corresponding objective function can be expressed as follows:

$$J = \sum_{t=0}^{N-1} (\lambda_1 \cdot E_t + \lambda_2 \cdot D_t) \quad (8)$$

Here,  $E_t$  is the energy consumption at time  $t$ ,  $D_t$  is denotes the indoor comfort index at time  $t$ , and  $\lambda_1$  and  $\lambda_2$  are represent the weights for each item. Based on this objective function, the optimal control input can be calculated to maximize the efficiency of the system and maintain the comfort level indoors.

The following is an algorithm that derives optimal control-scheduling data by reflecting the above objective function:

---

**Algorithm 1** MPC-based ACMV optimization control algorithm

---

- 1: **Input:** Energy-consumption-prediction data  $E_t$ , indoor-comfort-prediction data  $D_t$ , constraints, objective function
- 2: **Output:** Optimal control input  $\hat{u}(t)$
- 3: **Step 1: Entering the predicted data.**
- 4: Enter the energy consumption prediction data  $E_t$  and the indoor comfort prediction data  $D_t$
- 5: **Step 2: Calculating the target function.**
- 6: Calculate the target function  $J$  based on the input data:

$$J = \sum_{t=0}^{N-1} (\lambda_1 \cdot E_t + \lambda_2 \cdot D_t)$$

- 7:  $E_t$  denotes the energy consumption at time  $t$ ,  $D_t$  is the indoor comfort index at time  $t$ , and  $\lambda_1$  and  $\lambda_2$  represent weights.
- 8: **Step 3: Reflecting the constraints.**
- 9: Reflect the limits on control inputs, taking into account the system's constraints (precooling time, set temperature, maximum allowable range of temperature deviation)
- 10: **Step 4: Solving the optimization problem**
- 11: Calculate the optimal control input based on the objective function  $J$  and constraints:

$$\min_{\hat{u}(t)} J = \sum_{t=0}^{N-1} (\lambda_1 \cdot E_t + \lambda_2 \cdot D_t)$$

- 12: with the following conditions:

$$\underline{u}(t) \leq u(t) \leq \bar{u}(t)$$

- 13: Here,  $\underline{u}(t)$  and  $\bar{u}(t)$  represent the minimum and maximum values for the control input.
  - 14: **Step 5: Updating the control input.**
  - 15: Apply the optimized control input  $\hat{u}(t)$  to the system to update it to a new state
  - 16: **Step 6: Repeating.**
  - 17: It updates control inputs in real time every hour and solves the optimization problem by reflecting changes in the system status.
  - 18: Repeating this process minimizes the system's energy consumption and keeps the indoor environment comfortable.
  - 19: **Step 7: Returning the result.**
  - 20: Returns the optimal control input  $\hat{u}(t)$ .
- 

### 2.2.5. LSTM model and optimization details

This study proposes an LSTM model based on Multi-Input Bottleneck Architecture (MIBA) to solve the long-term dependency problem inherent in time series data (energy consumption  $X_t$ , scheduling  $S_t$ , environmental sensors  $T_t$ ) of ACMV systems. Considering the limited computing resources of existing Building Management Systems (BMS) and real-time processing requirements, each data stream ( $X_t$ ,  $S_t$ ,  $T_t$ ) is processed through independent LSTM branches and then undergoes hierarchical compression.

Specifically, each input branch (energy, schedule, environment) passes through separate LSTM layers to extract time-contextualized features. The extracted features are then integrated in a Concatenate layer and aggregated through subsequent LSTM and Dense layers with bottleneck structure. This replaces the complex structures required by tree-based models such as XGBoost and reduces the real-time processing load on BMS.

The layer-wise data processing mechanism of the proposed architecture is specified in Fig. 8, structurally demonstrating the process by which dynamic interactions of multi-input streams and hierarchical feature compression through bottleneck structure achieve optimal balance between energy prediction accuracy and computational efficiency.

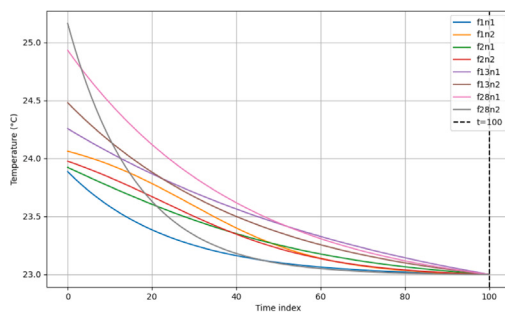
**Table 4**  
Space-specific optimal weight settings and pre-cooling strategy.

| Space zone          | Operation hours | Energy weight ( $\lambda_1$ ) <sup>a</sup> | Comfort weight ( $\lambda_2$ ) <sup>b</sup> | Characteristics and environmental considerations                                                                                                       |
|---------------------|-----------------|--------------------------------------------|---------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------|
| West Zone (Right)   | 8:00–18:00      | 0.45~0.55                                  | 0.55~0.45                                   | Strong afternoon solar radiation, high heat gain through walls and windows                                                                             |
|                     | 20:00–5:00      | 0.50~0.60                                  | 0.50~0.40                                   |                                                                                                                                                        |
| East Zone (Left)    | 8:00–18:00      | 0.25~0.35                                  | 0.75~0.65                                   | Morning solar radiation, relatively shaded in afternoon<br>Relatively low cooling load                                                                 |
|                     | 20:00–5:00      | 0.40~0.50                                  | 0.60~0.50                                   |                                                                                                                                                        |
| North Zone (Front)  | 8:00–18:00      | 0.35~0.45                                  | 0.65~0.55                                   | Moderate solar influence, high impact of outdoor temperature and humidity<br>Important ventilation and humidity control, moderate comfort requirements |
|                     | 20:00–5:00      | 0.45~0.55                                  | 0.55~0.45                                   |                                                                                                                                                        |
| Lobby/Common area   | 00:00–24:00     | 0.55~0.65                                  | 0.45~0.35                                   | High floating population, significant outdoor air infiltration. Energy saving while maintaining basic comfort                                          |
| Morning pre-cooling | 5:00–8:00       | 0.20~0.25                                  | 0.80~0.75                                   | Pre-cooling before work hours for initial comfort, high-efficiency cooling utilizing lowest outdoor temperature                                        |
| Evening pre-cooling | 18:00–20:00     | 0.30~0.40                                  | 0.70~0.60                                   | Removal of accumulated heat load during daytime                                                                                                        |

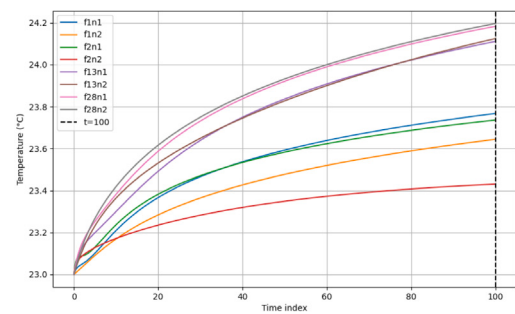
All weight pairs satisfy  $\lambda_1 + \lambda_2 = 1.0$  and are set to reflect hot and humid tropical climate and office building characteristics.

<sup>a</sup> Energy weight ( $\lambda_1$ ).

<sup>b</sup> Comfort weight ( $\lambda_2$ ).



(a)



(b)

**Fig. 9.** Simulation results of the indoor environment with and without ACMV operation: (a) ACMV operating, (b) ACMV stopped.

Model training was performed as an independent learning process for four MSBs (Main Switch Boards). To minimize seasonal bias effects during dataset construction, the entire data from June 2024 to January 2025 was divided into training (June–September), validation (October), and test (November–January) periods while preserving temporal order.

Hyperparameter optimization was performed using walk-forward validation technique, applying settings of initial window 40 days, step size 5 days, and prediction period 7 days. Adam (Adaptive Moment Estimation) optimizer was used for model training, and the temporal dependency processing capability and generalization performance of the proposed model were verified through evaluation using validation and test data.

Based on energy consumption data predicted through the LSTM model, this study proposes an optimization algorithm that achieves optimal balance between energy efficiency and indoor comfort of air conditioning systems using Model Predictive Control (MPC) framework. As presented in Algorithm 1, the main control process consists of three core mechanisms.

In the first stage (Step 2 of the algorithm), an objective function ( $J$ ) combining space-specific energy consumption data ( $E_t$ ) and comfort index ( $D_t$ ) predicted from the LSTM model is constructed and stored in the database to secure basic data for space-specific control. The optimal weights ( $\lambda_1, \lambda_2$ ) for each space are set to default values according to space-specific characteristics and dynamically adjusted within the range presented in Table 4.

In the second stage (Step 3), space-specific dynamic constraints were defined based on data collected from actual space users. Specifically, pre-cooling availability periods, temperature setpoint ranges, and maximum allowable temperature deviations were dynamically configured to reflect space-specific characteristics and user preferences.

In the final stage (Step 4), the objective function and constraints are integrated to generate optimal control schedules for 24-h periods, outputting comfort-optimized temperatures based on minimum and maximum temperature ranges. Additionally, during

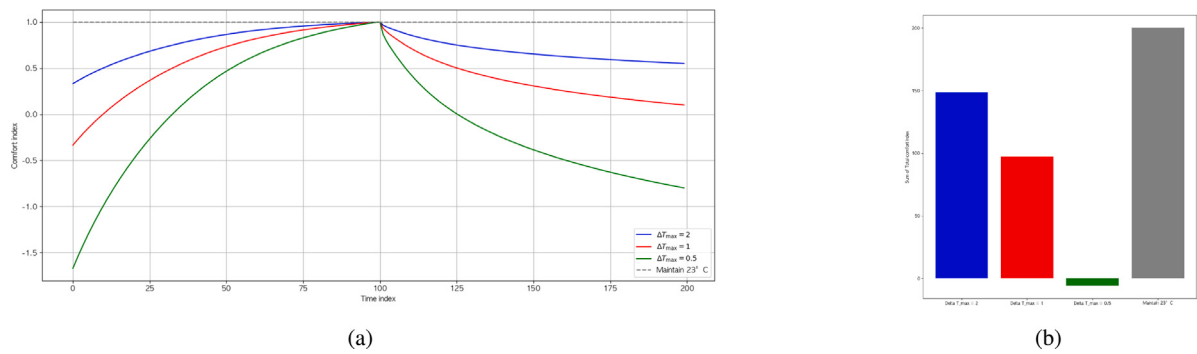


Fig. 10. Indoor-comfort simulation results: (a) Indoor-comfort hourly change graph, (b) Overall-comfort sum graph depending on the temperature deviation.

operation, a feedback loop is implemented that adjusts the control plan for the corresponding space with a 24-h delay when user discomfort complaints occur, simultaneously ensuring real-time comfort maintenance and system stability.

### 3. Results and discussion

This section analyzes and discusses the results of experiments conducted using the developed simulator. The experiments consist of indoor environment modeling, indoor comfort analysis, energy data analysis, ACMV-optimized scheduling evaluation, and long-term simulation. After presenting the results for each stage, the performance of the entire system is comprehensively evaluated.

First, the impact of the ACMV operation on changes in temperature and humidity will be analyzed via indoor-environment modeling. Based on this, an indoor-comfort assessment is conducted to examine the effect of an optimized cooling strategy on maintaining the indoor environment. Next, the relationship between ACMV operation and energy consumption patterns is identified by analyzing energy data in 5-min intervals, and the performance of ACMV-optimized scheduling is evaluated by comparing it with the existing method. This will output the optimal cooling strategy that considers both energy savings and indoor environmental maintenance. Finally, long-term simulations using one month of data will be conducted to examine whether the optimization strategy proposed in this study can be continuously applied in the real world.

#### 3.1. Indoor-environment simulation and comfort evaluation

The indoor-environment prediction model was used to assess whether the ACMV was operating. The results showed that when the ACMV was active, the predicted heat load varied based on the operating temperature and the set temperature. When the ACMV was inactive, the heat load was influenced by the outdoor temperature and duration.

Fig. 9 shows the results of the simulations for each floor when the indoor environment was set to a constant temperature of 23 °C and the ACMV was either running or stopped. Fig. 9(a) shows that the temperature quickly adjusts to a lower temperature as the height increases. Fig. 9(b) shows that when the ACMV stops operating, the temperature changes more rapidly as the height increases and then changes more slowly as it approaches the outside temperature.

The results of the indoor comfort assessment based on the simulation results are shown in Fig. 10. The comfort assessment was conducted for the same period as the indoor-environment simulation time ( $t = 200$ ). Fig. 10(a) is a graph of comfort calculated on a time basis that depends on the indoor changes. When the indoor temperature is kept constant at 23 °C, the comfort index remains at one, and as the temperature deviation decreases from 2.0 to 0.5, the comfort index changes rapidly. Fig. 10(b) is a graph showing the sum of the total comfort index for a period of based on the temperature deviation. The most comfortable environment was achieved when the set temperature was maintained, and the comfort index was the highest. The comfort index tended to decrease as the temperature deviation increased.

#### 3.2. Energy-consumption-forecast results

In this paper, we analyzed the characteristics of 5-min energy data and derived energy usage patterns by time of day and day of week. We identified the relationship between ACMV operation and the building's overall energy consumption and found potential for optimization.

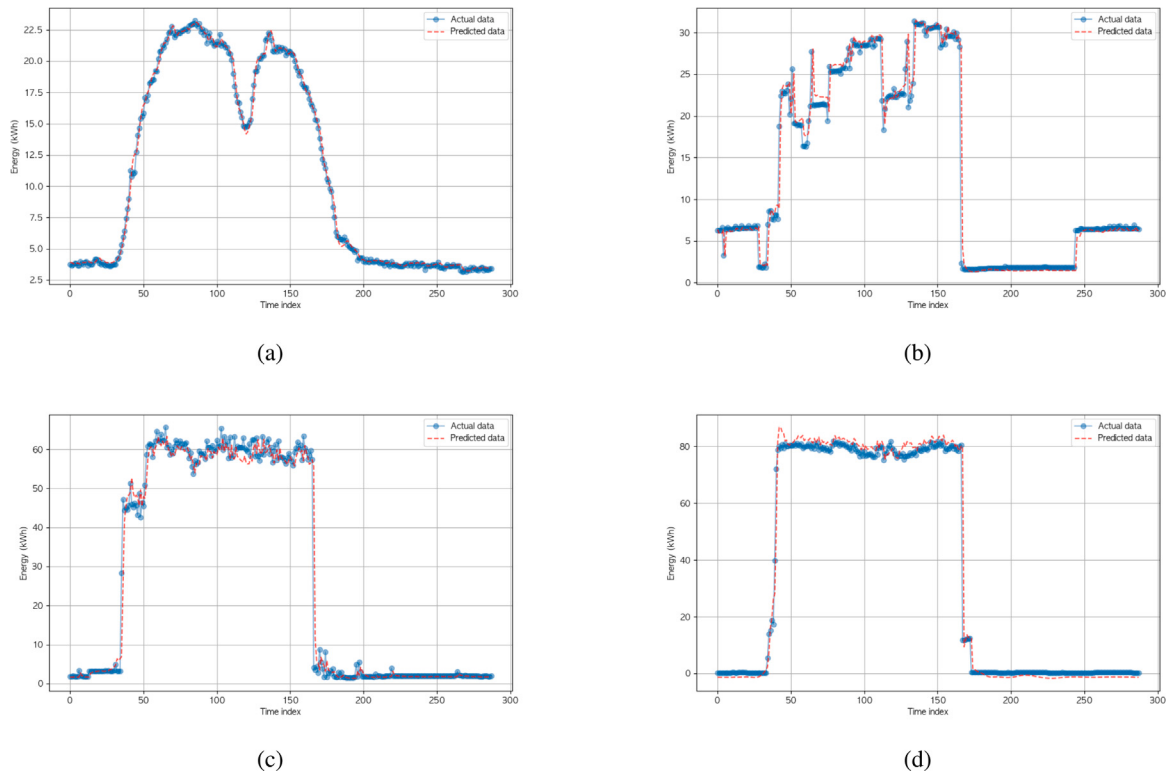
The energy-consumption forecast model was used to forecast the energy consumption of each MSB using walk-forward validation methodology, and the results are shown in Fig. 11. The validation process consisted of 21 time periods with initial window of 40 days, step size of 5 days, and prediction period of 7 days to ensure robust model evaluation.

When we analyze the prediction results using walk-forward validation across 21 time periods, we observe that all models demonstrate robust performance with  $R^2$  scores ranging from 0.880 to 0.926 (as detailed in Table 5). The confidence intervals

**Table 5**  
Energy consumption prediction model performance comparison through walk-forward validation.

| MSB  | Validation steps | RMSE   | MAE   | R <sup>2</sup> Score | CI (R <sup>2</sup> ) <sup>a</sup> |
|------|------------------|--------|-------|----------------------|-----------------------------------|
| MSB1 | 21               | 2.248  | 1.989 | 0.908                | (0.900–0.917)                     |
| MSB2 | 21               | 4.212  | 3.522 | 0.880                | (0.868–0.891)                     |
| MSB3 | 21               | 7.459  | 6.284 | 0.920                | (0.912–0.928)                     |
| MSB4 | 21               | 10.762 | 9.572 | 0.926                | (0.920–0.932)                     |

<sup>a</sup> 95% confidence intervals (CI) for R<sup>2</sup> scores.



**Fig. 11.** Simulation results using the energy consumption prediction model (blue is the actual energy consumption and red is the predicted result): (a) MSB1, (b) MSB2, (c) MSB3, (d) MSB4. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

indicate consistent model reliability across different validation periods, confirming the temporal stability of the proposed LSTM architecture.

An analysis of the error indicators RMSE and MAE reveals that the MSB1 model achieves the highest prediction accuracy with the lowest RMSE (2.248) and MAE (1.989), demonstrating exceptional performance for this specific electrical distribution system. The MSB2 model, while showing higher absolute errors (RMSE: 4.212, MAE: 3.522), maintains good predictive capability with an R<sup>2</sup> score of 0.880.

Interestingly, MSB3 and MSB4 models, despite exhibiting higher absolute errors due to their larger energy consumption scales, demonstrate superior R<sup>2</sup> scores of 0.920 and 0.926 respectively. This suggests excellent model fit and explanatory power for these higher-consumption systems, indicating that the MIBA-based LSTM architecture effectively captures the complex energy consumption patterns regardless of scale differences.

The model predicting MSB1 demonstrates optimal performance in terms of absolute error metrics, making it highly suitable for precise energy management applications. Conversely, MSB4 shows the highest R<sup>2</sup> score (0.926), indicating excellent variance explanation capability and robust pattern recognition for large-scale energy systems.

These findings confirm the efficacy of the proposed energy-consumption-prediction model in learning and predicting the energy usage patterns of each MSB across different scales and operational characteristics, as illustrated in Fig. 11. The prediction model showed trends closely matching actual energy consumption patterns (where blue represents the actual energy consumption and red denotes the predicted result).

Notably, the high prediction accuracy across all MSBs, with R<sup>2</sup> scores consistently above 0.88, suggests that the MIBA-based LSTM architecture successfully captures both temporal dependencies and scale-specific characteristics of building energy systems.

**Table 6**  
ACMV optimization simulation results (One month).

| Performance metric               | Savings   | Savings percentage (%) |
|----------------------------------|-----------|------------------------|
| Energy savings (kWh)             | 12,870.76 | 2.64%                  |
| Carbon emission reduction (kg)   | 5912.83   | 2.55%                  |
| Normal usage cost reduction (RM) | 4697.83   | 2.63%                  |
| Peak usage cost reduction (RM)   | 1605.90   | 2.12%                  |
| Total cost savings (RM)          | 6303.73   | 2.63%                  |

The variation in absolute error metrics (RMSE and MAE) primarily reflects the different operational scales of each MSB rather than model inadequacy.

The findings serve as fundamental data for the enhancement of building energy management systems and the development of effective energy-utilization strategies. The robust performance across different MSB scales demonstrates the scalability and adaptability of the proposed forecasting framework. Subsequent research should examine the integration of these prediction models with real-time control systems and explore methods to further enhance the temporal resolution of predictions for more granular energy management applications.

### 3.3. Daily ACMV-optimized scheduling

The ACMV-optimized control algorithm was verified using indoor predictions, indoor comfort values, and energy consumption predictions that had been verified. As illustrated in Fig. 12, the simulation results for ACMV-control scheduling at Level 28 were analyzed. The sequence of graphs in Fig. 12 is as follows: existing scheduling data, indoor environment graph, indoor comfort graph, energy consumption graph, and optimized control-scheduling graph. Previously, ACMVs No. 58 and 60, installed at Level 28, operated from 8:00 to 18:30, and No. 59 was not used as a spare. The application of the ACMV-optimization-control algorithm resulted in the pre-cooling process being initiated 30-min earlier and the introduction of three off periods to derive the optimal control scheduling. The simulation results demonstrated that the indoor environment could be optimized by commencing pre-cooling at 7:30 a.m., which results in the indoor comfort level converging to a comparable level (as observed in the standard schedule). With respect to energy consumption, while the initial usage increased due to the pre-cooling, the overall average usage per 5-min interval decreased. This led to a decline in total daily usage from 10,305.83 kWh to 9863.87 kWh and a daily peak from 84.33 kWh to 81.69 kWh.

The findings of this study demonstrate the efficacy of the proposed ACMV-optimization-control algorithm in achieving a balance between energy conservation and indoor comfort.

### 3.4. Results of long-term simulations

The results of the ACMV optimization simulation for one month for the entire floor are shown in Table 6. These findings provide a good amount of data to enable the analysis of the effects of the ACMV optimization strategy over an extended period and for the evaluation of energy and cost savings.

The simulation yielded a 12,870.76 kWh decrease in energy consumption and a 5912.83 kg CO<sub>2</sub> reduction in carbon emissions. The carbon emissions calculation employed the 2022 national greenhouse gas emission factor of 0.4747 kg CO<sub>2</sub>/kWh [54], which represents the emission factor for the consumption stage.

The financial analysis was conducted in Malaysian ringgit (RM). The fundamental rate [55] was RM 0.365 per kWh, and for peak usage, a rate structure was applied that charges RM 30.3 per kWh for the maximum monthly peak. The calculation yielded a total savings of RM 4697.83 for normal usage and RM 1605.90 for peak usage, which amounts to a total of RM 6303.73.

The findings of these long-term simulations indicate that the ACMV-optimization strategy has the potential to enhance energy efficiency and reduce costs to a considerable extent. Moreover, the reduction in carbon emissions is anticipated to exert a favorable effect on environmental sustainability. However, these results have been derived only from simulations, and additional verification is necessary for practical applications to account for various factors, such as seasonal variations and alterations in building-usage patterns.

### 3.5. Real-time operational verification results

As a result of applying the proposed optimization to optimal control of one AHU (East Zone) for 24 h, a new optimal control range differentiated from the conventional general comfort range was established and operated. Through the verification results, control was effectively applied within dynamic temperature constraint ranges, and pre-cooling (05:00-08:00) and evening control (18:00-20:00) strategies operated normally to reduce the energy burden for the following day.

Fig. 13 shows the 24-h real-time control performance of the East Zone AHU. In the upper graph, it can be confirmed that the actually measured temperature is stably controlled within the dynamically set constraint range (orange shaded area), and the lower graph represents the ON/OFF operation pattern of the AHU. Particularly in the pre-cooling section (05:00-08:00), preliminary cooling was performed in preparation for daytime operation through active cooling operation, and during nighttime hours (20:00-05:00), only minimal operation was conducted for energy conservation.

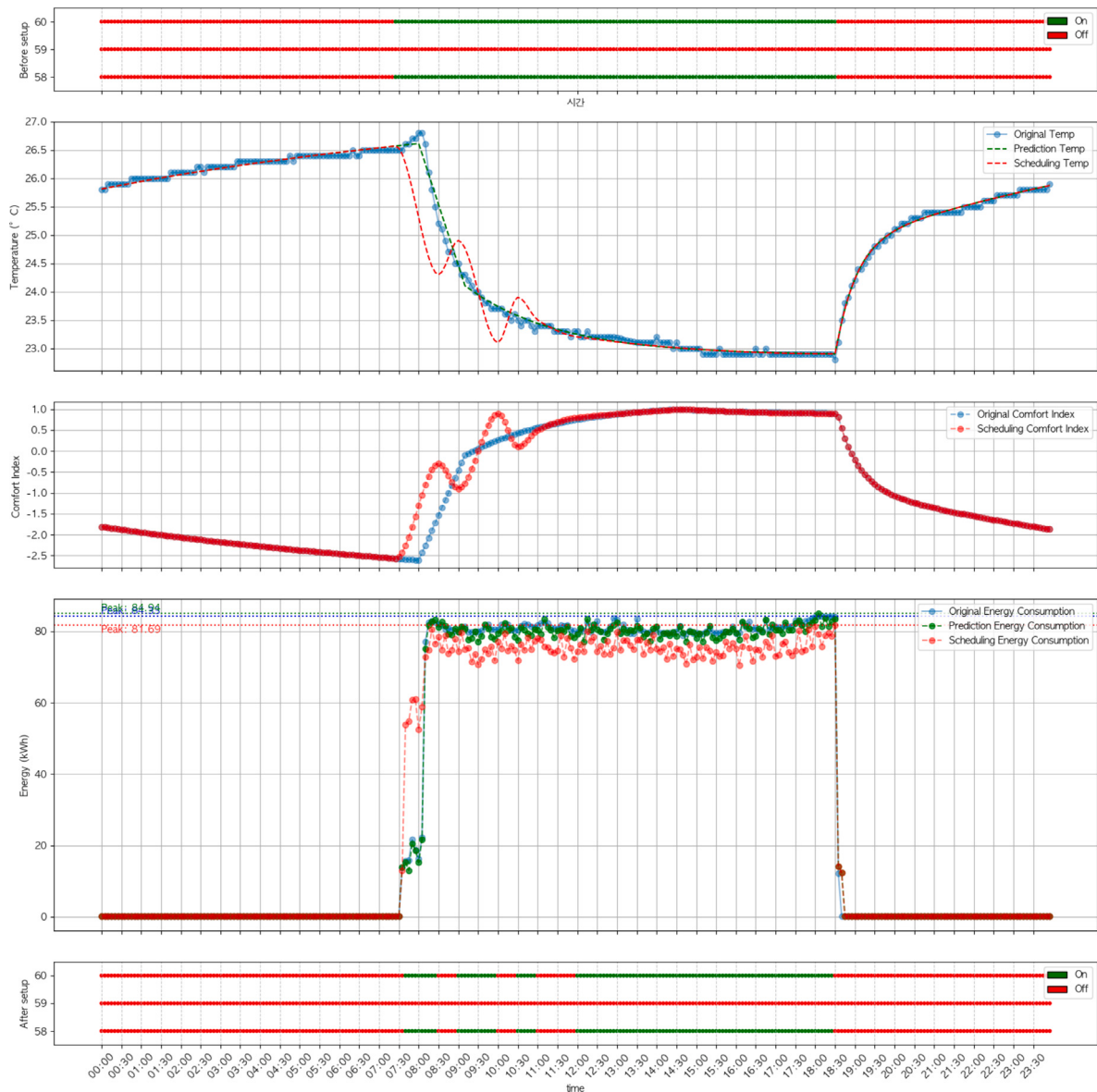


Fig. 12. Results of the daily scheduling graph for the Level 28 ACMV (daily-scheduling graph - MSB4 scheduling with High-rise group sensors).

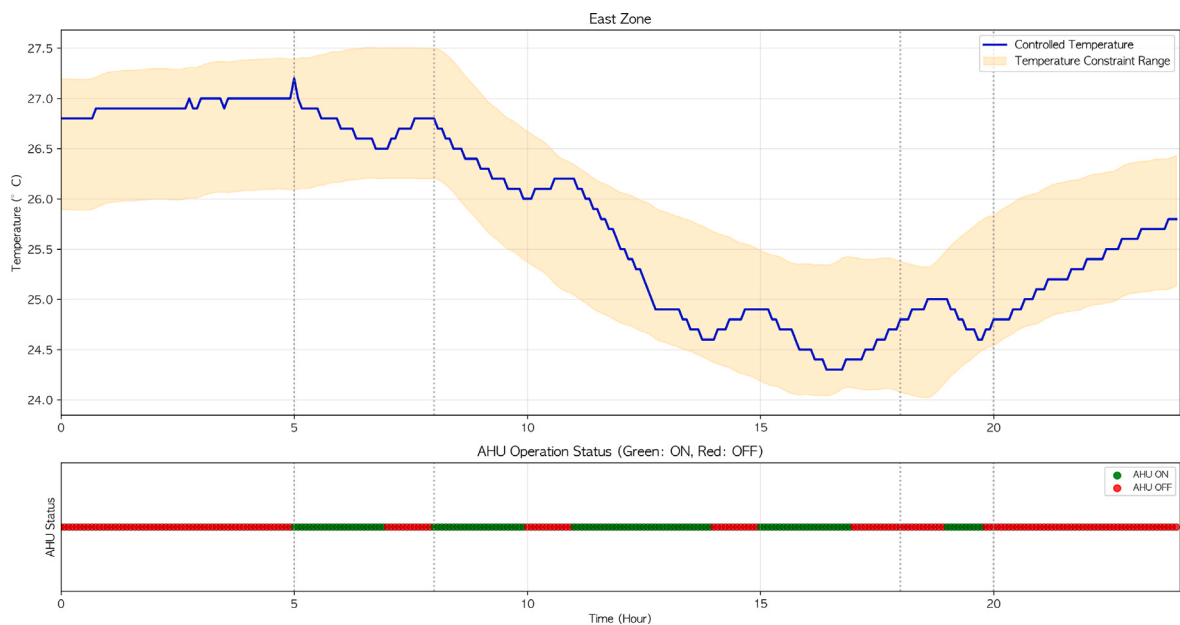
Table 7

MPC optimal control system performance comparison results (Daily operation basis).

| Performance metric       | Conventional system | MPC optimal control system | Improvement rate (%) |
|--------------------------|---------------------|----------------------------|----------------------|
| Daily operation time (h) | 10.0                | 9.83                       | 1.7                  |
| Energy consumption (kWh) | 24,705              | 24,695                     | 0.04                 |

As can be confirmed through Table 7, while the general AHU operation time was 10 h, using the proposed MPC-based system achieved operation for 9 h and 50-min, accomplishing approximately 10-min of operation time reduction.

More importantly, it was confirmed that the system operates stably within the dynamic temperature control range set by Algorithm 1. As shown in the upper graph of Fig. 13, temperature is adaptively controlled according to time-varying constraints, and it can be confirmed that the lower AHU operation pattern also efficiently responds to these temperature control requirements.



**Fig. 13.** East Zone AHU MPC-based temperature control and operation pattern (24-h operation results). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The energy consumption measured in this verification, 24,695 kWh, represents the total energy consumption of the target building, achieving a reduction effect of 10 kWh (0.04%) compared to the conventional system. When these verification results are applied to all 60 AHUs, a total daily reduction of 600 kWh is expected, which is evaluated as fundamental verification results for achieving the 2.64% energy reduction rate predicted in the previously conducted simulation studies. This is judged to be an important step in confirming the consistency between the theoretical modeling of the proposed MPC algorithm and actual application results.

### 3.6. Applicability to different climates and limitations

While the proposed ACMV optimization strategy was specifically developed and validated for hot and humid climates such as Kuala Lumpur, its modular and data-driven framework allows for adaptation to other climate zones. In temperate regions, the algorithm can be recalibrated to prioritize sensible cooling and heating loads, with humidity control logic simplified or omitted. In arid climates, the focus would shift toward maximizing cooling efficiency and potentially integrating evaporative cooling methods, while humidity constraints become less critical. Therefore, with appropriate adjustment of control parameters and retraining using local environmental and operational data, the core methodology can be extended to a wide range of climatic conditions, though the specific control priorities and anticipated energy savings may differ by region.

However, there are several limitations to practical implementation. First, the proposed framework relies on high-frequency data collection (every 5-min), which may not be feasible in buildings lacking IoT sensors or advanced BMS (Building Management System) infrastructure. Second, real-time optimization and control require integration with modern BMS platforms capable of actuator-level control, which may not be available in older or less-equipped buildings. These factors may limit the immediate scalability of the approach. Future research should explore solutions such as lower-frequency data adaptation, cloud or edge computing integration, and cost-effective retrofit strategies to broaden the applicability of the proposed methodology.

## 4. Conclusions

This paper proposes a cooling strategy optimized for the hot and humid climate characteristics of Southeast Asia, seeking regionally customized sustainable solutions. The simulation and empirical validation results integrating indoor environment modeling, comfort analysis, energy consumption prediction, and ACMV (Air Conditioning and Mechanical Ventilation) optimization scheduling have led to the following key conclusions:

1. The impact of ACMV operation on indoor temperature and humidity was analyzed through indoor environment simulation. Temperature changes occurred more rapidly as building height increased, suggesting this is a critical factor to consider when establishing ACMV control strategies.

2. Comfort evaluation results demonstrated that replacing conventional simplified PMV/PPD-based models with an Adaptive Comfort Model based on actual user temperature preference data achieved optimal comfort levels while maintaining ASHRAE Standard 55 [49] compliance. This represents a practical solution that ensures international standard conformity while maximizing actual user satisfaction.
3. **AI-based Energy Consumption Prediction Model Performance:** Walk-Forward Validation across 21 validation stages achieved exceptional performance with MSB1 ( $R^2 = 0.908$ , RMSE = 2.248), MSB2 ( $R^2 = 0.880$ , RMSE = 4.212), MSB3 ( $R^2 = 0.920$ , RMSE = 7.459), and MSB4 ( $R^2 = 0.926$ , RMSE = 10.762). All MSB systems recorded  $R^2$  scores above 0.88, validating the temporal dependency processing capability and scalability of the MIBA-based LSTM architecture.
4. **Real-time Operational Verification Results:** 24-h empirical experiments on East Zone AHU achieved 1.7% operation time reduction (10 h  $\rightarrow$  9 h 50-min) and 0.04% energy consumption reduction. When scaled to all 60 AHUs, daily savings of 600 kWh are expected, providing fundamental validation for achieving the 2.64% energy reduction rate predicted in simulations.
5. The long-term simulation over one month demonstrated a reduction in energy consumption of 12,870.76 kWh (2.64%) compared to the baseline system, which translated to a decrease of 5912.83 kg in CO<sub>2</sub> emissions (2.55%) and cost savings of RM 6303.73 (2.63%). While these achievements are relatively modest compared to the average reduction rates (4.9–30.2%) reported in existing HVAC optimization studies [40], they represent the outcome of a conservative approach that prioritizes user comfort, thereby demonstrating high applicability in real operational environments. Future implementation of metaheuristic optimization techniques such as reinforcement learning or genetic algorithms is expected to yield additional energy savings while maintaining occupant comfort levels.

**Methodological Innovation and AI Integration Contributions:** This research establishes unprecedented technical foundations through high-precision energy consumption prediction using Multi-Input Bottleneck Architecture (MIBA)-based LSTM models. The implementation of Walk-Forward Validation methodology with temporal dependency preservation across 21 validation stages presents a rigorous model evaluation framework that significantly advances the field. The integration of time-differentiated temperature constraints for nighttime, pre-cooling, and daytime periods, combined with real-time response system implementation through 5-min high-resolution data processing, demonstrates exceptional technical sophistication. Particularly, the validation of consistency between theoretical modeling and actual implementation results through empirical experiments establishes research reliability and presents a pioneering case study that effectively resolves the chronic comfort-efficiency trade-off problem in existing HVAC optimization research through AI-based adaptive control and empirical validation.

**Comprehensive Impact of Carbon Neutrality Achievement through AI Integration:** The AI-based ACMV optimization strategy proposed in this research presents an innovative and practical solution for sustainable building energy management in Southeast Asia. Based on empirical results, scaled implementation is expected to achieve approximately 95 tons of annual CO<sub>2</sub> reduction, and when applied to similar-scale Malaysian commercial buildings, it possesses substantial regional-level carbon reduction potential. The 5-min interval real-time data-based AI control system provides dramatically enhanced responsiveness compared to conventional hourly control systems, establishing critical technological infrastructure for achieving smart city and carbon neutrality policy objectives. The annual carbon reduction effect of approximately 71 tons calculated from monthly 5.9 tons demonstrates substantial environmental contribution potential when applied across the entire region.

**Practical Applicability and Scalability Validation:** Through comprehensive validation combining simulation and empirical verification, high consistency between predicted energy reduction effects and actual experimental results was confirmed. Stable operation within dynamic temperature control ranges set by the proposed algorithm demonstrates system reliability, while single AHU empirical results establish the foundation for performance prediction across all 60 AHU systems. The application of comfort models meeting ASHRAE Standard 55 [49] criteria ensures international standard compliance while demonstrating the practical applicability of the proposed MPC algorithm through stable real-time temperature control performance.

This research focused on implementing real-time response systems utilizing 5-min interval data. Although the data collection period spans approximately 8 months, Malaysia's consistent annual climate patterns enable effective real-time control. Currently, single AHU empirical validation has established the foundation for phased integrated validation across all 60 building AHUs. Scale expansion validation targets additional 20%–30% efficiency improvements through progressive implementation in Phase 1 (3 AHUs-1 floor), Phase 2 (18 AHUs-6 floors), and Phase 3 (60 AHUs-28 floors), utilizing load diversity and inter-system optimization for multi-AHU synergy effects.

The research results highlight building energy efficiency improvement potential in Southeast Asia's hot and humid climate while acknowledging the possibility of unforeseen variables in actual operational environments. Future research should focus on long-term validation and improvement through actual building implementation. As the scalability of the developed ACMV optimization strategy and simulation model accuracy have been empirically validated, more sophisticated prediction and control system development becomes possible. Future implementation of metaheuristic optimization techniques such as reinforcement learning or genetic algorithms is expected to achieve additional energy savings while maintaining occupant comfort levels.

In conclusion, this paper establishes a robust and reliable technological foundation for sustainable building energy management in Southeast Asia through rigorous research methodology integrating simulation and empirical validation, providing practical and innovative insights that can accelerate future energy policy formulation and carbon neutrality goal achievement, demonstrating substantial potential for regional-scale environmental impact and sustainable development advancement.

## CRediT authorship contribution statement

**Seunghwan Kim:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Byeongkwan Kang:** Resources, Conceptualization. **Sanghoon Lee:** Software, Data curation. **Tacklim Lee:** Writing – review & editing, Investigation. **Guwon Yoon:** Validation, Software. **Younghyun Baek:** Visualization, Investigation. **Myeong-in Choi:** Software, Data curation. **Sehyun Park:** Supervision, Project administration, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgments

This work was partly supported by the Institute of Information & Communications Technology Planning & Evaluation(IITP)-ITRC(Information Technology Research Center) grant funded by the Korea government(MSIT) (IITP-RS-2024-00436248, 50), and this work was supported by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant, funded by the Korean government (MOTIE) (RS-2024-00398346, ESS Big Data-Based O&M and Asset Management Technical Manpower Training).

## Data availability

Data will be made available on request.

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