A User-centered Interactive Optimization Approach based on Immersive Virtual Reality

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Abstract
The user's subjective perception is often overlooked in the optimization of design parameters in the pre-design phase of building design, although it is important for building performance and user satisfaction. To address this issue, a multi-objective optimization framework based on the linkage of Rhino, Grasshopper & D5 Render software is built to combine users' subjective evaluation with the building's objective performance. Moreover, a case study based on a small office is used to verify the effectiveness of the proposed method, compared with the traditional optimization method that solely focuses on objective indicators, while energy consumption and daylight performance are optimized. The results show that the method proposed in this paper leads to lower energy consumption and higher user satisfaction. This study expands the application of user-centered design ideas in early architectural design, demonstrating that making User-Centered Design an integral part of the development process can help improve the performance of the design results.

Highlights
- Combines subjective and objective indicators in Multi-objective optimization of building design parameters.
- Allow immersive user interaction in an unbuilt environment based on virtual reality.
- Provides a method for obtaining users' subjective feelings in the parameter optimization in an early stage of architecture design.

Introduction
Optimization methods based on performance simulation can optimize design parameters and provide solutions to improve energy savings or user comfort, productivity, and satisfaction, allowing architects to improve their designs in the early stages of building design (Hamdy et al., 2016; Wu et al., 2018; Gunantara, 2018). Considering the complexity of building systems, multi-objective optimization methods are applied in the building industry, which can weigh some conflicts, e.g., low energy consumption and providing visual comfort. Functions are often defined as objective evaluation metrics that can be obtained from tested building performance simulation tools, such as daylight, glare prediction, and building energy consumption (Kirimtat and Ondrej, 2018). However, it should be noted that these metrics may not necessarily reflect occupant preferences (Newsham et al., 2012; Bian and Luo, 2017).

Research has shown that user-centered attributes have a significant impact on the subsequent performance of indoor environments in terms of artificial lighting usage, energy consumption, and user comfort (Gaetani et al., 2016). The absence of users in the design process may limit the building's performance during later stages of use, as well as satisfaction with the building environment. However, the incorporation of user preferences into consideration during the design process may be challenging due to the difficulty of simulating complex real-world building environments early in the design process (Hvas et al., 2017) and quantifying the subjective preferences of users (Rockcastle and Andersen, 2015). As a result, user evaluations have not been widely incorporated as design parameters for multi-objective optimization in the early stages of building design.

With the current advancements in hardware and game engine technology, as well as the increasing use of ray tracing(Tsountani and Jabi, 2014), it is now possible for virtual reality (VR) to realistically replicate architectural environments, providing a promising tool for architects to immerse users in unbuilt spaces and gather their perceptions in the early stages of building design (Yin et al., 2020). Many studies have demonstrated the authenticity of VR technology in simulating architectural environments and even daylight conditions (Chamilothori et al., 2019a). Subjective questionnaires (Chamilothori et al., 2019b), task-specific performance indicators (Heydarian et al., 2015; Heydarian et al. 2017), and measurements of skin conductance and heart rate have been used to compare users' spatial perceptions (e.g., pleasantness, interest, excitement, complexity, and satisfaction), task performance (e.g., object identification, reading speed, and comprehension), and bodily symptoms in real and virtual environments, and no significant variations in perception were found between the two surroundings.

In this paper, a novel multi-objective optimization framework that combines subjectivity and objectivity is proposed. Specifically, a user-centered interactive optimization approach based on immersive virtual reality...
Figure 1: The user-centered multi-objective optimization algorithm framework.

is investigated. While the Honeybee plug-in of the Rhino platform is employed to simulate building energy consumption, the subjective satisfaction scores of users are collected after an immersive tour of virtual reality scenes. Using the particle swarm optimization algorithm, the user's subjective satisfaction and building energy consumption performance are incorporated into the multi-objective decision-making analysis. This results in the determination of optimal design parameters that take the user's subjective feelings into account and have the potential to improve both building performance and user satisfaction.

Methods

The user-centered multi-objective optimization algorithm framework is comprised of the following key components: (1) establishment of a multi-objective optimization model for design parameters, (2) obtaining objective function results, by subjective evaluation experiment of indoor lighting environments in virtual reality, and (3) acquiring objective function results through Building Performance Simulation (BPS). The optimization process is depicted in Figure 1. The detailed description of this workflow is based on a case study of a multi-objective optimization problem.

Optimization problem formulation

In optimization problems in building design, energy consumption and the utilization of daylight are the most commonly focused factors. The multi-objective optimization model established in this section aims to obtain the minimum cooling energy consumption and optimal daylight illumination on the summer solstice, both of which are conflicting indicators. The energy consumption and daylighting performance of buildings are influenced by various factors, such as building form, envelope materials, and window design parameters, among which the window design parameters are particularly important and are the focus of architects’ attention. The judicious configuration and proportions of windows play an indispensable role in the creation of an optimal indoor luminous environment. Additionally, they can precipitate considerable energy economies in HVAC systems. Consequently, the present investigation elects window design parameters as decision variables within the analytic optimization model.

3D model setup

The buildings that need to be optimized are modeled parametrically using Grasshopper (GH) control in Rhino. A GH script written in Python is used to read design variables sent by the particle swarm optimization algorithm and model the building in real-time. While any 3D modeling software can be used at this stage, it is important to note that the modeling process needs to be parametric in order to be linked to the optimization algorithm. This allows window positions and sizes on the wall to be determined by the window design parameters sent by the particle swarm optimization algorithm and updated in real-time as the optimization process progresses.
VR system development

The parametric mode is imported into the D5 Render for rendering, in order to create more realistic indoor lighting and materials. The D5 renderer uses real-time ray tracing (Burke et al. 2019) and physically-based rendering (PBR) techniques, providing accurate real-time lighting simulation. Additionally, D5 Render employs a new ReSTIR Surfel (Reservoir-based Spatio Temporal Importance Resampling and Surfel) GI algorithm, which can provide realistic global illumination and indirect sunlight effects that closely resemble real-world environments. For daylight settings, a single directional light source simulating sunlight is set up using the geographic sky feature. By specifying the latitude and longitude of the building location and the simulation time, the position of the sun can be accurately obtained (including the sun's altitude and azimuth). It is important to note that the sun intensity and color in this feature are only for artistic purposes and do not represent accurate physical values, so a comparison should be made between illuminance values and color temperature simulated by D5 Render and those generated by a verified light simulation tool in one scene.

To allow users to participate in the design optimization process with a combination of subjective and objective elements on a virtual reality interaction platform, the real-time linkage between the model-building platform and the virtual reality platform needs to be implemented. This is achieved through two plugins: the D5-converter-Rhino plugin, which enables real-time linkage between the model-building platform and the rendering platform, and the virtual reality component of the D5 Render, which transfers the rendered image to SteamVR and displays it on a head-mounted display (HMD), allowing users to immerse themselves in the experimental model scene. Users can use game controllers to change their position and fill out subjective rating questionnaires in the virtual environment.

Collect subjective indicator score

In terms of daylighting evaluation, the user’s satisfaction score with the light environment is used as the evaluation indicator. Due to the short duration of the immersive experience of each optimized scene in the virtual environment, the time when the summer peak cooling load occurs is selected to set up lighting. This time can be obtained through weather files. Users immerse themselves in the virtual reality experimental environment and rate the satisfaction of the light environment in each optimized scene during the optimization process. The score ranges from -5.0 to 5.0, with -5 indicating very dark, 5 indicating very bright, and 0 indicating satisfaction with the light environment. The absolute value of the score is taken as the objective function result, and the optimization goal is to obtain the light environment subjective evaluation closest to satisfaction (0 points).

Collect objective indicator value

The cooling energy performance of the corresponding shorter period of the summer peak cooling load on the design day is chosen as the objective function for energy consumption evaluation. The Honeybee plugin was used for energy simulation, which linked the model built in Grasshopper and Rhino environment to simulation engines EnergyPlus to obtain the energy consumption value for the building. To facilitate the comparison and evaluation of building performance, the peak cooling load per unit area was chosen as the objective function, and the optimization goal was to achieve the minimum peak cooling energy consumption per unit area.

Optimization Algorithms

Building energy models have many design variables, which along with their discrete, non-linear, and highly constrained characteristics, can lead to multi-modal and discontinuous simulation results. In such cases, stochastic population-based MOOAs like evolutionary optimization and swarm intelligence can effectively handle the search space's discontinuity without needing a smooth objective function. Particle swarm optimization (PSO) is a population-based optimization algorithm that is known for its excellent maneuverability and convergence.

In this paper, a multi-objective PSO algorithm is utilized to provide a comprehensive evaluation of optimization solutions, taking into account both the subjective indicator score and the objective indicator value for each objective. This approach allows for a more holistic assessment of optimization solutions. However, due to the conflicting nature of these objective values, finding an optimal solution for each objective can be challenging. To address this issue, the Pareto solution has been incorporated into the study, enabling the generation of a set of optimization solutions to tackle the problem at hand.

Case study

In this section, we present an optimization problem that centers on the design of a small office, as depicted in Figure 2. The problem aims to balance a wide range of trade-offs between daylight performance and energy consumption, thereby verifying the accuracy and

Figure 2: Case study plan (left) and Photograph of the virtual space taken from different viewpoints (right).
practicality of the user-centered multi-objective optimization algorithm framework. To provide a comprehensive evaluation, we conduct a comparative experiment that compares the proposed method against conventional multi-objective optimization techniques, which typically entail the simulation of two or more objective functions using simulation tools. In the comparative experiment, the daylight performance of the building was simulated using daylight simulation tools.

Daylight evaluation experiment
The subjective evaluation of indoor lighting environments was conducted through virtual reality experiments. Participants were immersed in a virtual scene where they could explore a building and experience the quality of the indoor lighting environment in real-time as the design parameters were optimized. The window design parameters shown to the participants in the virtual reality scene were randomly generated using a particle swarm algorithm during the optimization process. Multiple participants repeated the experiments to eliminate the effects of individual differences.

This experiment enables users to participate in the optimization of design parameters in the early stages of building design, providing a more satisfactory indoor environment for users. By involving users in the design process, the experiment offers a unique opportunity to enhance the overall user experience and satisfaction with the indoor environment.

Test room
The experiment was conducted in an artificial climate laboratory, allowing effective control over variables of the indoor environment. The indoor temperature, humidity, wind speed, and other irrelevant variables are controlled by radiant flooring and fan coils, ensuring their constant and uniform conditions during the VR experiments. To prevent sunlight from entering, no windows are installed in the room, and the doorway is covered with blackout fabric. In addition, artificial lighting in the climate laboratory was not activated.

Table 1: Parameters of HTC Vive Pro Eye Headset.

<table>
<thead>
<tr>
<th>Headset parameters</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Screen</td>
<td>Dual RGB low persistence LCD</td>
</tr>
<tr>
<td>Resolution</td>
<td>2448 × 2448 pixels per eye</td>
</tr>
<tr>
<td>Maximum brightness</td>
<td>143 cd/m²</td>
</tr>
<tr>
<td>Refresh Rate</td>
<td>90 Hz</td>
</tr>
<tr>
<td>Field of view</td>
<td>Up to 120 degrees</td>
</tr>
<tr>
<td>Sensors</td>
<td>G-sensor, gyroscope, proximity, IPD sensor, SteamVR Tracking V2.0</td>
</tr>
<tr>
<td>Connections</td>
<td>Bluetooth, USBC port for peripherals</td>
</tr>
</tbody>
</table>

Experiment equipment
The HTC Vive Pro Eye virtual reality device was chosen for this experiment. This device is equipped with dual AMOLED screens with a resolution of 2880 × 1600 pixels, which provide rich color saturation and contrast for vivid image presentation. In addition to the head-mounted display, the HTC Vive series devices also include wireless control handsets and Vive base stations, allowing users to freely move around the room for a deeply immersive experience. The specific parameters are shown in Table 1.

To ensure that the participants have a comfortable and smooth experience in the VR scene, a high-performance computing platform with strong graphics and image rendering capabilities is required for the VR device. The workstation used in this experiment is equipped with an Intel® CoreTM i7-10700 processor, NVIDIA® GeForce® RTX 3060 graphics card, and 32GB of memory. All performance parameters meet the recommended configuration in the Vive Pro official documentation.

Experiment environment
The small office is situated in Tianjin province, China, at 39 degrees North latitude and 117 degrees East longitude. This information enabled us to determine the weather files utilized in the building performance simulation (BPS) and the sun parameters set in the virtual reality environment. The building floor plan is rectangular, measuring 3m x 4m with a ceiling height of 3m. Inside the building, there are basic furnishings, including desks, chairs, and a single-person sofa. To regulate indoor lighting precisely and directly, we simplified the daylight situation by only allowing a window on the south-facing wall to provide direct sunlight. The dimensions and height of the window are adjustable.

To ensure that the virtual reality (VR) scenes represented real-world daylight conditions, a comparison was made between illuminance values simulated by D5 Render and those generated by Radiance, a verified light simulation tool. The average illuminance of the working surface was measured by an LS100 luminance meter from the VR head-mounted display and simulated by Radiance in six randomly generated scenes. The error percentage for each measurement in D5 was computed by taking into account the value simulated by Radiance as a reference and employing the designated Formula (1). The validation results are shown in Table 2.

$$Error \ percentage = \frac{|L_D-L_R|}{L_R} \times 100$$  \hspace{1cm} (1)

This comparison showed that the highest error percentage was 6.21%, while the average error percentage for all measured scenes remained below 5%. These results validated the photometric accuracy in a virtual reality environment created by D5 Render in luminance simulation.

Experiment procedures
Participants were first asked to complete a demographic questionnaire, which included questions about their age, gender, and vision correction, followed by experience in VR and daylight aspects, and physical symptoms to be sure of their physical eligibility. After completing these assessments, participants were taken to an experimental room where they underwent a three-minute virtual reality experience. During this process, they were presented with
pre-rendered scenes and provided with instructions on the purpose of the experiment, how to use the IVE equipment, and how to adjust the HDM device. If there were no physical discomforts reported after the virtual reality experience, the participants were allowed to proceed to the actual experiment.

Before the start of the experiment, participants were instructed to close their eyes. A scene model was constructed using design parameters optimized through an algorithm, and after a few seconds of rendering, the virtual reality experimental scene was prepared. Participants were then directed to sit in a chair at the center of the laboratory, which simulated the perspective of sitting at a desk in a virtual environment. Following this, participants were instructed to open their eyes and informed that they could explore the immersive virtual environment by rotating and walking around. This process lasted for a duration of 30 seconds. Subsequently, participants provided feedback on the indoor lighting environment using a scoring questionnaire that was presented in the virtual reality environment. Alternatively, participants could provide their feedback verbally. Upon completion of the experience, participants were instructed to close their eyes and wait for the next scene to be prepared. This procedure was repeated until the optimization algorithm produced the final result or until the set number of iterations was completed.

Upon completion of all virtual environment explorations, participants were requested to respond to report their physical symptoms once again to ensure that no motion sickness occurred during the experiment.

Experiment participants
Six participants (4 female, and 2 male) aged between 22 and 26 years, with education backgrounds related to architectural design, but without experience in daylight measurement or evaluation, were recruited for the experiment. Except for myopia, no other visual impairments were reported by the participants. All participants had previous experience using VR and did not report motion sickness during the experiment.

Energy performance simulation
By prior research on building performance simulation, the thermal parameters of the building maintenance structure required for energy consumption modeling were determined using the ASHRAE 90.1 2013 and IECC 2015 standards, which were embedded in the Honeybee platform. The personnel scheduling was based on the small office type, which is a default option in the Honeybee platform. The specific parameter settings are illustrated in the accompanying Table 3.

Multi-objective optimization
Using the multi-objective particle swarm optimization (MOPSO) algorithm discussed earlier, an optimization model is established. Three design parameters related to the window were chosen for optimization: window width, window height, and sill height. These design parameters are illustrated in Table 4. The parameter settings for the MOPSO algorithm can be found in Table 5.

Table 2: Average luminance values for different scenes in Radiance and D5 Render.

<table>
<thead>
<tr>
<th>Scenes</th>
<th>Window width (m)</th>
<th>Window height (m)</th>
<th>Sill height (m)</th>
<th>Luminance values in Radiance (cd/m²)</th>
<th>Luminance values in D5 (cd/m²)</th>
<th>Error percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>2.31</td>
<td>1.61</td>
<td>1.1</td>
<td>90.92</td>
<td>96.57</td>
<td>6.21</td>
</tr>
<tr>
<td>B</td>
<td>1.50</td>
<td>1.22</td>
<td>1.45</td>
<td>60.54</td>
<td>63.23</td>
<td>4.44</td>
</tr>
<tr>
<td>C</td>
<td>1.32</td>
<td>0.4</td>
<td>1.24</td>
<td>10.22</td>
<td>9.82</td>
<td>3.83</td>
</tr>
<tr>
<td>D</td>
<td>0.57</td>
<td>0.63</td>
<td>1.07</td>
<td>6.55</td>
<td>6.86</td>
<td>4.73</td>
</tr>
<tr>
<td>E</td>
<td>1.922</td>
<td>1.622</td>
<td>0.21</td>
<td>58.51</td>
<td>57.88</td>
<td>1.07</td>
</tr>
<tr>
<td>F</td>
<td>1.96</td>
<td>1.333</td>
<td>0.98</td>
<td>61.2</td>
<td>60.35</td>
<td>1.39</td>
</tr>
</tbody>
</table>

Table 3: Parameter settings for energy performance simulation.

<table>
<thead>
<tr>
<th>Climate zone</th>
<th>Vintage</th>
<th>Construction type</th>
<th>Program</th>
</tr>
</thead>
<tbody>
<tr>
<td>6-Cold</td>
<td>ASHRAE 90.1 2013 &amp; IECC 2015</td>
<td>Mass</td>
<td>Small office-closed office</td>
</tr>
</tbody>
</table>

Table 4: The ranges of design variables.

<table>
<thead>
<tr>
<th>Design Variables</th>
<th>Type</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>x₁</td>
<td>Window width (m)</td>
<td>Continuous</td>
</tr>
<tr>
<td>x₂</td>
<td>window height (m)</td>
<td>Continuous</td>
</tr>
<tr>
<td>x₃</td>
<td>sill height (m)</td>
<td>Continuous</td>
</tr>
<tr>
<td>Constraint condition</td>
<td></td>
<td>x₁+x₂&lt;3</td>
</tr>
</tbody>
</table>

Table 5: Main PSO parameters setting.

<table>
<thead>
<tr>
<th>Main Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of generations</td>
<td>15</td>
</tr>
<tr>
<td>Population size</td>
<td>15</td>
</tr>
<tr>
<td>Acceleration coefficient c1</td>
<td>2</td>
</tr>
<tr>
<td>Acceleration coefficient c2</td>
<td>2</td>
</tr>
<tr>
<td>Inertia weight</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Comparative experiment
In the comparative experiment, the energy performance indicator was selected to be the same as the peak cooling load on a summer design day as mentioned previously. However, the average illuminance on the working plane was selected as the evaluation indicator for daylight performance, and the goal was to obtain the maximum illuminance. The constraints are that the illuminance value on the working plane in office buildings should be above 450 lx, while the discomfort glare index (DGI) should be less than 25, according to the Standard for the daylighting design of buildings (GB 50033-2013). The
Honeybee plugin was used to link Radiance for daylight simulation. The same parameter settings are used for MOPSO as mentioned in the previous section.

**Results**

The optimization results use the multi-objective optimization approach combining subjective and objective for the six participants are shown in Figure 3. The border per individual has been well reserved at the end of the six combined subject-objective multi-objective, and the Pareto front appears. Thus, the multi-objective optimization method of building performance combined users' subjective evaluation and the building's objective performance has been successfully achieved. Each dark-colored point corresponds to a Pareto optimal solution, and the designer can choose any of these solutions as the optimal design solution if needed. The analysis in Figure 3 shows a smaller change in the peak cooling per unit area during the process of building design multi-objective optimization, with only 10% of the variation (the ratio of the range of variation to the maximum value in the optimization process). This means that there is a slight change in cooling energy performance with varying indoor light satisfaction with the variation of window design parameters. As a result, the Pareto solution which has minimum building energy consumption is more should be selected as the optimal solution design in the user-centered design. The corresponding Pareto solution represents the building The scenario is shown in Figure 4.

However, there are some differences compared to the results of the comparison experiments. The optimization runs requiring 225 simulations for the comparison experiment took about 3 h to complete, which is slightly longer than the combined subject-objective optimization method proposed in this study, which requires 1.5~2 h for each optimization. The optimization results of the comparison experiments are shown in Figure 5. From the figure, it can be seen that the individuals of the entire population are uniformly distributed into the set of optimal solutions and more Pareto solutions are obtained than the combined subject-objective optimization experiment. Illuminance values are varied between 558 lx and 2711 lx simulated by Radiance and the cooling energy consumption value gets bigger, and the daylight amount the inside gets higher, since the size and position of the windows of the office room changes.

By analyzing Figure 6, it is evident that under similar optimization problem settings, the distribution of multi-objective optimization solutions from the comparison experiment, where the objective function was selected, was broader, with the cooling energy consumption values ranging between 60 W/m² and 110 W/m². Conversely, the Pareto solutions obtained using the combined subjective-objective optimization method had a concentrated cooling energy consumption value between 69-77 W/m², which was proximate to the minimum energy consumption value obtained from the comparison experiment.

**Discussion**

Compared with the comparison experiments, the optimization results use the multi-objective optimization approach combining subjective and objective to obtain a lower peak cooling energy consumption with a shorter experimental time. Also, although the number of Pareto solutions is smaller, still the Pareto front appears.

The above differences may be explained by several factors:

- The simulated value of the light environment does not fully reflect the user's preference for the illumination of the working surface. In the subjective evaluation experiments of the indoor light environment, user satisfaction scores do not change unidirectionally with increasing illuminance values. Although the indoor light environment becomes
Figure 4: Photograph of the virtual space taken from the participant’s viewpoint.

Figure 5: Result of the comparative experiment

- Brighter with increasing window size (subjective rating from -5.0 to 0, decreasing in absolute value), oversized windows with inappropriate window positions lead to objectionable intense reflections and even glare (subjective rating from 0 to 5.0, increasing in absolute value), which is the opposite of the optimization goal. In contrast, in the comparison experiments, the optimization goal of the light environment is to obtain the illuminance maximum (despite the constraint of the glare index maximum), which does not carry a complete representation of a more comfortable indoor light environment.

- The subjective evaluation mechanism of the daylight environment prefers dimmer environments in the optimization process. In the user-centered multi-objective optimization algorithm framework in this study, the evaluation criterion for indoor lighting is the absolute value of the user's subjective rating. Specifically, regardless of whether the current scene is brighter or darker than the completely comfortable environment, it will be considered the same value and incorporated into the optimization process when the user perceives the same distance from the completely comfortable lighting environment. A dimmer environment usually corresponds to a smaller window size, resulting in lower energy consumption. Therefore, such individuals are more likely to gain an advantage in the multi-objective particle swarm optimization algorithm.

Figure 6: Pareto solutions for all the experiments

- The participants are unstable. Unlike the building performance simulations, participants involved in the optimization could not provide fully correct subjective ratings regarding the difference between the daylight performance of the observed scenes and what they considered to be a fully comfortable light environment, which led to the possibility of missing some optimal solutions. Both the order in which scenes appeared and the contrast in indoor brightness of scenes in adjacent order can affect these errors. To mitigate potential errors, a fully randomized order was employed for presenting scenes to the subjects during the experiment, by the optimization process. Furthermore, after concluding a scene visit, participants were instructed to close their eyes and await the preparation of the next scene. The experiment was conducted with multiple participants to minimize errors. Despite the limited number of Pareto solutions, a distinctive Pareto frontier was evident in the optimization results for each participant.

Conclusion

The proposed algorithmic framework creates a multi-objective optimization problem for architectural design parameters that supplements the current practice of considering only objective indicators. By emphasizing the importance of user preferences, this approach enables the derivation of a more comprehensive solution, which
improves user satisfaction with design results. Rhino, Grasshopper, and D5 platforms are used to facilitate the generation, display, rendering, and iterative update of architectural scenes, where users are allowed to immerse themselves in the optimized architectural scene and participate in the process of optimizing design parameters. The performance of the traditional objective multi-objective optimization method is compared with that of the proposed subjective-objective multi-objective optimization method. Results indicate a significant difference between the two outcomes, with the former providing a solution with lower energy consumption, as well as higher user satisfaction. By allowing users to participate in the design optimization process, this study innovatively helps to improve the performance of architectural design, while expanding the application of user-centered design ideas in architectural design.

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