

Study on Low-Carbon Retrofit of Existing Teaching Buildings in Severe Cold Regions in Winter Based on an Adaptive Thermal Comfort Model

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Received: 25 June 2026; **Accepted:** 10 July 2026; **Published:** 4 August 2026

Abstract:

Existing teaching buildings in severe cold regions have long heating seasons, significant envelope heat loss, and high operational carbon emissions, with indoor thermal comfort jointly influenced by heating systems, insulation performance, and students' adaptive behavior. The traditional PMV thermal comfort evaluation model does not consider users' adaptive behavior, making it difficult to accurately reflect actual thermal sensation and easily leading to deviations in low-carbon retrofit schemes. Taking an existing university teaching building in a severe cold region as the research object, based on field measurements in winter and 281 valid thermal sensation questionnaires, a winter adaptive thermal comfort correction model (aPMV) applicable to teaching spaces in severe cold regions is developed. Through regression analysis, the winter adaptive coefficient $\lambda = -0.19$ is determined, and its fitting accuracy for actual thermal sensation under slightly cold conditions is verified to be better than that of the traditional PMV model. Based on this, a Design Builder dynamic energy model is developed, and the aPMV-based Thermal Discomfort Time Ratio (DTR) is introduced to evaluate retrofits such as wall and roof insulation and window replacement. Results show that wall insulation most effectively reduces heating loads, window replacement best improves local thermal comfort, and the combined retrofit achieves the best overall performance in carbon reduction, energy saving, and comfort improvement. This study incorporates human thermal adaptation into building energy evaluation, overcoming the disconnect of traditional methods from real use, improving the accuracy of low-carbon retrofit decisions for existing campus buildings in severe cold regions, and providing theoretical and technical references for similar energy-saving renovations.

Keywords:

Severe Cold Region, Existing Teaching Building, Low-carbon Retrofit, Adaptive Thermal Comfort, aPMV, Building Energy Simulation

1. Introduction

Against the background of global carbon neutrality and the green low-carbon transition of buildings, energy-saving and low-carbon retrofitting of existing university buildings has become an important component of campus infrastructure renewal [1]. Compared with newly constructed buildings, early-built existing teaching buildings usually suffer from insufficient thermal performance of envelope structures, poor air tightness of external windows, and aging insulation systems, resulting in high winter energy consumption and low energy efficiency [2]. For universities in severe cold regions, the heating period is long, and winter heating load accounts for a very high proportion of annual building energy consumption, becoming the main source of carbon emissions during building operation, which makes energy-saving retrofit and thermal environment optimization of existing teaching buildings highly region-specific and practically necessary [3].

Indoor thermal comfort is a core indicator for evaluating both residential environmental quality and energy-saving retrofit effectiveness, and most current studies adopt the steady-state PMV thermal comfort model proposed by Fanger [4]. This model has a well-established thermodynamic heat balance mechanism and is widely used, but it does not fully consider dynamic thermal adaptive behavior in real teaching scenarios. In long-term centrally heated teaching buildings in severe cold regions, students develop environmental adaptation through clothing adjustment, behavioral modification, and changes in psychological expectations [5]. As a result, deviations occur between traditional PMV predictions and actual student thermal sensation, which may lead to misjudgment of indoor thermal environments and subsequently affect the scientific validity and accuracy of retrofit strategies [6].

To address the aforementioned research gaps, this study takes a typical existing university teaching building in a severe cold region as the research object. Based on field measurements of the indoor environment during winter and occupants' thermal sensation questionnaires, a winter adaptive thermal comfort correction model (aPMV) suitable for teaching spaces in severe cold regions is developed [7]. On this basis, a dynamic building energy simulation is conducted, and an evaluation index that integrates both energy consumption and thermal comfort is introduced [8]. The study systematically investigates the performance of envelope retrofit strategies such as external wall insulation, roof insulation, and window replacement, and analyzes the energy-saving, carbon-reduction, and thermal comfort improvement mechanisms of different retrofit schemes [9][10]. The results can provide references for green and low-carbon renovation as well as refined energy-saving retrofitting of existing university teaching buildings in severe cold regions.

2. Research Methodology

2.1. Research Object

The research object of this study is an existing university teaching building constructed around 2002 in a severe cold region. In this period, university building design mainly focused on basic teaching functions and construction cost control, while green energy-saving and low-carbon concepts were not yet widely adopted. Therefore, building envelope thermal performance and energy-saving construction measures have typical limitations of the era, making it representative among existing campus buildings in severe cold regions. The building is a four-story "courtyard-

shaped” internal corridor structure, with a total height of about 15 m and a standard floor height of 3.6 m. Classrooms are mainly arranged in the north–south direction, and internal circulation is organized through a ring corridor system. The building mainly includes large classrooms of about 120 m² and small classrooms of about 70 m², which are representative of typical university teaching spaces. In addition, there is an irregular stepped classroom that is not representative; therefore, it is not included in this study.

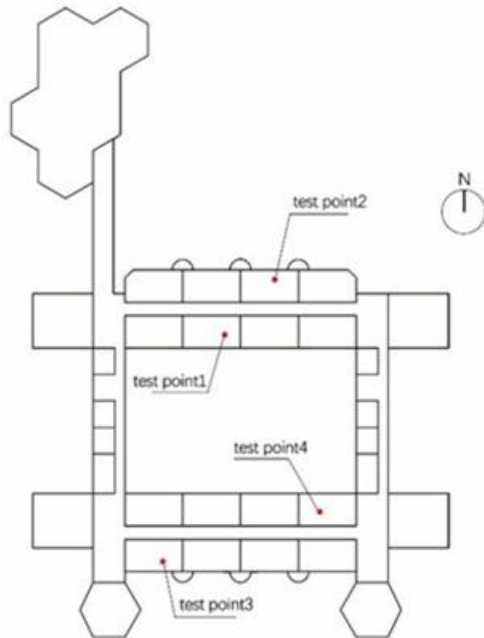


Figure 1. Plan of teaching building.

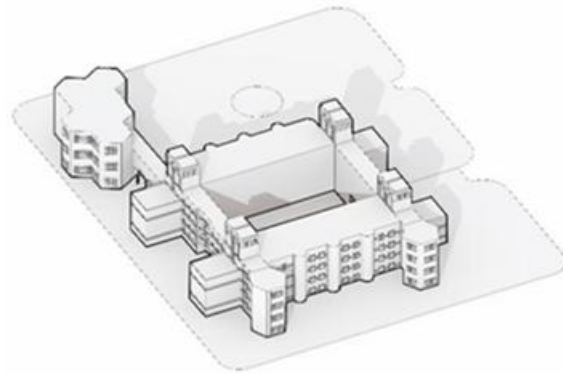


Figure 2. Model of teaching building.

The overall building envelope has weak thermal performance and no dedicated insulation design. Detailed construction forms and thermal transmittance parameters of building components are shown in Table 1.

Table 1. Envelope structure and thermal parameters of teaching building.

Structural components	Construction method	Heat transfer coefficient K/[W/ (m ² ·K)]
exterior wall	20mm cement mortar+370mm solid clay brick+20mm cement mortar	1.50
roofing	Waterproof layer+slope making layer+100mm reinforced concrete+20mm cement mortar	1.80
exterior window	Single layer ordinary glass aluminum alloy window	5.80
interior wall	20mm cement mortar+240mm hollow brick+20mm cement mortar	2.05

2.2. Climatic Conditions and Usage Scenarios

The building is located in a severe cold climate region, characterized by long, extremely cold winters, low outdoor temperatures, and large fluctuations. Heating demand lasts for a long period [11]. The local heating season is from mid-October to mid-April, with a total duration of approximately 183 days per year. Heating energy consumption accounts for the dominant proportion of total building energy use. The

special climatic conditions lead to significant heat loss through building envelopes and obvious cold air infiltration through windows, which are the key external factors determining indoor thermal environment and energy consumption in winter.

From the perspective of usage and occupant characteristics, the building is mainly used by university students. Occupants mainly engage in sedentary activities such as attending lectures and self-study, with an average metabolic rate of about 1.1 met. During the heating season, students generally develop clothing habits adapted to indoor environments, with an average clothing insulation of about 1.2 clo. Students in long-term heated environments exhibit significant thermal adaptation ability. Their thermal sensation is influenced not only by physical environmental parameters, but also by psychological expectations and behavioral adjustments [12]. Therefore, in teaching buildings in severe cold regions, traditional steady-state thermal comfort models may not accurately reflect actual occupant experience [13].

2.3. Data Collection

Field measurements were conducted during the winter heating period in January 2026, over three consecutive working days. Four typical classrooms at different orientations and floors were selected as measurement points: second-floor south-facing, third-floor south-facing, second-floor north-facing, and third-floor north-facing classrooms. Measured parameters included indoor and outdoor air temperature, relative humidity, air velocity, and globe temperature. Measurement points were arranged at the center of classrooms, 0.5 m from walls, and at a height of approximately 1.2 m to simulate seated occupants. Outdoor meteorological data were collected simultaneously.

Statistical results of the measured environmental data are shown in Table 2. During the measurement period, outdoor temperature ranged from -15.5°C to -2.3°C, while indoor temperature ranged from 16.2°C to 22.5°C, with an average value of about 19.3°C. Indoor air velocity was generally low, consistent with static classroom conditions.

Table 2. Collation results of measured data.

Parameters	Outdoor temperature /°C	Indoor temperature /°C	Black ball temperature /°C	Relative humidity /%	Air velocity m/s
average value	-12.8	19.3	18.9	32	0.07
maximum	-15.5	22.5	22.0	45	0.15
minimum	-2.3	16.2	15.8	25	0.05

Simultaneously with environmental measurements, a subjective thermal sensation questionnaire survey was conducted to ensure one-to-one correspondence between objective environmental data and subjective perception. A total of 281 valid questionnaires were collected. The respondents were mainly university students. Under classroom conditions, metabolic rate was set as 1.1 met, and clothing insulation was approximately 1.2 clo. The ASHRAE seven-point thermal sensation scale was adopted as the subjective evaluation method [14]. As shown in Table 3:

Table 3. ASHRAE seven-point thermal sensation scale.

Cold	Cool	Slightly Cool	Moderate	Slightly Warm	Warm	Heat
-3	-2	-1	0	+1	+2	+3

Survey results show that thermal sensation votes mainly fall within the range of -1 to +1, indicating that the indoor winter heating environment generally meets basic teaching requirements. However, a relatively high proportion of slightly cold votes exists, and about 45% of respondents expressed a need for higher indoor temperature, indicating local thermal discomfort in the building.

2.4. Thermal Comfort Model Development

2.4.1. MTS Model

To quantify subjective thermal sensation, the Mean Thermal Sensation (MTS) model is established using operative temperature binning. Operative temperature is divided into intervals of 0.5°C. The arithmetic mean of thermal sensation votes (TSV) within each interval is taken as the MTS value [15]. The midpoint of each temperature interval is used as the independent variable, and MTS as the dependent variable, to establish the relationship between operative temperature and group thermal sensation. As shown in expression (1):

$$MTS_j = \frac{\sum_{i=1}^{n_j} TSV_{ij}}{n_j} \quad (1)$$

MTS_j —— the mean thermal sensation in the j -th temperature interval.

TSV_{ij} —— the thermal sensation vote of the i -th subject in the j -th interval.

n_j ——the sample size in the j -th temperature interval.

This grouping method reduces the influence of individual variability and reflects the overall thermal adaptation behavior of occupants in severe cold regions.

2.4.2. PMV Deviation and aPMV Model

Based on Fanger's steady-state heat balance theory, PMV values are calculated using measured parameters including air temperature, humidity, air velocity, mean radiant temperature, clothing insulation, and metabolic rate [16]. As shown in expression (2). Then, PMV predictions are compared with MTS values derived from questionnaire statistics.

$$PMV = [0.303 \times 10^{-3} \times e^{-0.036M} + 0.028]\{M - W - 3.05 \times 10^{-3}[5733 - 6.99(M - W) - P_a] - 0.42[(M - W) - 58.15] - 1.7 \times 10^{-5}M(5867 - P_a) - 0.0014M(34 - t_a) - 3.96 \times 10^{-8}f_{cl}[(t_{cl} + 273)^4 - (t_{mr} + 273)^4] - f_{cl}h_c(t_{cl} - t_a)\} \quad (2)$$

To improve applicability in severe cold teaching environments, the adaptive thermal comfort correction framework proposed by Yao et al. is introduced, and an aPMV model is established [17]. As shown in expression (3):

$$aPMV = \frac{PMV}{1 + \lambda \cdot PMV} \quad (3)$$

The adaptive coefficient λ represents occupants' ability to buffer thermal environmental deviations through psychological and behavioral adaptation. Using regression analysis, the coefficient is determined based on median estimation methods commonly used in field studies. As shown in expression (4):

$$\lambda_i = \frac{PMV_i - MTS_i}{PMV_i \cdot MTS_i} \quad (4)$$

2.5. Building Energy Simulation and Evaluation Indicators

2.5.1. Dynamic Energy Simulation

A dynamic energy simulation model of the teaching building is established using Design Builder [18]. A 3D geometric model is built based on CAD drawings and field-measured dimensions. The building is divided into thermal zones including classrooms, corridors, and auxiliary spaces. The thermal properties of envelope components are input according to Table 1. Occupant schedules, equipment loads, and ventilation conditions are defined according to actual usage patterns and relevant building energy standards. The heating period is set from October 15 to April 15, totaling 183 days.

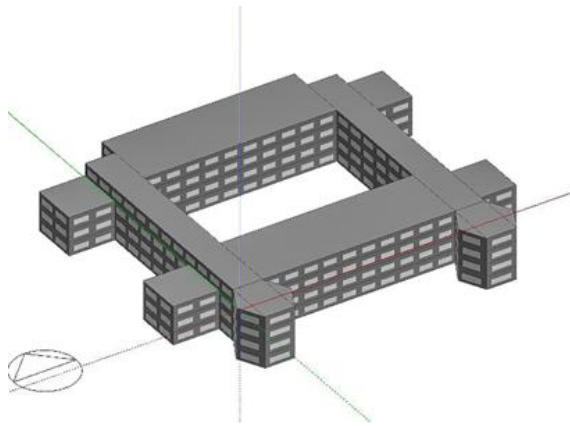


Figure 3. Design Builder simulation model diagram.

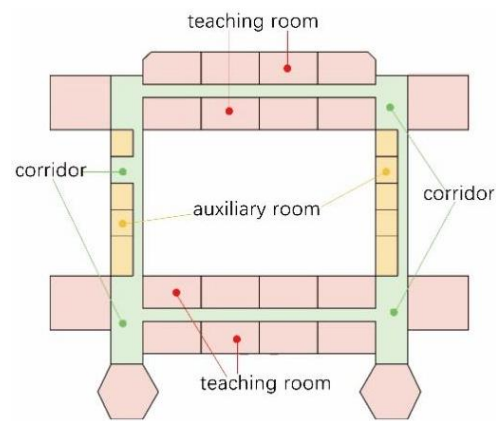


Figure 4. Model thermal zoning diagram.

Five simulation scenarios are established: baseline, external wall insulation, roof insulation, window replacement, and combined retrofit. The construction adjustments of each scenario are shown in Table 4. All cases are simulated using Design Builder for full-year hourly dynamic energy consumption calculations.

Table 4. Retrofit scheme of enclosure structure under various simulated working conditions.

Optimization scheme	Exterior wall	Roofing	Exterior window
S0 baseline	370mm solid brick wall	Original roof	Single layer ordinary aluminum alloy window
S1 external wall insulation	Add external wall insulation layer	Original roof	Single layer ordinary aluminum alloy window
S2 roof insulation	370mm solid brick wall	Add roof insulation layer	Single layer ordinary aluminum alloy window
S3 window replacement	370mm solid brick wall	Original roof	Low-E insulating glass
S4 Combined retrofit	Add external wall insulation layer	Add roof insulation layer	Low-E insulating glass

2.5.2. Thermal Discomfort Time Ratio (DTR)

To evaluate indoor thermal environment performance, the Thermal Discomfort Time Ratio (DTR) is defined based on the aPMV model [19]. The thermal comfort range is set as $-0.5 \leq \text{aPMV} \leq 0.5$. The number of hours outside this range is counted and divided by the total annual hours to obtain DTR. A lower DTR indicates better thermal comfort performance over the year. As shown in expression (5):

$$DTR_{aPMV} = \frac{\sum_{h=1}^{8760} 1_{|aPMV_h| > 0.5}}{8760} \times 100\% \quad (5)$$

$aPMV_h$ — the corrected thermal sensation predicted value at the h -th hour, calculated using the aPMV model established in the previous sections.

$1_{|aPMV_h| > 0.5}$ — the indicator function, which takes the value of 1 when $|aPMV_h| > 0.5$, and 0 otherwise.

The smaller the calculated DTR_{aPMV} value, the higher the proportion of time during which the building remains within the thermal comfort range throughout the year, and the higher the overall annual thermal comfort level.

3. Results and Discussion

3.1. Adaptive Thermal Sensation Model (aPMV)

Based on the field measurement data and subjective thermal sensation votes collected in the previous sections, and through binning analysis and parameter regression calibration, an adaptive thermal comfort correction model suitable for winter heating teaching buildings in severe cold regions is established. Based on the measured data fitting, the winter thermal adaptation correction coefficient in this study is determined as $\lambda = -0.19$. The final aPMV adaptive thermal sensation model applicable to existing teaching buildings in severe cold regions is expressed as (6):

$$aPMV = \frac{PMV}{1 - 0.19 \cdot PMV} \quad (6)$$

The aPMV model constructed in this study introduces the adaptive coefficient $\lambda = -0.19$, quantitatively reflecting the moderate thermal adaptation ability formed by university students in severe cold regions under long-term centralized heating conditions. It extends the single physical steady-state evaluation framework into a dynamic thermal comfort evaluation system coupling physiological, behavioral, and psychological factors. The corrected model better reflects the real thermal perception characteristics of student groups in winter continuously heated environments in severe cold regions, providing a more reliable theoretical model for subsequent analysis.

3.2. Comparative Analysis of PMV, MTS, and aPMV

To systematically reveal the differences and applicability among the theoretical model (PMV), measured perception model (MTS), and adaptive corrected model (aPMV), regression analyses between operative temperature and the three thermal sensation indicators (PMV, MTS, aPMV) were conducted [20]. The regression equations and determination coefficients for each group are shown in the following expression (7)- (9):

$$MTS = 0.17 \cdot t - 3.83, R^2 = 0.86 \quad (7)$$

$$PMV = 0.182 \cdot t - 4.138, R^2 = 0.84 \quad (8)$$

$$aPMV = 0.148 \cdot t - 3.4, R^2 = 0.85 \quad (9)$$

The regression distributions and comparative results are shown in Figure 5 and Figure 6. Overall, all three thermal sensation indices show a significant positive correlation with operative temperature. As indoor temperature increases, thermal

sensation gradually shifts from slightly cold to neutral and then to slightly warm, showing consistent overall trends. However, significant differences exist in temperature sensitivity, low-temperature applicability, and overall stability among the three models.

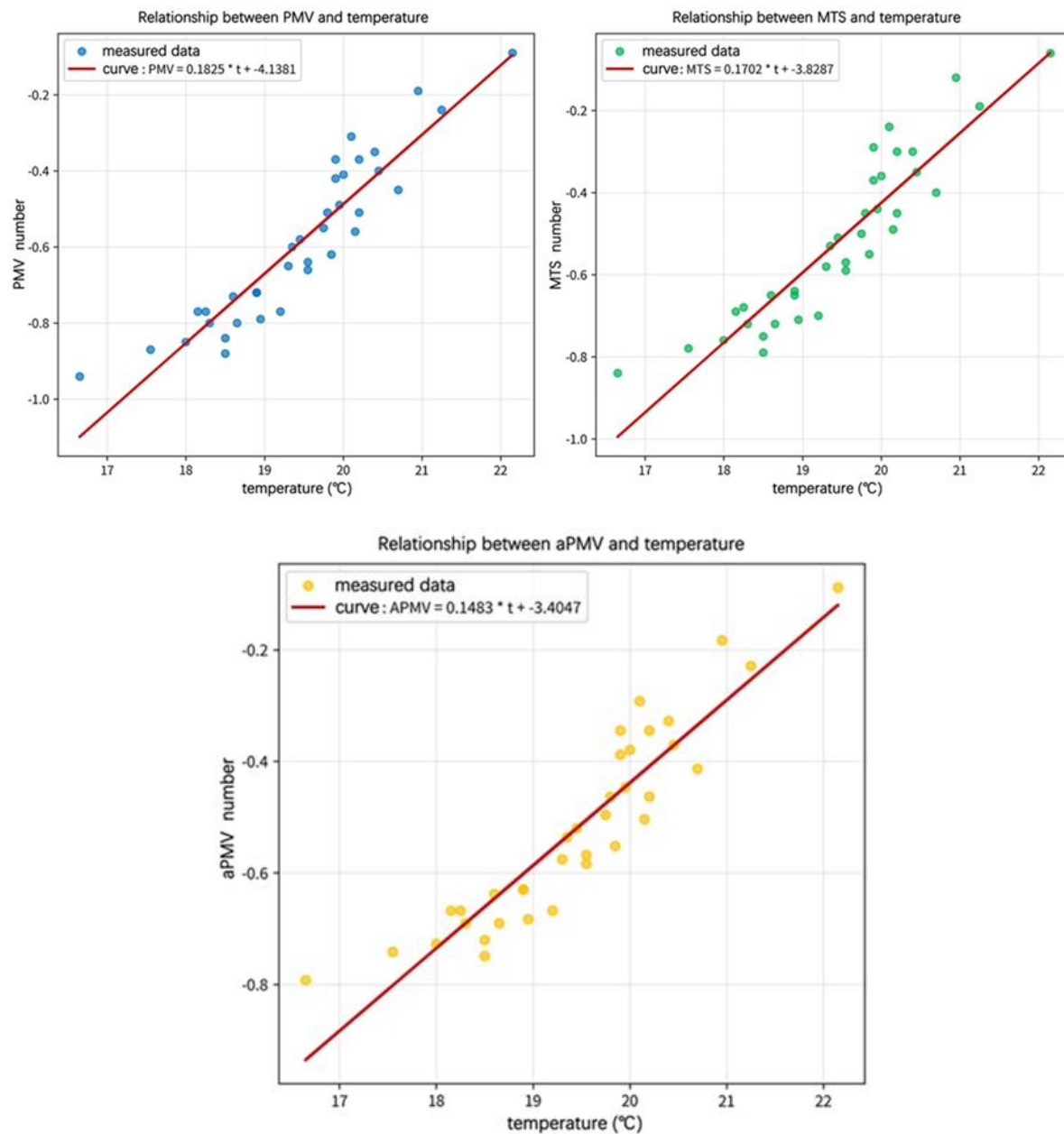


Figure 5. Regression analysis diagram of PMV, MTS, aPMV and operating temperature T in winter.

In terms of temperature sensitivity, the standard PMV model has the largest regression slope and is most sensitive to indoor temperature fluctuations. However, its steady-state heat balance assumption limits its applicability in low-temperature conditions, leading to underestimation of actual thermal sensation and systematic deviation from students' votes, while failing to reflect thermal adaptive buffering in long-term heated environments.

As a questionnaire-based group thermal sensation indicator, MTS directly reflects actual thermal perception distribution across different temperature ranges and aligns

well with real field conditions. However, due to uneven sample distribution and individual subjective differences, the MTS curve shows fluctuations in low-temperature or low-sample regions, resulting in limited stability and difficulty in use as a universal predictive model.

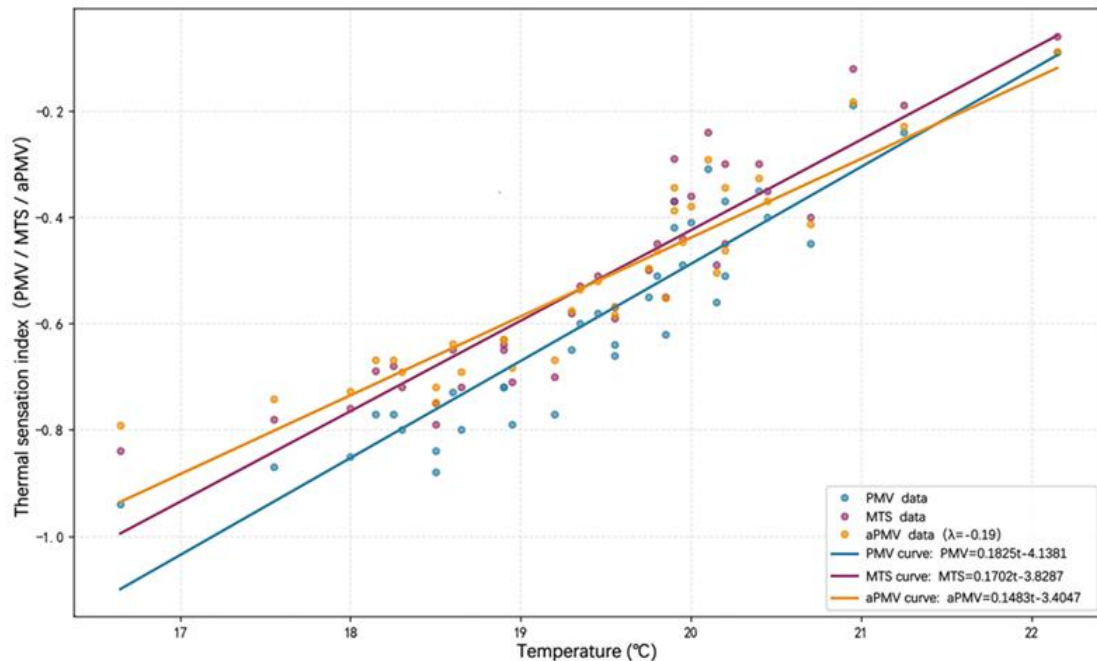


Figure 6. Regression comparison chart of PMV vs MTS vs aPMV in winter.

Compared with the above two models, the corrected aPMV model shows better overall performance. Its regression slope lies between PMV and MTS, indicating moderate temperature sensitivity and better consistency with actual thermal sensation variation. In low-temperature conditions, aPMV effectively increases the underestimated values of PMV, significantly improving agreement with measured MTS distributions and reducing systematic cold bias. In the thermal neutral range (20–22°C), all three models converge, indicating that physical environmental parameters dominate thermal sensation under near-comfort conditions, while adaptive effects are weaker.

From a modeling perspective, PMV is a purely physics-driven steady-state model; MTS is a purely data-driven empirical perception result; aPMV combines both physical mechanism and adaptive correction advantages.

3.3. Energy and Thermal Comfort Performance of Retrofit Scenarios

To ensure retrofit analysis reliability, the energy simulation model is validated by comparing simulated and measured indoor temperatures. The results show consistent temperature trends, with indoor temperatures mainly ranging from 16–23°C and deviations within an acceptable range, indicating that the model can reproduce the actual operation of teaching buildings in severe cold regions and support further analysis.

Based on simulation results, heating load, carbon emissions, and Thermal Discomfort Time Ratio (DTR) under different retrofit scenarios are obtained, as shown in Figure 7, Figure 8, Figure 9, Figure 10.

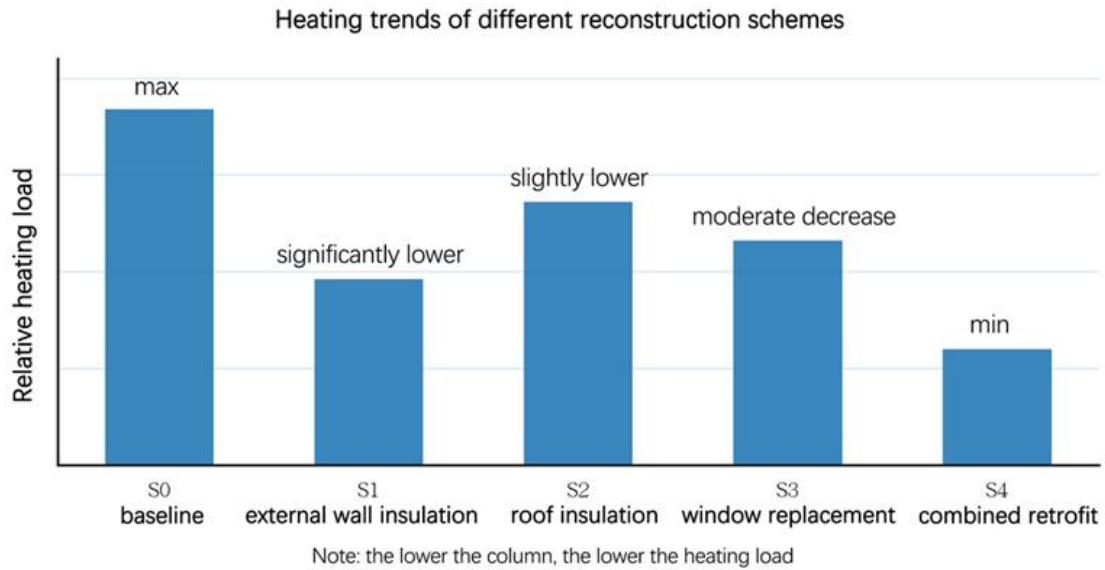


Figure 7. Heating load change diagram of transformation scheme.

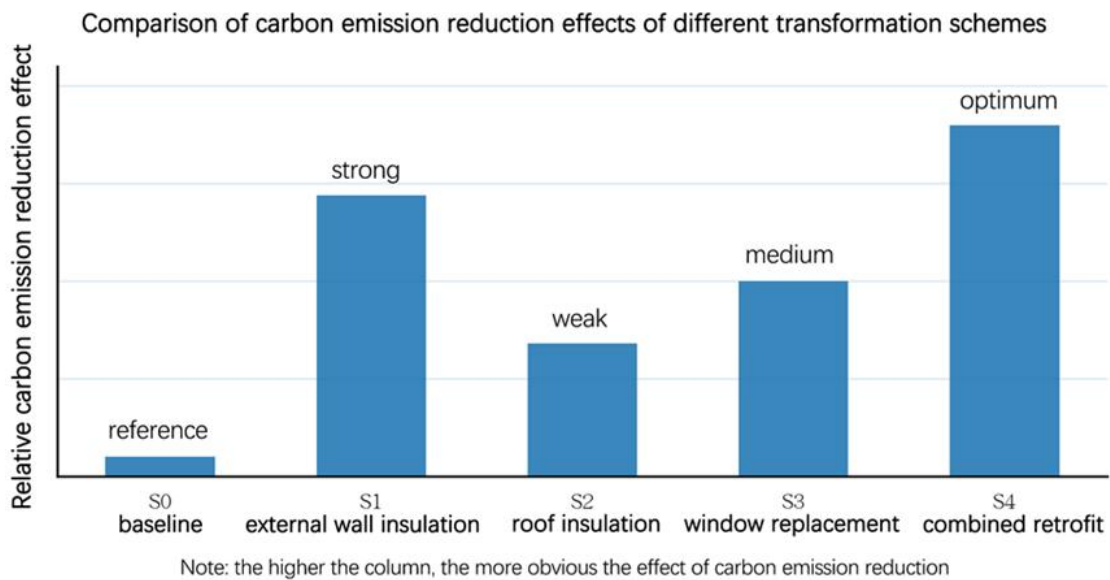


Figure 8. Change diagram of carbon reduction effect of transformation scheme.

Comparison of DTR thermal discomfort time proportion in different reconstruction schemes

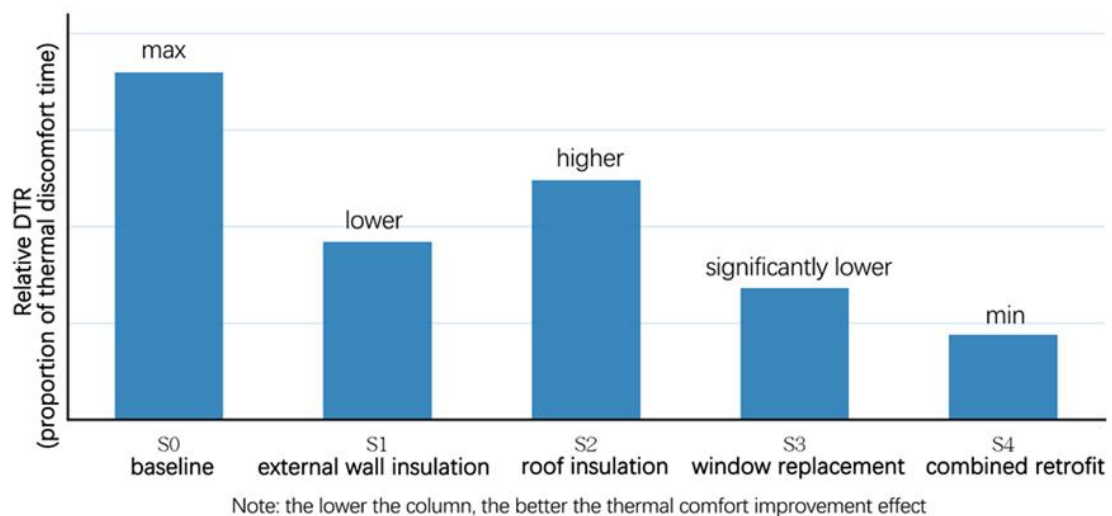


Figure 9. Transformation scheme DTR scale change diagram.

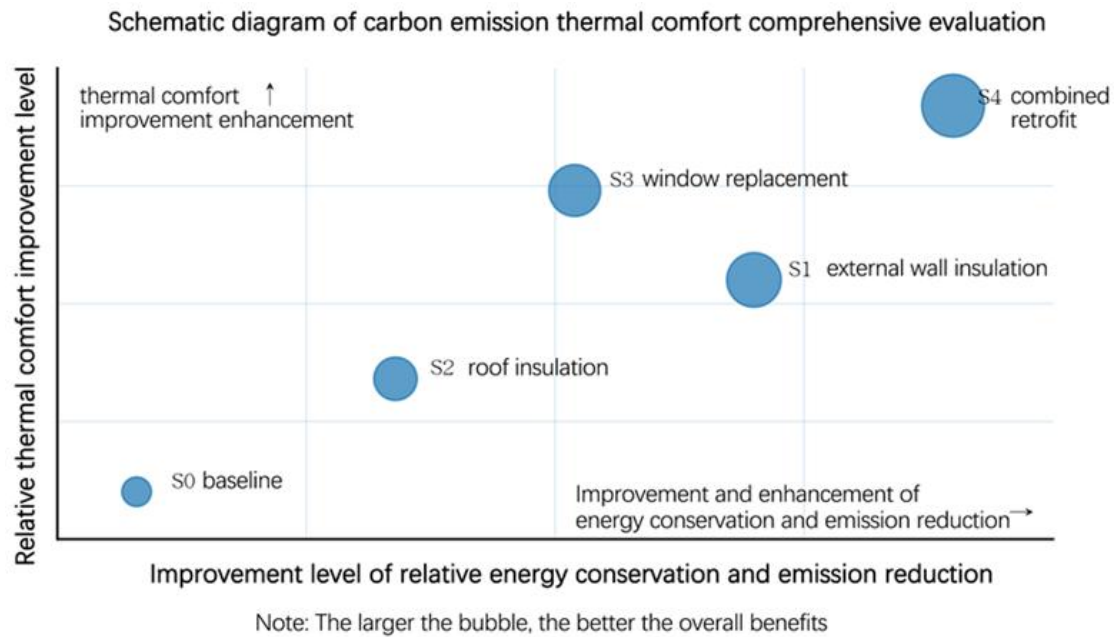


Figure 10. Schematic diagram of comprehensive evaluation of energy consumption thermal comfort.

Baseline simulation results show that weak envelope thermal performance causes significant winter heat loss in the original teaching building. Prolonged low-temperature operation leads to large deviations of aPMV from the neutral range and a high DTR, indicating that thermal discomfort mainly results from envelope heat loss and that the building has strong potential for energy-saving retrofit and thermal improvement.

Individual retrofit measures show different effects and optimization focuses. External wall insulation provides the greatest energy-saving and carbon-reduction benefits, as large indoor–outdoor temperature differences make walls the main heat transfer pathway. Added insulation improves wall thermal resistance, reduces heat loss, and stabilizes indoor temperature.

Roof insulation mainly improves top-floor thermal conditions. Although the roof area is smaller than the wall area, direct exposure to outdoor cold makes it important for top-floor comfort. Roof insulation reduces vertical heat loss and improves indoor temperature uniformity and stability on the top floor.

Window replacement significantly improves local thermal comfort, especially in reducing cold radiation and infiltration near windows. Replacing single-glazed aluminum windows with Low-E double-glazed windows improves insulation and air tightness, effectively reducing local discomfort.

The combined retrofit strategy achieves the best overall performance, simultaneously optimizing energy consumption, carbon emissions, and thermal comfort (DTR).

4. Conclusions

This study examines an existing university teaching building in a severe cold region. Based on winter field measurements and thermal sensation surveys, an adaptive thermal comfort model (aPMV) for teaching spaces is developed. Coupled with dynamic energy simulation, the study evaluates the energy-saving, carbon-reduction,

and comfort-improvement effects of wall insulation, roof insulation, window replacement, and combined retrofits, forming a refined framework that integrates building energy performance and human thermal adaptation. The main conclusions are as follows:

(1) The traditional PMV model has clear limitations under long-term heating conditions in severe cold regions, as it underestimates thermal sensation in low-temperature environments. With a calibrated adaptive coefficient of $\lambda = -0.19$, the aPMV model better matches measured MTS and improves the accuracy and applicability of comfort evaluation in teaching buildings.

(2) Envelope retrofit measures differ in their effects. Wall insulation is the key measure for reducing heat loss, roof insulation mainly improves top-floor thermal stability, and window replacement reduces local discomfort from cold radiation and infiltration. The combined retrofit achieves the best overall performance by addressing multiple envelope weaknesses.

(3) The aPMV-based Thermal Discomfort Time Ratio (DTR) enables integrated evaluation of energy saving and occupant comfort. Compared with traditional PMV-based steady-state methods, it better reflects occupants' dynamic thermal perception and improves the reliability of retrofit decisions.

(4) This study is limited to one representative teaching building in a severe cold region, so the calibrated λ coefficient and quantitative results are scenario-specific. Its main contribution is establishing a "field measurement–thermal adaptation correction–energy-comfort coupled evaluation" framework, providing methodological reference for similar campus retrofit studies.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Author Contributions

Conceptualization: Qianwen Cheng.; Methodology: Chengjun Ma.; Software: Qianwen Cheng.; Validation: Yan Zhuang.; Formal analysis: Yan Zhuang.; Investigation: Qianwen Cheng.; Data Curation: Qianwen Cheng.; Writing – original draft preparation: Qianwen Cheng.; Writing – review and editing: Chengjun Ma.; Visualization: Chengjun Ma.

Funding

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

Acknowledgments

The author would like to acknowledge supervisor for the continuous guidance and careful advice offered during the whole research process.

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