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Research on Adaptive Control Systems for Building Shading Based on Decision Tree and Random Forest Classification Algorithms

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ABSTRACT

Dynamic shading systems for buildings, due to their variable mechanisms and high adaptability, have the potential to reduce energy consumption in buildings significantly. However, the performance of dynamic shading is largely influenced by the control system employed. This study aims to explore an adaptive control method for building shading based on decision tree and random forest classification algorithms (machine learning), with the objective of minimizing energy demands related to lighting and cooling as much as possible. The adaptive control system model may independently modify the location of building shading in response to input environmental conditions, thereby achieving energy savings for both lighting and cooling. According to the findings, the automated control system model may reduce building energy consumption by 38% overall, which is close to the ideal level of energy conservation.

KEYWORDS

Decision Tree; Random Forest; Shading; Adaptive Control System; Machine Learning

1. INTRODUCTION

The roller blind shading system is a widely used method in buildings for obstructing sunlight by rolling up the blinds, thereby facilitating cooling, insulation, and energy savings [1]. However, traditional roller blind shading systems often necessitate manual adjustments, which preclude the possibility of adaptive control. Dynamic shading systems, characterized by their variable mechanisms and high adaptability, have the potential to further decrease energy consumption in buildings. Nevertheless, the performance of dynamic shading is significantly influenced by the employed control system [2]. This study seeks to investigate a machine learning-based adaptive control system for building shading, aiming to minimize energy demands while allowing for automatic regulation to reduce the costs associated with manual intervention. Consequently, research into a machine learning-based adaptive control system for building shading is of substantial practical significance.

2. REVIEW OF RELATED LITERATURE

The goal of machine learning, a significant area of artificial intelligence, is to automate the creation of analytical models based on information already in the public domain and data that can be used to perform cognitive tasks on unknown data. It helps users with a variety of activities, including modeling, prediction, regression, classification, and control, and it also offers dependable decision-making support by learning from past data and extracting patterns [3].

To maximize energy performance and meet near-zero energy construction targets, estimating building energy usage is essential. To predict energy consumption, researchers frequently use building performance prediction programs like ESP-r, EnergyPlus, DOE-2, and IDA ICE. Users can acquire the most precise computations thanks to the rigorous validation of these products' accuracy and reliability. However, users face difficulties due to the growing complexity of computational models, as well as the requirements for a large number of specific input parameters and lengthy simulation times. As a result, there has been a growing interest in machine learning algorithms. Computers can quickly and correctly anticipate energy usage based on fewer physical characteristics and building information once a machine learning model has been created.

Zhao et al. [4] introduced a machine learning regression-based approach for estimating office loads that was validated using energy consumption data from a single office building in Tianjin. The validation findings showed that the proposed model predicts energy loads with good accuracy, with mean absolute relative errors (MARE) of 2.60% for cooling and 3.99% for heating. Furthermore, the study underlines the importance of input parameter accuracy in the model's prediction performance.

Singaravel et al. [5] used data from 201 examples to evaluate the computational speed and accuracy of a neural network-based predictive model with that of EnergyPlus software for predicting building energy use. The results showed a considerable advantage: the simulation time was reduced from 1145 seconds to 0.9 seconds, and the neural network-based model showed prediction accuracy comparable to that of building performance simulation software.

Chen et al. [6] used linear regression algorithms to create an energy prediction regression model for high-rise office buildings in Guangzhou. The model was then validated against the EnergyPlus predictions, demonstrating a high degree of prediction accuracy with a R^2 value of 0.95.

Zheng et al. [7] used eleven standard supervised learning algorithms to forecast the air conditioning load of business complexes in the Pearl River Delta region, and discovered that the gradient boosting method had the highest prediction accuracy.

Xie and Sawyer [8] created a glare prediction model employing machine learning algorithms and pre-simulated solar radiation data, with the goal of improving eye comfort while lowering lighting energy usage. They then examined glare for venetian blinds at various tilt angles using real-time sunshine data from sensors, eventually determining the best blind angles to optimize natural light intake while minimizing glare. The study used algorithms such as K-nearest neighbors, support vector machines, and random forests to show that the proposed control approach could eliminate 86.5% to 96.9% of glare while reducing lighting energy usage by 80.8%.

Luo et al. [9] presented a blind control approach that improves visual comfort by preventing glare and using artificial neural network (ANN) techniques. The outcomes showed that all observation points were free from glare thanks to the suggested approach. Additionally, the summer and winter lighting demands were lowered by 77% and 64%, respectively, in comparison to a situation with fully closed shades. To maximize dynamic shading's overall energy efficiency, the researchers also created a control method based on machine learning energy consumption prediction models. A model for predicting energy consumption for buildings with shading systems was created as the first step in this process. Each time step's ideal shading state could be identified by comparing forecasts of energy usage under different shading conditions.

Yeon and colleagues [10] employed artificial neural networks to create a total load prediction model for blind-equipped buildings. Based on their predictions, the authors then improved the blinds' tilt angles. Comparing the ANN model-controlled blinds to fixed blinds, the results showed a considerable reduction in the buildings' heating and cooling loads as well as a 9.1% reduction in cumulative building load.

Machine learning helps users with modeling, prediction, regression, classification, control tasks, and trustworthy decision-making by automatically learning from available data and information and extracting patterns. It has been shown in recent studies to be an excellent way to create adaptive control systems for building shading.

3. CONCEPTUAL FRAMEWORK

Figure 1 illustrates the conceptual framework of the adaptive control system model developed using the Decision Tree (DT) classification algorithm and the Random Forest (RF) classification algorithm. The shade control optimization results obtained using EnergyPlus and Python are used as the training dataset for the adaptive control system model, which seeks to minimize energy demand. The generated model was trained and cross-validated using a total of 20,097 data points. When the RF and DT models were being established, different input environmental characteristics would result in different shading positions corresponding to different expected outcomes. These characteristics show the energy requirements for building lighting and cooling in addition to giving a general picture of the surrounding area. After the model was created, its performance was assessed using Xiamen, China, meteorological data that was measured in 2024.

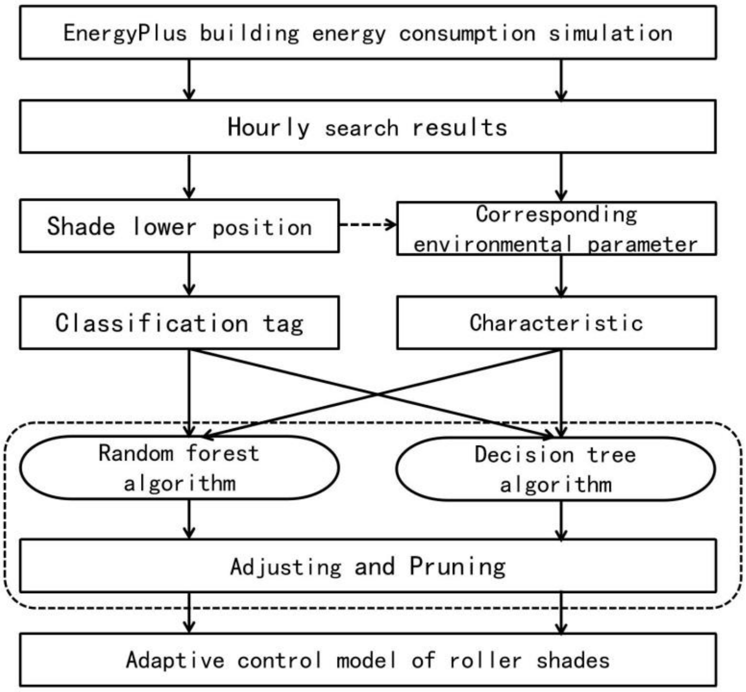

Figure 1. Conceptual Framework of the Study

4. METHODOLOGY/RESEARCH DESIGN

4.1. Research Instrument

Python programming and the EnergyPlus energy consumption simulation software are used in this investigation. A building energy consumption simulation program called EnergyPlus was created collaboratively by the U.S. Energy Department and Lawrence Berkeley National Laboratory. EnergyPlus is widely utilized in research relating to dynamic shading and adaptive facades, and its accuracy has been proven in multiple studies [11]. Python is also used to make it easier to compile the EnergyPlus energy model simulation parameters in bulk, which allows for automated continuous simulation of building energy use and post-processing of the simulation output.

4.2. Machine Learning

This study employs decision tree classification algorithms (Decision Tree, DT) and random forest classification algorithms (Random Forest, RF) to develop a model for an adaptive shading control system.

4.2.1. Decision Tree(DT)

The decision tree classification algorithm is a supervised learning method used for classification and regression tasks, particularly suitable for such applications. Its primary concept involves recursively splitting data to construct a tree structure, where each node represents a test on a feature, each branch indicates the result of the test, and each leaf node represents the predicted outcome. Specifically, the prediction made by a decision tree can be expressed using the following formula:

$$y\hat{} = f(\mathbf{x})$$

In this context, x represents the input feature vector, y^denotes the predicted class label, and f is a function defined by a series of conditional tests and decision rules.

In the decision tree classification algorithm, the core step in constructing the tree is selecting the optimal feature for partitioning the dataset. This is typically measured using information gain, which is expressed by the following formula:

$$IG(D,\ A) = H(D) - \sum_{v} \frac{|D_v|}{|D|} H(D_v)$$

Among them, D represents the given dataset, A denotes the feature, |D| indicates the total number of samples in dataset D, and |Dv| represents the number of samples in subset Dv.

4.2.2. Random Forest(RF)

Random forest is an ensemble learning method comprised of multiple decision trees. It trains these trees on different subsets of samples and features, ultimately deriving predictions through a voting mechanism. The advantages of random forest include its ability to effectively reduce the risk of overfitting while enhancing both the accuracy and stability of the model. Specifically, the predictions made by a random forest can be expressed using the following formula:

$$y\hat{} = \frac{1}{N} \sum_{i=1}^{N} f_i(\mathbf{x})$$

Among them,y^ represents the final prediction result, N denotes the number of decision trees in the forest,fi(x)indicates the prediction result of the i -th decision tree, and x is the input environmental parameters.

These two algorithms are straightforward to implement and provide fast prediction speeds, thereby imposing minimal computational burden on the controllers in practical applications. They are among the most common and widely used classification algorithms in similar studies. Once adequately trained, the models they establish can predict the optimal shading position based on input environmental parameters, allowing dynamic shading systems to respond rapidly to complex and changing environments, ultimately reducing energy consumption in buildings and improving indoor lighting conditions.

4.3. Data Collection

To evaluate energy consumption simulations and model projections, this study uses measured meteorological data for Xiamen in 2024 as well as meteorological data for Xiamen in usual years. The Chinese Standard Weather Data (CSWD) source, which is produced in cooperation with

Tsinghua University and the National Meteorological Information Center of the China Meteorological Administration, provides meteorological data for an average year. It contains hourly meteorological data for average years from 270 weather stations around China, which is widely used in the nation's building energy efficiency studies. The weather data for Xiamen in 2024 that has been measured comes from observations made by South China University of Technology's National Key Laboratory of Subtropical Building Science.

4.4. Parameter Settings

The research subject for this study is a typical office room, measuring 6 meters wide by 4 meters deep by 4 meters high, with a window-to-wall ratio of 0.60. Since the floor, ceiling, and three of the office's walls are next to other rooms, it is expected that just one of the room's outer walls is exposed to the outside air, keeping the interior temperature almost constant. As a result, it is possible to think of the internal envelope as an isothermal surface devoid of heat transfer. The thermal transmittance (K-value) of the outside wall is set at 1.5 W/(m²·K), with a solar radiation absorption rate of 0.75, based on a typical building model developed for the Xiamen region [12]. The solar heat gain coefficient of 0.21 and visible light transmittance of 0.35 are combined to give the external window system a K-value of 2.6 W/(m²·K). 0.4, 0.7, and 0.25 are the relative values for the interior surface reflectance of the inner walls, ceiling, and floor. During weekdays, the roller blinds are expected to be in operation from 7:00 to 18:00, with an external surface reflectance of 85% and a visible light transmittance of 5%.

The interior heat sources of the office building are the heat generated by the residents, the electrical equipment, and the lighting fixtures. The lighting power density in this study is set at 9 W/m2, the electrical equipment power density is set at 13 W/m2, and the occupancy density is set at 0.25 persons/m2. In addition, the office space is equipped with an optimal air conditioning system, which has a coefficient of performance (COP) of 4. The "General Regulations on Building Energy Efficiency and Renewable Energy Utilization" serve as the basis for the schedules for lighting, HVAC systems, electrical equipment, and occupants, as seen in Figure 2.

A zonal lighting control system that is continually dimmable is also included in the simulation. The lighting control reference points are located in the center, one and three meters away from the external window, respectively, with the reference point being 0.75 meters above the floor. The reference point at 1 meter controls illumination within a 2 meter radius of the exterior window, and the reference point at 3 meter controls lighting between 2 and 4 meters. The control area doesn't need extra illumination when the daylight illuminance at the reference points reaches 500 lx.

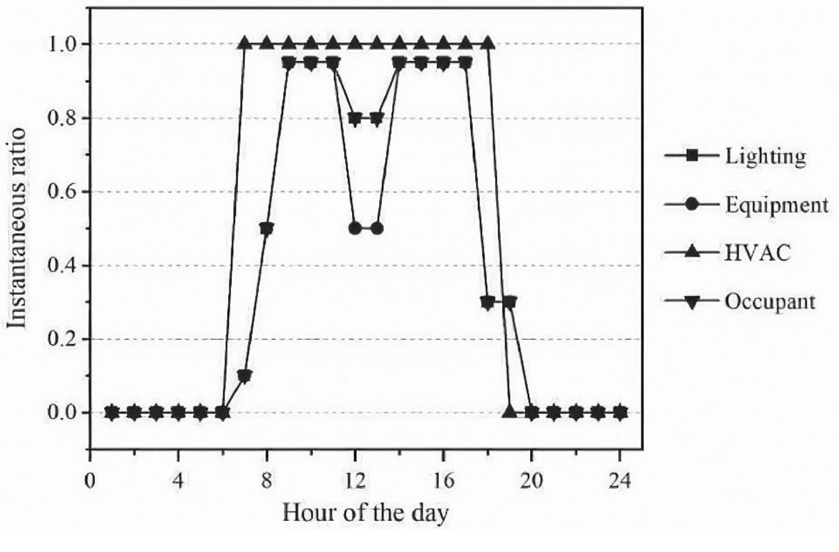

Figure 2. Schedule for lighting, electrical equipment, HVAC systems, and occupants in the room

5. PRESENTATION AND DISCUSSION OF RESULTS

5.1. Model Performance

The prediction accuracy of the adaptive control model is displayed in Figure 3 for various orientations. The percentage of predictions where the model's anticipated shading position coincides with the ideal shading position is known as prediction accuracy. The RF and DT models have average accuracy values of 87.1% and 80.2% for the east, south, and west orientations, respectively. This suggests that the DT model's accuracy is inferior to the RF model's. Since the suggested adaptive shade control system aims to lower the building's overall energy consumption, it is imperative to evaluate the model's performance of the adaptive control system in terms of energy consumption.

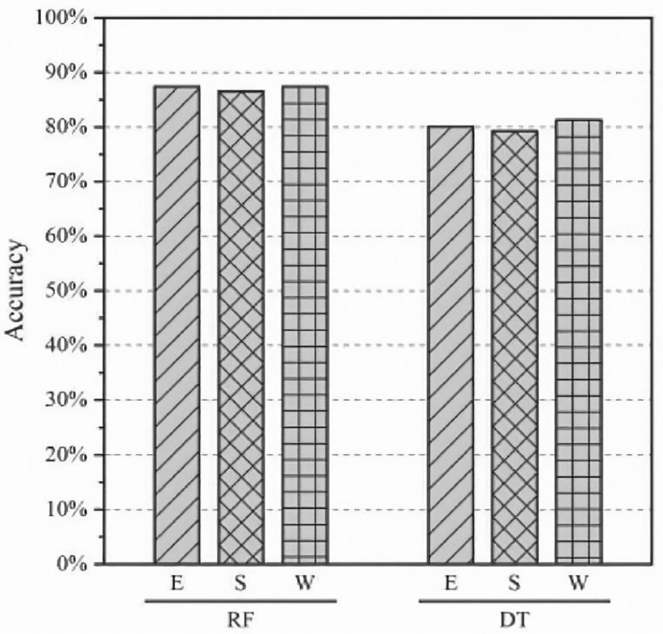

Figure 3. Prediction Accuracy of the Adaptive Control Model.

5.2. Energy Consumption Performance

The energy consumption performance of the suggested adaptive control system model is examined by contrasting it with other shading control strategies of a similar nature. The following is a description of the several shading control strategies for the shading system:

(1) Ctrl-Optimal: Shading control strategy derived from the shading control optimization results.

(2) Ctrl-RF: Shading adaptive control strategy predicted by the RF adaptive control system model.

(3) Ctrl-DT: Shading adaptive control strategy predicted by the DT adaptive control system model.

(4) Ctrl-Solar: During working hours, if the incident solar radiation exceeds 100 W/m², the roller blinds completely cover the window.

(5) Ctrl-DG: If the line of sight is parallel to the window during working hours, the roller blinds completely cover the window.

(6) Ctrl-Work: The roller blinds completely cover the window during working hours.

Figure 4 illustrates that there is minimal difference in cooling energy usage between the different control schemes. The annual energy consumption intensity for cooling varies from 28.1 to 29.2 kWh/(m²·a). The lowering of lighting energy consumption is a clear advantage of the shading adaptive control system techniques (Ctrl-RF and Ctrl-DT). The suggested shade adaptive control system solutions result in an annual lighting energy consumption intensity as low as 8.5 kWh/(m²·a), which is a drop in lighting energy demand of over 60% when compared to the baseline settings. With overall energy savings rates of 8.7% and 38.3%, respectively, Ctrl-RF and Ctrl-DT outperform other controls when it comes to lowering lighting and cooling use. Other orientations show similar patterns and conclusions, with the adaptive control techniques' energy-saving results varying by less than 1% in each direction. Moreover, under Ctrl-RF and Ctrl-DT, the energy usage for cooling and lighting is nearly the same as it is under Ctrl-Optimal, suggesting a low level of overall consumption. This shows that it can still yield energy savings that are almost ideal even when there are some differences between the optimal control strategy and the adaptive control system model.

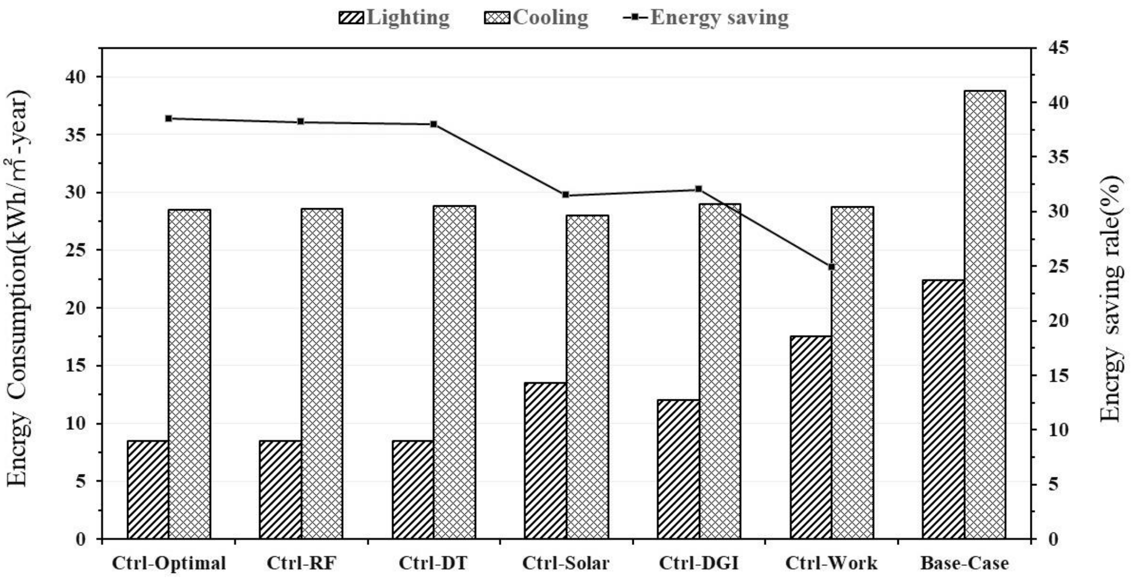

Figure 4. Different from the shading policy slightly south - oriented annual energy consumption intensity between rooms

5.3. Lighting Performance

In order to assess the daylighting effectiveness of adaptive shade control, this study gives the useful daylight illuminance (UDI) in three ranges: 100–500 lx, 500–1000 lx, and 1000–2000 lx [13]. The shading system has a considerable impact on building daylighting. The percentage of working plane illuminance under various operating conditions over the course of the working year was statistically quantified using hourly illuminance data from a reference point close to the window.

A comparison of the annual UDI values for various shade control schemes is provided, as illustrated in Figure 5. Interestingly, the shading adaptive control system techniques (Ctrl-RF and Ctrl-DT) have UDI values (100–2000 lx) that are above 70% but comparatively lower than Ctrl-Optimal. All control measures achieved greater UDI values and decreased the percentage of readings exceeding 2000 lx when compared to the baseline conditions. Similar control schemes (Ctrl-Solar, Ctrl-X,-1, and Ctrl-Work) have UDI values that are usually dispersed in the range of 100–500 lx. But in the 500–1000 lx and 1000–2000 lx ranges, Ctrl-RF and Ctrl-DT show a larger percentage. The ranges between 500 and 1000 lx and between 1000 and 2000 lx are very important since they show situations where there is enough natural illumination to not require artificial lighting. In terms of lowering lighting energy consumption, these lighting results further clarify the benefits of the shading adaptive control system solutions.

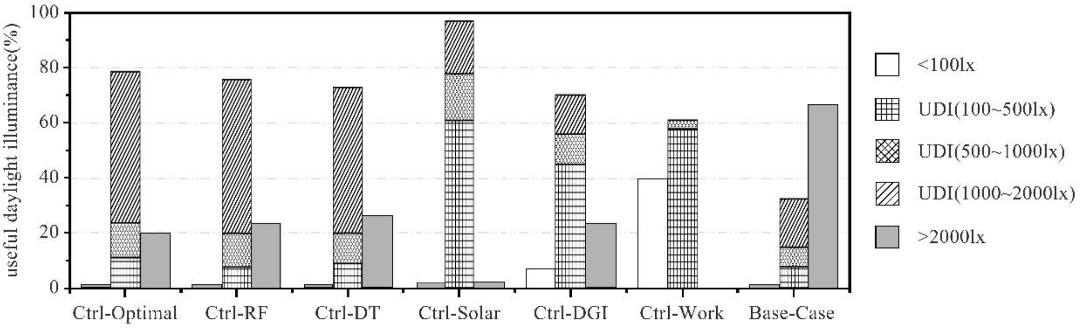

Figure 5. Different from the shading policy under the effective lighting illuminance

6. CONCLUSIONS

(1) The machine learning-derived shade position prediction model is applicable to a variety of facades, exhibiting average forecast accuracies of 87% and 80% for the RF and DT system models, respectively, throughout the southeast and west orientations.

(2) The Ctrl-RF and Ctrl-DT adaptive shading control system techniques show the lowest total energy consumption and the most noticeable energy-saving effects when compared to other shading control systems. Ctrl-RF and Ctrl-DT have energy savings rates of 38.7% and 38.4% in the south orientation, respectively. The UDI (100–2000 lx) for Ctrl-RF and Ctrl-DT, in terms of daylighting performance, are 75.7% and 72.9%, respectively. The energy and daylighting performance of the adaptive shading control system strategies (Ctrl-RF and Ctrl-DT) established by the predictive system model are identical to the optimization findings, proving their feasibility and accuracy.

(3) By creating systems for adaptive shade management that balance the energy savings associated with cooling and lighting, the study's findings can lead to energy conservation outcomes that are almost ideal. They also help to reduce problems that are frequently linked to conventional shading techniques, like uncomfortable glare or inadequate lighting at work areas. In order to maximize savings in building operating energy consumption and guarantee a comfortable indoor lighting environment for users, this research has the potential to offer workable dynamic shading solutions in real-world applications.

7. RECOMMENDATIONS

In practical applications, several challenges remain to be addressed in future research. Due to limitations in simulation software and weather data, the predictive model currently facilitates only hourly dynamic control. This control interval appears lengthy compared to the continuously changing environment encountered in real conditions. When considering shorter control intervals, it is essential to address the smoothness of shading control and its stability under uncertain conditions. For instance:

(1) Sudden fluctuations in light intensity may cause discomfort or blurriness for users.

(2) Changes in shading positions can obstruct users' lines of sight, particularly for those requiring focused attention for tasks.

(3) The noise generated by shifting shading positions may distract users, especially in quiet environments such as libraries and research labs.

(4) Frequent alterations in shading positions can impact users' psychological states, potentially leading to feelings of anxiety or annoyance.

To minimize user disruption, further research is necessary for adaptive shading control systems that consider various perspectives [14]. In the future, algorithms and system designs can be optimized to enhance the performance and stability of adaptive shading control systems, thereby contributing more significantly to energy conservation and environmental protection in buildings.

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