

Deep Learning-Based Architectural Visual Style Transfer Simulation and Functional Performance Optimization

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Architectural style transfer methods have difficulty achieving a balanced optimization of both visual aesthetics and functional performance, resulting in frequently unpragmatic solutions that fail to meet real-life architectural needs. The paper explores the unique difficulties experienced by researchers engaged in architectural visual style transfer simulation and proposes a multi-objective optimization framework utilizing deep learning that addresses these difficulties. This paper addresses the issue of maintaining a high level of fidelity while adhering to physical constraints without jeopardizing structural safety. The proposed framework utilizes a CycleGAN (Cycle Generative Adversarial Network), which incorporates an attention mechanism to increase the sensitivity to the transfer of local characteristics, and combines matrix representations with a VGG-19 (Visual Geometry Group 19) network to provide two types of loss (style and content) that ensure a high level of visual fidelity. The NSGA-II (Non-Dominated Sorting Genetic Algorithm II) algorithm is included in the framework to dynamically optimize both architectural style and functional performance by using energy use and daylighting calculated by EnergyPlus and Radiance as hard constraints. Achieving this will require a closed-loop generation-simulation-evaluation-feedback process. Real-time imports of style transfer designs go into a Building Information Modeling (BIM) and Virtual Reality (VR) simulation where EnergyPlus and Radiance will compute the designs' performance. The performance data are then used as feedback for the NSGA-II algorithm to modify generator settings and produce an optimal design. Finally, the architectural model shows the trade-offs between the aesthetics, energy use, and daylight use of the various design solutions to provide designers with visual assistance for deciding upon which is best. Experimental results indicate that this approach resulted in better scores in user satisfaction surveys and 16.4% less EUI than pre-transfer models. The post-transfer sDA increased 8.2% as compared to StyleGAN and average use of space increased 22.3% over pre-transfer models. The average maximum deformation was 7.8 mm and average maximum stress was 18.1 MPa, with no detrimental effect to the safety of the building structure. The research provides both theoretical and practical tools supporting intelligent building design that offers both aesthetic and practical value.

Keywords: Deep learning; style transfer; architectural simulation; architectural functional performance optimization; generative adversarial network

1. INTRODUCTION

The rate of innovation within the architecture domain is increasing due to advancements in science and technology. New technologies and techniques are constantly emerging, drastically altering how architecture has traditionally been designed and constructed. Nowadays, artificial intelligence

offers countless algorithms and methods for the design of architecture [1–2]. Architectural design and optimization have evolved progressively from conventional, labor-intensive design processes to computationally automated processes as a result of the growth of building informatization and intelligentisation [3–5]. There are two key aspects to remember about style transfer for architecture. First, it focuses on the aesthetic attributes of facades. Second, it has strict engineering requirements imposed by the physical

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structure of the building. For example, architectural styles need to ensure the appropriate ratio of windows-to-walls to meet the requirements related to day lighting and energy efficiency. Most current studies focus too much on the aesthetics of architectural styles and do not concurrently optimize the functional performance of architectural styles. Traditional methods have not been able to effectively balance high fidelity style transfers with functional requirements under high complex constraints. This limitation not only restricts the application of style transfer technology in practical architectural design, but also leads to significant deficiencies in the generated designs in terms of daylighting efficiency and energy efficiency.

For architectural design, both visual aesthetics and practicality are crucial. Pei et al. pointed out that architectural aesthetics research usually focuses only on the visual attributes of architecture. Ghom et al. believe that aesthetics is an important attribute of architecture, on par with practicality [6–7]. Alhammad et al. attach importance to the functionality of architecture and improve energy efficiency by building information models and energy models [8]. The core contradiction of current architectural visual style transfer research lies in the separation of visual aesthetics and functional performance: on the one hand, designers pursue artistic expression in facade form, materials, and decorative details; on the other hand, as a functional entity, buildings' physical indicators, such as daylighting efficiency (sDA/ASE), energy use intensity (EUI), and space utilization, are directly related to operating costs and user comfort [9–10]. Existing methods optimize visual effects while ignoring the impact of key design variables such as window-to-wall ratio on daylighting. While the resulting solutions may be visually impactful, they also result in high ASE (Annual Sunlight Exposure), leading to glare [11–13]. Or they may overlook issues such as the selection of materials for sunshade components and thermal engineering. Appropriate materials can reduce cooling loads, lower building energy consumption, and improve practicality of a building [14–15]. This contradiction highlights the urgency of simultaneously embedding physical performance constraints in style transfer. To address these issues, various algorithms and models have been proposed. For example, Fu et al. and Peng et al. used CycleGAN to achieve style transfer, but the lack of spatial details makes it difficult to use in architectural design [16–17]. Asperti et al. and Zhang et al. attempted to generate diverse styles through latent space interpolation using StyleGAN, but failed to effectively embed physical performance constraints [18–19]. Wei developed a CNN-based style transfer method, but due to the lack of an adversarial training mechanism, the visual fidelity of the transfer results was low [20]. The EnergyPlus tool can model energy control and simulate building energy consumption to analyze and optimize energy control [21–23]. Zhang R et al. pointed out the importance of multi-objective optimization in architectural design [24], while Dong Y et al. proposed a multi-objective optimization framework for daylighting and energy performance, but did not consider the architectural aesthetics [25]. Although these methods have achieved certain results in specific scenarios, they are unable to meet simultaneously the requirements of co-optimization of visual aesthetics and functional

performance. The purpose of this current study is to propose a multi-objective optimization framework based on deep learning to achieve the co-optimization of visual aesthetics and functional performance in architectural style transfer. Specifically, a style transfer model was constructed using CycleGAN combined with an attention mechanism. The Gram matrix and VGG-19 network were used to define the style transfer loss and content preservation loss, respectively, to ensure the visual fidelity and structural integrity of the transferred results. Furthermore, the NSGA-II algorithm was applied to embed physical performance constraints such as daylighting efficiency and energy consumption, and the EnergyPlus and Radiance tools were used to calculate the physical performance indicators of the transferred building in real time. In conclusion, through the combined optimization of the style transfer loss, the content preservation loss, and the functional performance constraint loss, the study has created a high-quality architectural model from both aesthetic and functional perspectives. The experiments show that this method increases the fidelity of style transfer and also improves transparency and energy efficiency of the building's daylighting, thus providing both theoretical guidance and practical support for the design of buildings.

2. METHODS

2.1 Construction of a Deep Learning Style Transfer Model

To create a deep learning model for transferring styles, we used CycleGAN as our primary architecture and trained it on unpaired data from different style architectures to extract architectural visual features and transformation styles [26–29]. One of the key benefits of the CycleGAN is that it enables the mapping between different domains (i.e., a source domain and a target domain) without requiring exact correspondences between source and target domain data, thereby significantly reducing the costs associated with collecting and annotating data for architectural style transfer projects. We also used an attention mechanism in the generator to improve the transfer of local detail; this mechanism weights the input feature map to give more emphasis to key part feature responses, which improves both the fidelity and visual coherence of the transferred result [30–31].

Specifically, the generator's structure is based on an improved U-Net. The encoder uses multi-layer convolution operations to extract multi-scale features, while the decoder gradually restores spatial resolution through deconvolution. An attention module is embedded in the skip connection, utilizing the combined computation of channel attention and spatial attention to dynamically adjust the feature map weight distribution. Using global average pooling across all channel dimensions of the feature map provides a channel descriptor $z_c \in R^C$ where C is the number of channels. This channel descriptor is then processed by two fully connected layers followed by a sigmoid activation function in order to obtain a channel weight vector α_c . Spatial attention combines all channel information into one feature map by using a



Figure 1 The schematic diagram of style transfer.

1×1 convolution operation, applying the Softmax function to obtain a spatial weight matrix $\beta_s \in R^{H \times W}$ (where H and W are respectively the height and width of the feature map). After applying attention to the weights, the result can be denoted as F' :

$$F' = (\alpha_c \otimes F) \odot \beta_s \quad (1)$$

where $\otimes$ represents channel-by-channel multiplication, $\odot$ represents element-by-element multiplication, and F represents the original feature map. This formula ensures that the generator focuses on key visual elements of architectural style while avoiding interference from irrelevant background information.

To further optimize the style transfer effect, a hybrid loss function is designed to balance the conflict between content preservation and style transfer. The style transfer fidelity loss calculates the style difference based on the Gram matrix and is defined as:

$$L_{style} = \frac{1}{4N^2M^2} \sum_{i,j} (G_{ij} - G'_{ij})^2 \quad (2)$$

where G_{ij} and G'_{ij} represent the Gram matrices of the source style and target style feature maps, respectively, N is the number of channels of the feature map, and M is the spatial size of the feature map. The Gram matrix indicates the global style information by calculating the inner product between the channels of the feature map, so this loss term can effectively capture the macro characteristics of the architectural style. At the same time, the content preservation loss is based on the similarity of the feature map extracted by VGG-19, and constrains the consistency of the content structure by comparing the activation values of the source image and the generated image at a specific convolutional layer. Specifically, let x be the source image and y be the generated image, then the content loss is defined as:

$$L_{content} = \frac{1}{C \cdot H \cdot W} \sum_{i=1}^C \sum_{j=1}^H \sum_{k=1}^W (F_{ijk}^x - F_{ijk}^y)^2 \quad (3)$$

where F_{ijk}^x and F_{ijk}^y are the feature maps of x and y at a specific layer of VGG-19, respectively. C , H , W are the number of channels, height, and width of the feature maps, respectively. By jointly optimizing L_{style} and $L_{content}$, the model can achieve high-fidelity style transfer while

maintaining the integrity of the architectural structure. A schematic diagram of style transfer is shown in Figure 1.

An adversarial loss is introduced during training to enhance the realism of generated images. Using the PatchGAN discriminator, the generative component produces finer quality textures and detail by assessing how real or fake each of the generated local image patches appear relative to each other. To find the Nash Equilibrium and complete the transfer of architectural visual style, the adversarial loss along with the previously mentioned style and content losses comprise the overall loss function, and the system iteratively optimizes the parameters of both discriminator and generator.

2.2 Multi-Objective Optimization Framework Design

In designing the multi-objective optimization framework, NSGA-II functions as the main optimization method while employing a deep learning model for combined style transfer and functional performance optimization [32–35]. NSGA-II allows for the generation of a wide range of Pareto-optimal solutions by utilizing fast non-dominated sorting and crowding distance calculations in order to effectively balance multiple objectives. The main goal of the framework will then be to formulate an overall joint optimization objective function from the style transfer loss, content preservation loss, and physical performance constraints, and subsequently optimize the generator parameter iteratively until the optimal solution is reached.

The Gram matrix is used to compute the fidelity loss for style transfer, denoted by $L_{style}(x)$, which represents a global style of the contents of an image via an inner product between all the channels of a feature map from a generated image and a source image. The L_{style} term can capture the large or macroscopic properties of an architectural style. $L_{content}(x)$ is a measure of similarity between feature maps obtained from VGG-19 [36] that will maintain the consistency of the structure of the contents of the generated image and will ensure that no details will change when comparing the activations at different convolutional layers in the feature maps of a generated and source image.

Functional performance constraint loss $L_{functional}(x)$ combines the two indicators of lighting efficiency and energy consumption value and is defined as:

$$L_{functional}(x) = \lambda_1 \cdot EUI(x) + \lambda_2 \cdot (1 - sDA(x)) \quad (4)$$

where $EUI(x)$ represents energy intensity, which measures the energy consumption per unit area of the building throughout the year; $sDA(x)$ represents spatial daylight autonomy, which reflects the proportion of the area within the building that meets the lighting requirements; λ_1 and λ_2 are weighted coefficients used to balance the impact of the two indicators. Utilizing both EnergyPlus and Radiance for data integration allows physically measurable performance parameters (annual energy usage and light distribution for the newly moved building) to be dynamically determined and used as constraints in an optimized framework for adjusting generator parameters dynamically [37].

NSGA-II is an evolutionary algorithm that first sorts individuals from the population into various categories depending on their fitness (objective function value) during the optimization process. Next, for those individuals in the same category, solutions that are evenly distributed according to a crowding distance metric will be selected for the next generation. The population is then updated from generation to generation by mapping generator parameters to the objective function input and recomputing the loss value for use to help guide the optimization process. After multiple generations, a set of Pareto-optimal solutions is obtained that represents both an artistic style transfer outcome and the associated physical performance.

2.3 Embedding Physical Performance Constraints

The embedding of the physical performance constraint allowed the integration of EnergyPlus with Radiance, which enabled the accurate calculation of EUI and daylight distribution for the migrated building model. The dynamic feedback of the physical performance metrics into the optimization framework was used to modify the style transfer parameters. EnergyPlus calculates the energy consumption for all environmental conditions over the course of an entire year, and Radiance provides the analyses of light. Together, the two give a balanced representation of visual aesthetic qualities and functioning performance of the generated building model.

First, EnergyPlus was used to calculate the energy use intensity (EUI) of the migrated building using the following formula:

$$EUI = \frac{\sum_{t=1}^T E_t}{A} \quad (5)$$

where E_t represents the building's total energy consumption in time step t (unit: kWh), T is the total number of time steps in a year (usually measured in hours, i.e., $T = 8760$), and A is the building's total floor area (unit: square meters). EnergyPlus uses its built-in thermal model and meteorological data to calculate the building's cooling and heating loads, lighting energy consumption, and equipment energy consumption under different climate conditions, ultimately deriving the annual energy consumption per unit area. This metric quantifies the energy consumption differences caused

by changes in building materials, window-to-wall ratios, and other factors after a building's style transfer.

The Radiance program determined the daylight distribution chosen for the interior of the building. Primary metrics from the spacing daylight autonomy were SDA and ASE. SDA represents the number of hours per year in which the minimum light level (e.g. 300 lux) was reached during the total number of hours worked. The formula for calculating SDA is:

$$sDA = \frac{1}{N} \sum_{i=1}^N I(L_i = L_{min}) \quad (6)$$

where N represents the total number of working time steps throughout the year; $I()$ is an indicator function that takes the value 1 when $L_i = L_{min}$ is reached and 0 otherwise; L_i represents the spatially averaged light intensity (in lux) at the i th time step; and L_{min} is the minimum light requirement threshold (typically set at 300 lux). This metric directly indicates the adequacy of natural daylighting within a building, preventing a decrease in daylighting efficiency due to style transfer.

The annual daylight exposure index is used to assess the risk of excessive light exposure. The formula is:

$$ASE = \frac{1}{N} \sum_{i=1}^N I(L_i > L_{max}) \quad (7)$$

where L_{max} is the maximum allowable light intensity threshold (typically set to 1000 lux). By jointly analyzing sDA and ASE, the relocated building ensures that it provides sufficient natural light while avoiding the discomfort and increased energy consumption caused by excessive light exposure.

To make simulations more efficient, we also use a surrogate model built from EnergyPlus and Radiance. The surrogate model uses historical simulation data to create a quick prediction of the final result of complex physical performance metrics. It uses Gaussian Process Regression (GPR) to create the surrogate model that can significantly reduce the time spent calculating physical performance while still providing very accurate predictions [38].

2.4 Loss Function Design

A comprehensive loss function is designed as a factor to weigh the balance between fidelity in style transfer is equal to content structure preservation as well as a factor to satisfy functional performance constraints. This comprehensive loss function is comprised of three primary loss components for style transfer fidelity: L_{style} , content structure preservation $L_{content}$, and functional performance constraints $L_{functional}$. The multi-objective collaborative optimization process uses a weighted average approach. The formula is:

$$L_{total} = w_1 L_{style} + w_2 L_{content} + w_3 L_{functional} \quad (8)$$

where w_1 , w_2 , w_3 are weight coefficients, 0.4, 0.4, and 0.2, respectively, used to adjust the importance of each sub-loss term. To achieve an ideal composition of aesthetic and performance characteristics for the pieces,

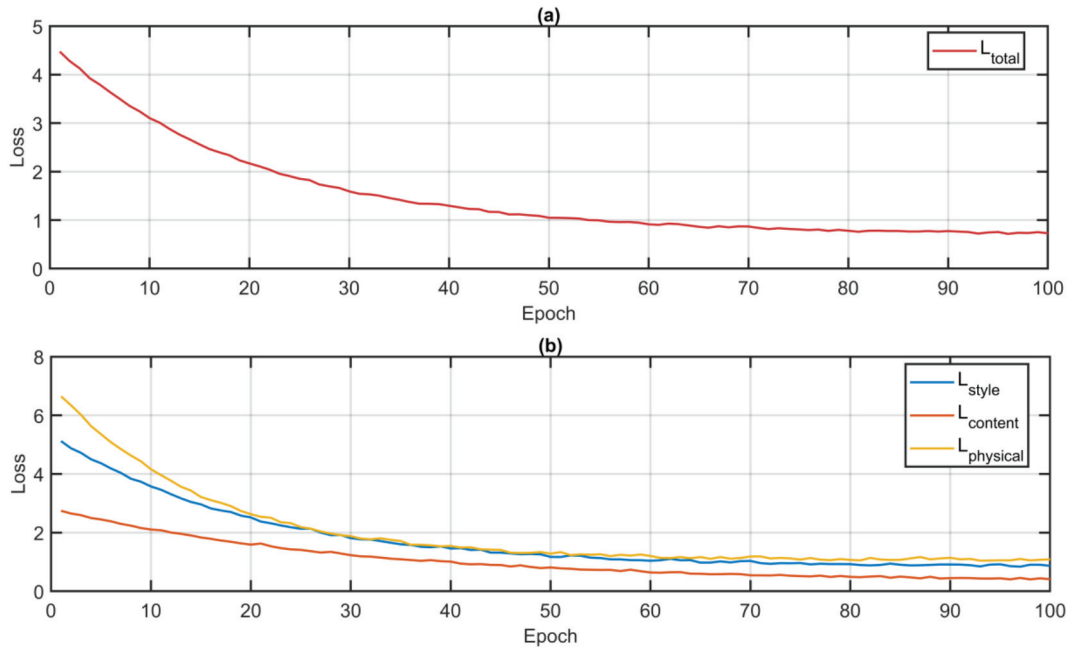


Figure 2 Loss Function Convergence Curve. (a) Model Total Loss Function Convergence Curve. (b) Change Curves of Each Component's Original Loss Function.

the weightings were developed by conducting experimental tuning. By implementing this embedding approach, the created representations could satisfy both their purposes and needs visually. The graph showing the loss function convergence is presented in Figure 2.

The comprehensive loss function L_{total} was optimized through the use of gradient descent during the training process. For example, to calculate the Style, Content, and Functional Performance Loss of the generated image, firstly, we used forward propagation and then updated the parameters of the generator via backpropagation. Additionally, to improve convergence times and mitigate local optimality, the Adam Optimizer was utilized via the following update equation:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \quad (9)$$

where θ_t is the generator parameter at iteration t , η is the learning rate, $\hat{m}_t$ and $\hat{v}_t$ are the bias correction values for the first-order moment estimate and the second-order moment estimate, respectively, and ϵ is a smoothing term to prevent the denominator from reaching zero. The dynamic adjustment of the learning rate and momentum parameters ensures the stability and efficiency of the optimization process.

2.5 Simulation Environment Setup

During the construction of the architectural simulation environment, a BIM+VR simulation platform was developed based on the Unity engine to import the migrated architectural model and perform real-time rendering and interactive evaluation [39]. By integrating lighting simulation, material rendering, and user perspective switching functions, the platform provides a high-precision visual verification

method for the generated architectural model and ensures that its optimization effects in terms of visual aesthetics and functional performance can be intuitively presented.

First, a physical lighting model was built in Unity to simulate the lighting conditions in a real environment. The ray tracing algorithm was used to calculate global illumination, using the formula:

$$L_o(p, \omega_o) = L_e(p, \omega_o) + \int_{\Omega} f_r(p, \omega_i, \omega_o) L_i(p, \omega_i) (\omega_i \cdot n) d\omega_i \quad (10)$$

where $L_o(p, \omega_o)$ represents the radiant intensity of light emitted from point p along direction ω_o ; $L_e(p, \omega_o)$ is the luminous intensity of the point p . $f_r(p, \omega_i, \omega_o)$ is the bidirectional reflectance distribution function, which describes the surface reflectance characteristics; $L_i(p, \omega_i)$ is the radiant intensity of the incident light; and $\omega_i \cdot n$ is the cosine of the angle between the incident light and the surface normal. The propagation paths of direct and indirect light can be calculated with these equations to achieve accurate lighting simulation results that replicate the relocated building's light distribution.

To solve the rendering materials problem, the researchers used Physically Based Rendering (PBR) technology to represent and simulate the surface material of the buildings. Essentially, using microplane theory, PBR determine how surfaces reflect light. The formula is:

$$f_r(\omega_i, \omega_o) = \frac{D(h)F(\omega_o \cdot h)G(\omega_i, \omega_o)}{4(\omega_i \cdot n)(\omega_o \cdot n)} \quad (11)$$

where $D(h)$ is the normal distribution function, describing the directional distribution of microfacet normals h ; $F(\omega_o \cdot h)$ is the Fresnel term, reflecting the reflectivity of light at different angles; $G(\omega_i, \omega_o)$ is the geometric occlusion



Figure 3 Schematic diagram of the building simulation environment.

term, accounting for the mutual occlusion effects between microfacets; ω_i and ω_o are the incident and outgoing light directions, respectively; and n is the surface normal. This formula accurately simulates the optical properties of various materials (such as glass, metal, and concrete), enhancing the realism of rendered images.

In order to support user perspective switches, we created a mechanism for free-roaming. Using Unity's camera system, users can freely roam the scene with a keyboard or VR device, dynamically modifying their perspective angle. Scripting also allows for the quick location of key nodes, which means users can set the view to predetermined perspectives using one click (e.g. indoor lighting hotspots and energy-sensitive spaces). In this way, users can quickly review changes in the functional performance of the relocated building. Figure 3 shows the environment of the building simulation.

In relation to data interaction, the migration of the building model into the simulation platform occurs using the FBX (Filmbox) format. Additionally, the thermal overlay created from the results of the EnergyPlus and Radiance evaluations is based on the imported building model. An example of this is the annual energy intensity of the building being represented as a colour gradient on its exterior:

$$C(p) = C_{min} + (C_{max} - C_{min}) \cdot \frac{EUI(p) - EUI_{min}}{EUI_{max} - EUI_{min}} \quad (12)$$

where $C(p)$ represents the color value of point p ; C_{min} and C_{max} are the minimum and maximum values of the color range, respectively; $EUI(p)$ is the energy consumption per unit area at point p ; EUI_{min} and EUI_{max} are the minimum and maximum energy consumption values, respectively. This formula visualizes energy consumption distribution as intuitive color differences, allowing users to quickly identify areas with high energy consumption.

Furthermore, the system has been built to support real-time interactive capabilities that let users change different amounts of variables (for example: window/door ratio or materials) and instantly see the results of optimization. This way of evaluating changes also makes the verifying of changes much easier, as well as providing quick feedback for future optimizations. The use of this type of simulation environment also enables the full evaluation of architectural style-transfer

at both visual and functional levels, thereby confirming both the feasibility and effectiveness of the style-transfer model in real-life applications.

3. EXPERIMENTATION AND VERIFICATION

3.1 Experimental Design

The dataset of Architecture has 25 architectural design types and approximately 5,000 images. The types of architecture represented include traditional styles such as Gothic and Romanesque as well as contemporary styles like Post Modern and Art Deco. High-resolution pictures of the outside of a building along with structure-related descriptions of the building (e.g., window layout, façade material, etc.) accompany each sample image. The dataset was divided into training, validation, and test sets, with a ratio of 70%, 15%, and 15%, respectively. After each training session, the model's performance on the validation set was recorded, and hyperparameters (such as learning rate and weight coefficients) were adjusted based on the results.

Three groups were established, one for each method. The experimental group: The method proposed in this paper, based on CycleGAN, uses unpaired image training to achieve style transfer through adversarial training between the generator and the discriminator. Furthermore, a multi-head self-attention mechanism was embedded in the generator to enhance the ability to transfer local details. StyleGAN: Based on StyleGAN, it leverages its latent space interpolation properties to generate diverse style transfer results and incorporates physical performance constraints for post-processing optimization. CNN: Based on CNN (Convolutional Neural Networks), it achieves style transfer through layer-by-layer feature extraction and reconstruction, but does not incorporate attention mechanisms or adversarial training. All three methods are trained using the Adam optimizer, with an initial learning rate set to 0.0002 and gradually decayed during training. To avoid overfitting, early stopping is used to monitor validation set loss and ensure the generalization of the model.

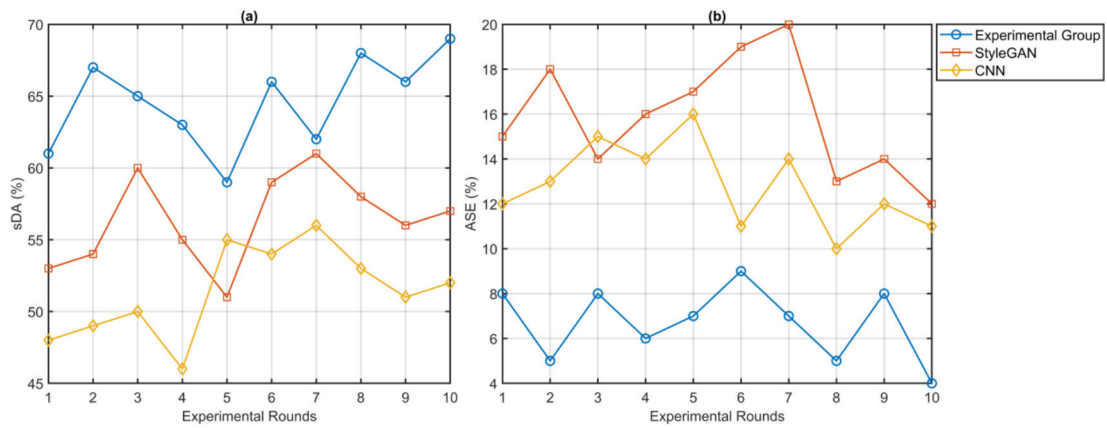


Figure 4 Comparison of sDA and ASE for Each Group. (a) sDA for Each Group. (b) ASE for Each Group.

3.2 Daylighting Performance Evaluation

To quantify the impact of architectural style migration on daylighting performance, the paper used SDA and ASE as the core metrics, combined with the Radiance tool, to accurately simulate and analyze the building's daylighting distribution before and after migration. The specific implementation process is as follows:

Firstly, the radiance tool was used to take the hourly indoor illuminating data from the building model and calculate the SDA value for each spatial point. The SDA value is defined as the percentage of time a specified threshold of illumination, in this case 300 lux, is achieved during standard working hours (8 am-6 pm) at a specific point in time throughout the year. The SDA value of each functional area within the building is calculated by sampling the space in a point-by-point method so that the percentage of the total area of each functional space that meets or exceeds the required daylighting requirement can be calculated. In order to ensure an accurate calculation, a high-resolution mesh will be used to discretize the interior volume of the building. A Monte Carlo ray-tracing algorithm is used to simulate the light path from each window and calculate the total effect of the window location, material reflectance, and any obstructions to daylight caused by the external environment on the total availability of daylighting. The pre-transfer SDA for the building model described above was 41% and the corresponding ASE for the building model was 6%.

The second step involved determining the area of over-illumination to estimate the risk associated with it. The area of over-illumination was determined using the ASE method, which defines the area at a specific time in the year in which the illumination exceeds an excessive illumination threshold (e.g., 1000 lux) during normal working hours. The paper shows the potential areas of exposure due to style transfer by mapping the illumination on a point basis in the building, and recording the locations and area percentages of those points. It is important to note that if large amounts of glass are utilized in the relocated building façade, or a reduction in shading occurs, this could result in significant increases to the ASE value in certain areas, which may potentially impact user comfort. By comparing the ASE distribution before and after the relocation of the building,

the paper demonstrated how style transfer may have impacted the balance of daylighting within the building. The average sDA and ASE value of each floor were established from the data prior to and after the building relocation to quantify the influence of optimizing the daylighting performance. Figure 4 shows the ASE and sDA value information for each of the design categories.

Group comparisons of sDA and ASE are illustrated in Figure 4. With an average of 8.2% sDA improvement compared to StyleGAN (over 10 runs) for the experimental group and an acceptable ASE score of 6.7%, the experimental group performed better in terms of style transfer, meaning the experimental group enhanced the illumination of materials without causing excessive illumination. On the other hand, while both styles demonstrated improved sDA scores compared to all runs, the ASE scores for both also improved considerably, which may produce an excessive amount of illumination.

3.3 Energy Performance Evaluation

The EnergyPlus software was used to determine the effects of an architectural style transfer on energy performance by accurately simulating and calculating the annual energy consumption of a building both prior to and after the transfer was completed. The parameters associated with the architectural style transfer were dynamically and programmatically adjusted based on feedback obtained from the functional performance constraints.

Once the building model was transferred, EnergyPlus was utilized to develop a one-year energy use simulation including the major components such as heating, cooling, lighting and operation of equipment. During the data prep process, the geometry, material and spatial configuration of the building were imported into EnergyPlus. Meteorological files were assigned to the Climate Zones to ensure that the environmental conditions for the energy use simulations were realistic. In addition to all this information, the operation schedules, occupant density, equipment power levels and light fixture wattage of each area of the building were defined based on how the building will be used to improve the accuracy of the energy use calculations. The

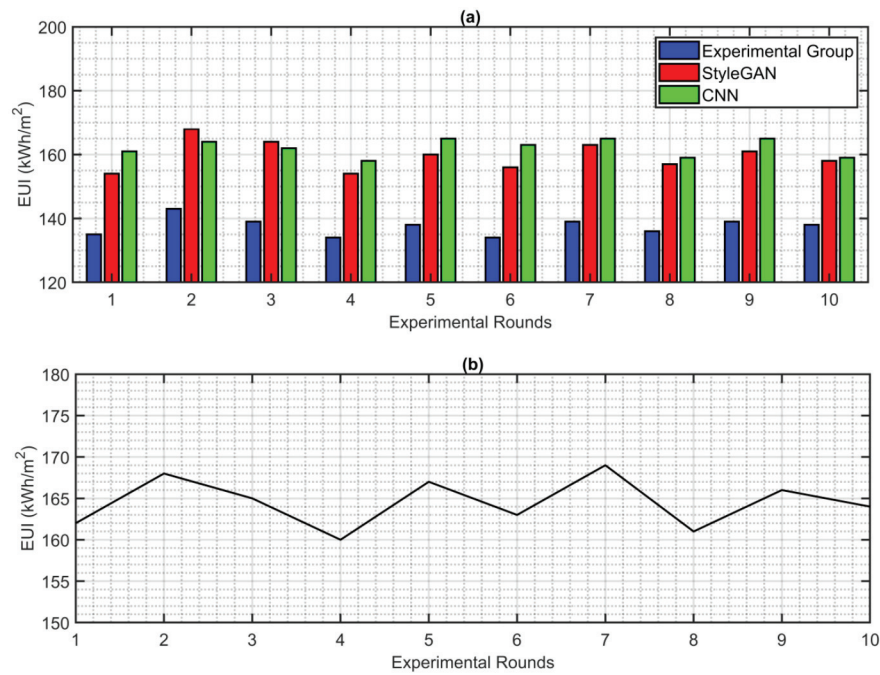


Figure 5 EUI Comparisons among Groups. (a) EUI Comparisons after Relocation. (b) EUI Comparisons of Different Building Models Before Relocation.

Table 1 EUI standard deviations for each group.

Rounds	Experimental Group (kWh/m ²)	StyleGAN (kWh/m ²)	CNN (kWh/m ²)
1	4.3	5.1	6.2
2	4.9	5.5	5.2
3	5.2	5.7	7.2
4	5.4	5.8	6.7
5	4.7	5.2	5.8
6	4.9	5.5	6.3
7	4.4	5.9	6.5
8	4.8	6.2	6.8
9	4.2	5.5	6.3
10	4.7	5.9	6.8

building's overall energy consumption was calculated by simulating the distribution of energy consumption over 8,760 hours. All changes in energy consumption (before and after migration) were analyzed for differences in thermal performance, including those caused by the style transfer. Energy consumption for summer cooling may be significantly greater at the relocated building if its facade incorporates a large amount of glass or has less shade. Conversely, if the relocated building has more insulation or has had its window layout optimized, overall energy consumption (per year) may decrease. The experiments were conducted for a total of ten one-hundred calculations using each experimental building example. The energy performance optimization for each experimental building was quantified using the energy use index before and after relocation. The comparison of energy use indices for each experimental building is shown in Figure 5.

Figure 5 shows the EUI comparisons of the groups. After relocation, the annual energy consumption per unit area of the experimental group decreased from an average of 164.5 kWh/m² to 137.5 kWh/m². The seventh experiment saw

the largest reduction, from 169 kWh/m² to 139 kWh/m², a reduction of 35 kWh/m². The other two groups saw smaller reductions, demonstrating only modest energy savings. The EUI standard deviations for each group are shown in Table 1.

The EUI standard deviations for each group are shown in Table 1. In terms of relative stability of the reduction in EUIs after migration, the experimental group had the smallest average standard deviation (4.75 kWh/m²), while both the StyleGAN and CNN groups exhibited larger average standard deviations of energy savings (5.63 and 6.38 kWh/m², respectively), indicating less stability or consistency in the amount of energy savings achieved by the respective methods used by these two groups.

3.4 Structural Safety Verification

Finite element analysis (vastly preferred over traditional methods of analysis) was conducted to determine whether or not the migrated architectural style would adversely affect structural safety. Ansys software was used to calculate both

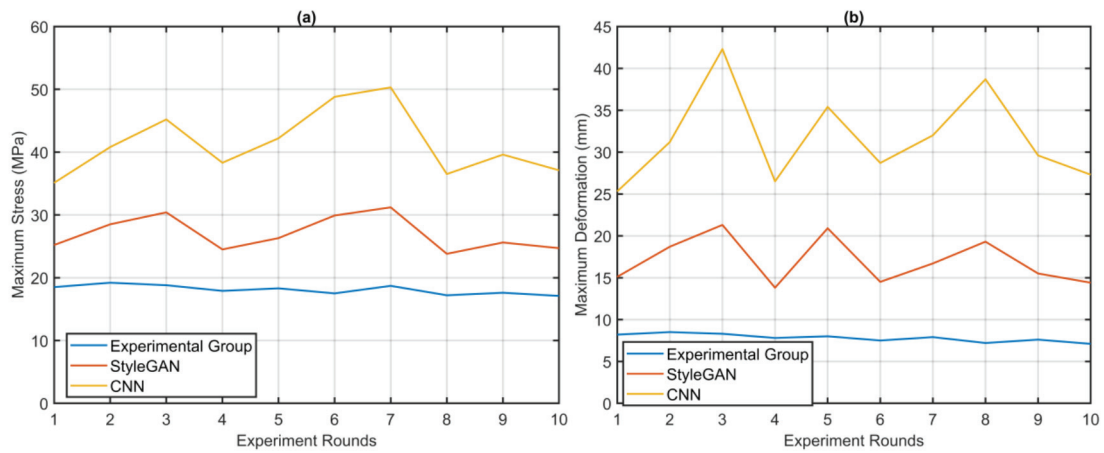


Figure 6 Comparison of Maximum Stress and Maximum Deformation. (a) Maximum Stress (b) Maximum Deformation.

maximum stress and maximum deformation for the migrated building. At the same time, stress was also extended to the key nodes of the in-situ building by examining them using the proper distribution documentation based upon the approved design. The specific procedure for implementing this method is outlined below.

The Ansys software program was used to import the building's migrated model and define each of its component's mechanical properties (e.g., modulus of elasticity, Poisson's ratio, density and yield strength) according to the way those properties are measured for the materials being used to build the structure. To increase the accuracy of calculations performed using the finite element method, a high-resolution finite element mesh was generated from the geometric data representing the building, and local refinements of the mesh were created near areas of interest (for example, at beam-column connections and around window openings). Then, necessary boundary conditions and load cases (fixed support conditions, dead-weight loads due to gravity, wind loads and seismic loading) were determined so as to provide a means of simulating the forces that would exist in a real building during its use. The static analysis module was used to calculate the overall stress distribution and deformation of the building, and the maximum stress and maximum deformation were extracted as core evaluation indicators. The maximum stress and maximum deformation are shown in Figure 6.

Figure 6 shows the comparison of maximum stress and maximum deformation. The average maximum stress for all runs in the experimental group was 18.1 MPa, with a peak of 19.2 MPa. The average maximum deformation was 7.8 mm, with a peak of 8.5 mm. Both StyleGAN and CNN had higher maximum stress and deformation, with average maximum stresses of 27 MPa and 41.4 MPa, respectively, and average maximum deformations of 17 MPa and 31.7 MPa, respectively.

3.5 Space Efficiency Statistics

To assess the impact of architectural style migration on space efficiency, this study used space utilization as a core metric, based on the functional zoning and actual usable area changes

before and after migration. It combined BIM data analysis with statistical analysis to quantify the optimization effect.

Based on the migrated building model, a BIM plugin was used to extract the geometric information and spatial attributes of each functional area, including the total building area, actual usable area of each functional area, and its layout distribution. Any layout adjustments resulting from style transfer (such as changes in wall position, addition of decorative elements, or adjustments to window openings) were updated in the BIM model, and the actual usable area of each functional area was recalculated. Ten rounds of experiments were conducted, with ten transfers performed each round. The average result was taken as the overall result, using a different building model for each round. Figure 7 shows the rate of building space utilization.

The average space utilization rate for the ten rounds of experiments before transfer was 59.2%. The average space utilization rate for the experimental group after transfer was 81.5%, an improvement of 22.3%. The average space utilization rate after StyleGAN transfer was 70.7%, while that for CNN was 67.8%, demonstrating that the experimental group significantly improved the utilization of space in the building after transfer. The standard deviation of space utilization is shown in Table 2.

The standard deviation of the average space utilization rate for the experimental group was 1.99%, compared to 3.47% for StyleGAN and 5.04% for CNN. The experimental group had the smallest standard deviation, indicating a relatively stable effect in improving space utilization.

3.6 User Satisfaction Survey

To evaluate the overall visual aesthetics and practicality of the relocated buildings, a structured questionnaire was designed and 20 architects and lay users were invited to give their ratings. Using a scoring scale of 1 to 10 points, the participants evaluated the relocated buildings according to: aesthetics, rational spatial planning, lighting comfort and practicality. The scores were statistically analyzed in order to determine a correlation between subjective scoring and objective performance measures. The survey was conducted in the following manner.

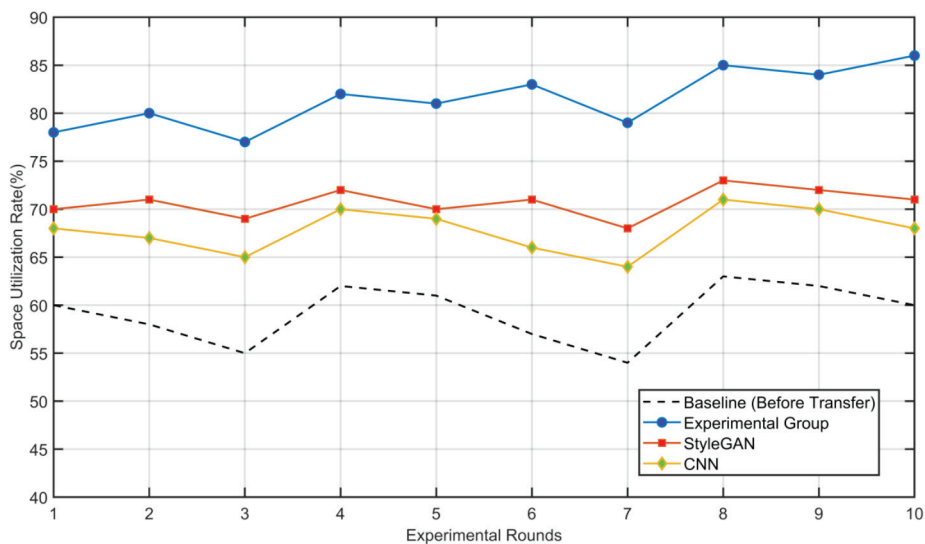


Figure 7 Comparison of the Impact of Different Style Transfer Methods on Building Space Utilization.

Table 2 Standard Deviation of Space Utilization by Group.

Rounds	Experimental Group (%)	StyleGAN (%)	CNN (%)
1	1.6	3.4	5.8
2	1.7	3.9	5.1
3	2.2	3.6	5.3
4	2.7	3.4	4.9
5	1.6	3.8	5.5
6	1.7	3.1	5.1
7	1.8	3.7	4.5
8	2.8	3.4	4.8
9	2.3	3.1	5.3
10	1.5	3.3	4.1

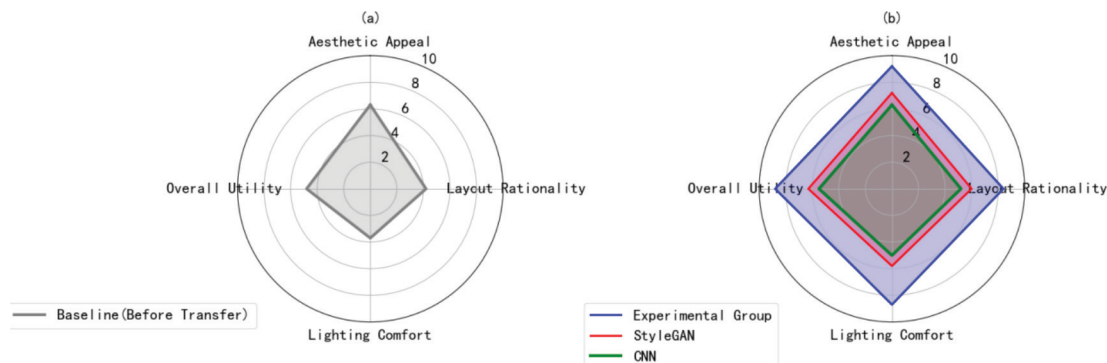


Figure 8 Satisfaction Scores. (a) Satisfaction Scores Before Relocation. (b) Satisfaction Scores for Each Group After Relocation.

Utilizing a BIM+VR simulation platform, participants experienced the architectural style transfer through the creation of high-fidelity images and interactive virtual environment in the building's relocated condition (i.e., participants had direct experience of the effects). For the questionnaire, specific scoring criteria were developed for each evaluation dimension to guide participants' evaluation and subsequent scoring. These criteria were: the rationality of the spatial layout of functional areas and spaces; the lighting comfort—how much the lighting in an indoor environment is spread evenly throughout the entire room and how well the natural

light alone is used. The practicality concerns overall functionality, safety and the user's experience with the building. All participants were asked to complete a questionnaire about their impressions, including specific information about their evaluation of each site.

Figure 8 shows a radar chart of satisfaction scores before and after the relocation. Before the relocation, all aesthetic and practical indicators were at a medium-to-low level, with aesthetic appeal scoring 6.3, spatial layout rationality scoring 4.2, lighting comfort scoring 3.7, and overall practicality scoring 4.8. After the transfer, the experimental group

achieved improvements in all four categories, with aesthetic appeal reaching 9.2, spatial layout rationality 8.4, lighting comfort 8.7, and overall practicality 8.8, significantly outperforming the StyleGAN and CNN methods. While StyleGAN and CNN methods showed improvements, their highest individual score was only 7.2.

4. CONCLUSION

This paper proposes a multi-objective optimization framework that integrates CycleGAN and NSGA-II to achieve the coordinated optimization of architectural visual style transfer and functional performance. In terms of method, it first embeds the attention mechanism in the CycleGAN generator, combining the Gram matrix with the VGG-19 loss function to ensure high visual fidelity; then, physical indicators such as EUI, sDA, ASE calculated by EnergyPlus and Radiance, are used as hard constraints, and the NSGA-II algorithm is used to dynamically optimize both visual and functional goals. Experiments show that this method outperforms StyleGAN and CNN in terms of user satisfaction, while achieving an average 16.4% reduction in EUI before migration and an 8.2% improvement in SDA after migration compared to the StyleGAN method. This method also improves structural safety. This demonstrates the ability to use deep learning to ensure aesthetic performance and engineering quality, and introduces a new way of designing buildings based on intelligent design that incorporates both aesthetic and functional design elements.

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