

Spectral Selective Energy-Saving Design of Three-Layer Glass Based on Neural Network Optimization

Peng Xu^{1*}

¹ School of Innovation and Entrepreneurship, University of Science and Technology Beijing, Beijing, China

Email Address

U202340123@xs.ustb.edu.cn (Peng Xu)

*Correspondence: U202340123@xs.ustb.edu.cn

Received: 18 November 2025; **Accepted:** 14 December 2025; **Published:** 31 December 2025

Abstract:

In summer, air conditioning systems account for a very high proportion of building energy consumption in southern China. The key to building energy-saving design lies in reducing radiative heat gain while ensuring adequate natural lighting. Although previous shading measures and low-emissivity coated glass can reduce incident radiation to some extent, they still have problems such as complex manufacturing, high cost, or reduced visible light transmittance. This paper takes a three-layer glass structure with adjustable thickness as the research object and uses the Artificial Neural Network (ANN) optimization algorithm to optimize the thickness of each glass layer, to minimize the energy transmitted in the 700–2000 nm band (near infrared region) of the solar spectrum, thereby reducing the heat load inside the building. This paper first establishes a spectral transmittance calculation model for a three-layer glass system based on the distribution characteristics of solar radiation power density in the range of 300–2000 nm. The optimization part adopts a shallow feedforward neural network (3 hidden layers) to construct the input-output mapping relationship and iteratively adjust the glass thickness parameters through the backpropagation algorithm. This research will provide new ideas for the design of low-cost, engineerable multilayer energy-saving glass.

Keywords:

Multilayer Glass, Solar Spectrum, Building Energy Conservation, Neural Network Optimization, Spectral Transmittance

1. Introduction

In the hot and humid summer, the air conditioning system accounts for a very high proportion of building energy consumption. How to reduce solar radiation heat gain while ensuring lighting is one of the key issues in building energy-saving design [1]. Traditional shading measures and low-emissivity coated glass can reduce incident radiation, but they have problems such as complex manufacturing, high cost or reduced visible light transmittance [2][3].

As early as 1994, Zhou, Sun, and Cao pointed out at the National Conference on Heating, Ventilation, Air Conditioning and Refrigeration that the heat gain of multi-layered window glass is closely related to the transmittance and arrangement order of each layer: when the transmittance of the innermost layer of glass is high (the absorption rate is low), the overall heat gain is actually lower. This provides a theoretical basis for achieving passive energy saving through thickness and arrangement design [2]. In recent years, Zhang Huanhuan has further expanded the application of spectral modulation of multilayer structures in her master's thesis at Beijing University of Chemical Technology. Her "polymer/metal/polymer" structure achieved a high reflectivity of 69.35% in the near-infrared band and a high transmittance of 67.74% in the visible band, and achieved a cooling range of approximately 21.9 K through structural optimization [3]. In summary, this study achieved a similar spectral selectivity effect in millimeter-thick glass through geometric parameter optimization.

Due to its superiority in nonlinear function approximation and high-dimensional search, ANN has been gradually applied to engineering optimization problems [4][5]. In the field of optics, ANN can quickly predict the transmittance distribution and search for the global approximate optimum in complex interference and material distribution parameter spaces. Combined with the requirements of building energy-saving design, this optimization strategy based on surrogate model can significantly reduce the computational cost and has good generalizability [6].

This paper focuses on the 700–2000 nm solar spectrum band, which has the greatest impact on the internal heat load of buildings. The research mainly includes the following: A multi-layer glass transmission model was established: Based on the standard solar radiation spectrum and Fresnel reflection correction, a transmittance calculation model for a three-layer glass structure was established; using glass thickness as the optimization variable and minimizing the near-infrared transmission energy integral as the objective, a shallow feedforward neural network was used to achieve nonlinear parameter search [7]. This research combines a neural network surrogate model with traditional optical transmission theory, replacing complex analytical solutions with a data-driven approach, and realizing a passive energy-saving glass design method that does not require nanofilm layers [8].

2. Methodology

2.1. Solar Spectrum Data and Computational Models

The solar radiation energy spectrum data used in this paper comes from the "Solar Spectrum Distribution in the Standard for Solar Radiation Tests", with a wavelength range of 300–2000 nm, covering the ultraviolet, visible, and near-infrared bands [1]. The data were normalized after linear interpolation at 0.1 nm intervals to ensure that the spectral energy density meets the requirements.:

$$\int_{300\text{ nm}}^{2000\text{ nm}} I_{\text{sun}}(\lambda) d\lambda = 1 \quad (1)$$

Where $I_{\text{sun}}(\lambda)$ represents the relative irradiance at a unit wavelength λ .

The band division adopts the internationally accepted standard: 300nm to 450nm is ultraviolet light, 450nm to 700nm is visible light, and 700nm to 2000nm is infrared light.

This study focuses on optimizing the transmission energy in the infrared band (700–2000 nm) to reduce solar heat gain, while also considering visible light transmittance to maintain indoor lighting comfort.

2.2. Three-Layer Glass Transmission Model

The glass system consists of three parallel glass layers with thicknesses of L_1, L_2 and L_3 , respectively. The refractive index of each layer is set to $n_i=1.5$, and the refractive index of the outside air is $n_0=1.0$ (Figure 1).

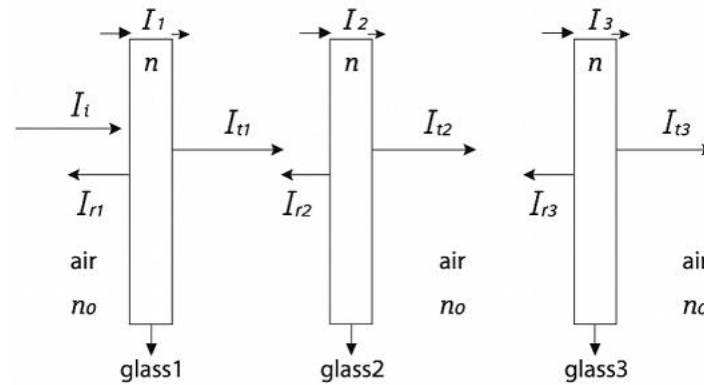


Figure 1. Three-Layer Glass Transmission Model (Original).

Under the assumption of perpendicular incidence, the transmittance of a single-layer glass to a specific wavelength λ can be approximated as:

$$T_i(\lambda) = \frac{(1-R_i)^2}{(1-R_i)^2 + 4R_i \sin^2(\delta_i/2)} \quad (2)$$

Where n is the relative refractive index, R_i is the reflectivity of a single interface, and δ_i is the phase difference, $R_i = ((n_i - n_0)/(n_i + n_0))^2$, $\delta_i = 2k_0 n_i L_i$, and $k_0 = 2\pi/\lambda$.

Considering the overall effect of Fresnel reflection at both the incident and exit interfaces, the total transmittance is corrected as follows:

$$T_{\text{total}}(\lambda) = (1-R_{\text{in}})(1-R_{\text{out}}) \prod_{i=1}^3 T_i(\lambda) \quad (3)$$

Here, R_{in} and R_{out} represent the reflectivities of the air-glass and glass-air interfaces, respectively. This correction term allows the model to account for the coupling effects of interface reflection loss and multilayer interference.

The computational framework is based on the optical theory of multilayer thin films. However, in this paper, the thickness of the glass layer is 3–15 mm, which is much larger than the thickness of the film structure. Therefore, higher-order terms of absorption coefficient and phase dispersion are not considered, and only an approximate interference model is used.

2.3. Optimization objectives and constraints

The optimization objective is to minimize the infrared energy transmittance under the constraint of visible light transmittance performance.

$$\min_{L_1, L_2, L_3} J = w_{\text{IR}} \eta_{\text{IR}} + w_{\text{vis}} \eta_{\text{vis}} + w_{\text{UV}} \eta_{\text{UV}} \quad (4)$$

In which:

$$\eta_k = \frac{\int_{\lambda \in \Omega_k} I_{\text{sun}}(\lambda) T_{\text{total}}(\lambda) d\lambda}{\int_{\lambda \in \Omega_k} I_{\text{sun}}(\lambda) d\lambda} (k = \text{UV, vis, IR}) \quad (5)$$

I represents the energy transmittance of each band, specifically the intensity within a unit band.

w represents a variable weight. It sets $w_{\text{IR}}=1.0$, $w_{\text{vis}}=0.2$, $w_{\text{UV}}=0.0$, to reflect the comprehensive goal of “suppressing infrared heat gain while ensuring visible light transmission”.

The range of values for the design variable, the glass thickness L_i of the i -th layer, is limited to:

$$L_i \in [1, 15] \text{ mm}, i=1, 2, 3 \quad (6)$$

2.4. Neural Network Surrogate Modeling and Hybrid Optimization Algorithms

Neural networks have many advantages in dealing with optimization problems. First, their general approximation ability enables them to learn complex objective function shapes in high-dimensional, strongly nonlinear parameter spaces, thereby significantly reducing the dependence on analytical models or explicit gradients. Second, ANNs can achieve orders of magnitude acceleration on graphics processing units (GPUs) through parallel computation and batch processing mechanisms, making it possible to quickly explore high-dimensional design variables. In addition, surrogate models can effectively avoid the problem of repeated computation of objective functions in traditional optimization, and are particularly suitable for engineering scenarios involving integral operations or multi-physics coupling. Recent studies have shown that in problems such as optical design, structural optimization, and material inversion, Zhao et al. in 2021 and Rao in 2022 have demonstrated that surrogate modeling based on ANNs can improve optimization efficiency and convergence stability [9][10]. This advantage makes it an important tool in complex engineering optimization.

On the simulation platform, 320,000 candidate thickness vectors were first generated through Latin hypercube sampling, and the objective function was computed in parallel on the GPU. The top 1,000 optimal samples were selected as the starting point for local optimization. Subsequently, the multi-starting-point `fmincon` algorithm (sequential quadratic programming, SQP) was used to find the optimal solution in the constraint space.

To further improve accuracy and convergence speed, this paper establishes a three-layer feedforward neural network surrogate model:

$$[3] \rightarrow [50, 40, 30] \rightarrow [1] \quad (7)$$

The neural network was trained using the `trainbr` (Bayesian Regularization) algorithm with a training set of 40,000 samples. Training and inference were performed on a GPU, serving as a fast energy estimator for the optimizer. Figure 2 shows a schematic diagram of the neural network structure.

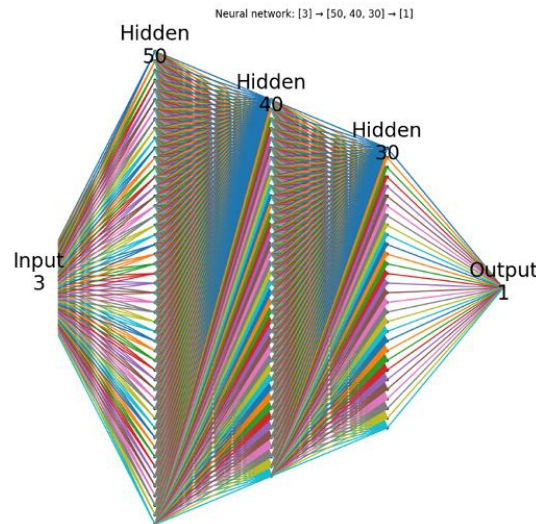


Figure 2. Neural network diagram (original).

3. Experimental Study and Results Analysis

3.1. Optimization Results

Through GPU batch screening and multi-starting point refinement, the optimal thickness combination was finally obtained as follows:

$$L_1=3.167\text{mm}, L_2=11.910\text{mm}, L_3=4.939\text{mm} \quad (8)$$

The energy transmission performance of this structure under the influence of the solar spectrum is shown in Table 1 below:

Table 1. Comparison of performance between triple-layer glass with optimized thickness and triple-layer glass of equal thickness (5 mm–5 mm–5 mm).

Spectral Band	Optimized Transmittance(%)	(5 mm–5 mm–5 mm) Structural Transmittance(%)
Visible Light (450–700 nm)	72.10	72.35
Infrared Light (700–2000 nm)	71.32	73.48

Table 1 shows that the optimized structure reduces infrared energy transmittance by approximately 2.17% while maintaining almost the same transmittance in the visible region. Although the decrease is limited, considering the constraints of manufacturing processes and mechanical properties on the thickness of the triple-glazed glass, this improvement still has practical significance in energy-saving designs. The reduction in infrared energy means less solar heat gain indoors during summer, thus reducing the air conditioning load.

3.2. Analysis of Spectral Distribution Changes

Figure 3 shows the wavelength on the horizontal axis and the relative intensity on the vertical axis. The difference between the red and black curves illustrates the comparison of the transmission spectrum before and after optimization. It can be seen that the optimized transmission curve shifts slightly downwards in the 700–2000 nm range, while maintaining a smooth transition in the visible region. This indicates that the algorithm effectively adjusts the multilayer interference conditions, causing destructive interference in the infrared band, thereby reducing the overall transmission energy.

Figure 4 compares the transmittance of the three-layer glass to infrared, visible, and ultraviolet light. The bar chart of average transmittance by band shows that the transmittance of the ultraviolet band decreases, mainly due to absorption by the glass material; the transmittance of the visible band remains above 70%, meeting the lighting requirements; and the transmittance of the infrared band decreases, achieving the energy-saving goal.

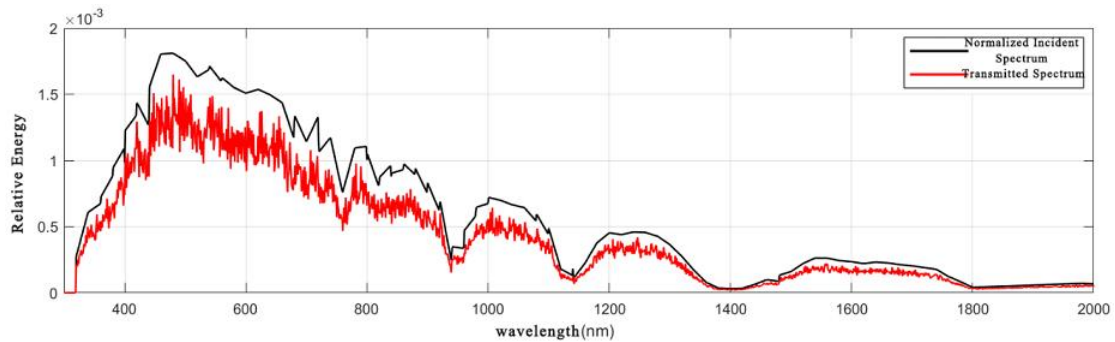


Figure 3. Incident and Transmitted Spectra of Three-Layer Glass Window with Optimized Parameters (original).

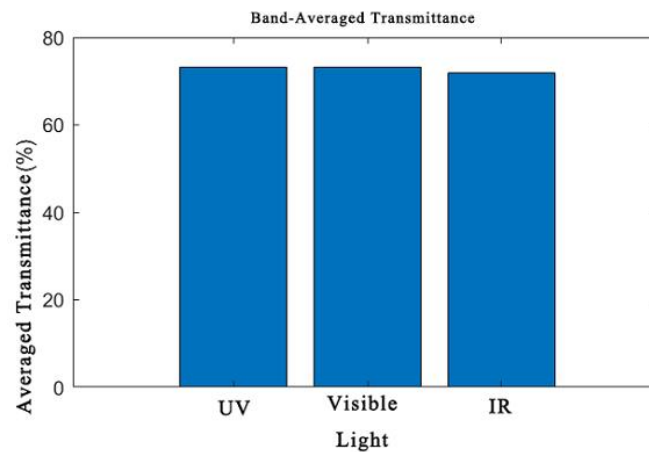


Figure 4. Transmittance of Each Spectrum for Three-Layer Glass Window with Optimized Parameters (original).

3.3. Computational Performance and Algorithm Advantages

Batch processing of 320,000 candidate points on an NVIDIA GPU takes only a few minutes, about 18 times faster than serial CPU computation. The introduction of a neural network agent increases the speed of objective function evaluation in the subsequent optimization stage by about 20 times. Compared with traditional glass layer thickness optimization methods based on analytical gradients or genetic algorithms, the hybrid framework of “GPU batch search + ANN agent + fmincon refinement” proposed in this paper shows good convergence and scalability, and is suitable for further extension to multilayer film composite structures.

3.4. Limitations of the Method

Although the “GPU batch search + ANN surrogate model + multi-starting point optimization” method proposed in this study has significant advantages in efficiency, it still has certain limitations. First, the generalization ability of the neural network depends on the coverage of the training data. If the sampling is insufficient or the objective function changes drastically in a local region, the surrogate model may be

biased, affecting the reliability of the final optimization result [11]. In addition, ANN is a typical “black box model” that lacks interpretability, making it difficult to analyze its prediction and optimization behavior from a physical perspective [12].

The surrogate model is built on a simplified optical model, such as assuming perpendicular incidence, homogeneous material, and neglecting absorption and dispersion. This means that the simplification errors inherent in the training data may be amplified or solidified by the ANN, potentially leading to deviations in practical engineering applications (such as different incident angles or complex composite structures).

Overall, this method is suitable for low- to medium-dimensional problems with relatively clear physical laws, but it still needs further verification and expansion in multi-physics coupling or high-dimensional structure design.

4. Conclusions

This paper addresses the indoor thermal control problem under high-temperature conditions in southern China during summer by proposing a method for optimizing the thickness of three-layer glass based on GPU-accelerated computation and neural network agents. Through comprehensive analysis of the 300–2000 nm solar spectrum and the establishment of a three-layer glass transmission model, this paper achieves an optimized design that minimizes infrared energy transmission. The main conclusions are as follows:

The total transmittance of a triple-pane glass system can be approximated by multiplying the transmittance of each individual layer and combining this with Fresnel correction terms at the front and back interfaces. While maintaining computational simplicity, the model accurately reflects the impact of different thickness combinations on visible and infrared energy transmission, providing a reliable foundation for energy-saving design of thick glass.

By constructing a three-layer feedforward neural network surrogate model and training it on a GPU, a rapid prediction of the thickness-infrared energy transmission relationship was achieved. This method significantly reduces the computational burden of traditional full-grid search or serial numerical integration, enabling high-dimensional optimization problems to obtain near-optimal solutions in a short time.

The optimized thickness combination is $L_1=3.167\text{mm}$, $L_2=11.910\text{mm}$, and $L_3=4.939\text{mm}$. While maintaining a visible light transmittance of approximately 72%, the infrared energy transmittance decreases by 2.17%. This means a reduction in indoor solar heat gain during summer, effectively alleviating the air conditioning load and thus achieving energy savings. Although the reduction is not significant, this optimization still has practical application value due to limitations in thickness and manufacturing processes.

During the optimization process, by setting a weight for visible light transmittance, the optimization result reduces infrared transmission without significantly affecting indoor lighting conditions, thus balancing energy conservation and indoor environmental comfort. This multi-objective trade-off method has reference value in practical building design.

This study assumes that the incident light is perpendicular and that the glass is an ideal homogeneous material, without considering factors such as angle dependence, glass absorption, reflection polarization effects, and changes in ambient temperature.

Future development could extend the model to optimize full-band, non-perpendicular incident, multi-layered composite structures, combining building energy consumption simulations and actual climate data to achieve more accurate and scalable energy-saving window designs.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

Funding

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

References

- [1] Li, J.; Zhang, Y.; Wang, H. Thermal characteristics and energy consumption analysis of Building transparent envelope. *Building Technical Sciences*, 2020, 36(5), 45-52.
- [2] Zhou, X.Q.; Sun, L.H.; Cao, S.W. Analysis of Heat Gain and Energy-Saving Performance of Multi-Layer Window Glass[C] // Proceedings of the 1994 National HVAC&R Academic Conference. Beijing: HVAC&R Society of the Architectural Society of China, 1994.
- [3] Zhang, H.H. Study on Radiative Cooling Windows Based on Polymer/Metal/Polymer Structures and Stacked Multilayer Films. Beijing: Beijing University of Chemical Technology, 2025.
- [4] Gopalakrishnan, K.; Poornima, B. Artificial Neural Networks Based Optimization Techniques: A Review. *International Journal of Computational Intelligence Research*, 2018, 14(2), 225-239.
- [5] Demuth, H.; Beale, M.; Hagan, M. Neural Network Toolbox User's Guide. Natick, MA: MathWorks. 2014.
- [6] Smith, P.; Jones, R. Spectral Analysis of Multi-Layer Glass Structures for Building Energy Efficiency. *Solar Energy*, 2017, 145, 234-245.
- [7] Chen, T.; Li, M.; Zhao, X. Summer Cooling Load Contribution from Window Glazing in Southern China. *Energy and Buildings*, 2016, 124, 98-106.
- [8] Arasteh, D. et al. Laboratory and Field Validation of the Performance Benefits and Costs of Thin Triple Pane Windows in Residential Buildings. Lawrence Berkeley National Laboratory Report, LBNL-59965. 2006.
- [9] Zhao, L.; Chen, Y.; Kumar, S. Neural-network-based surrogate models for optical thin-film optimization: A review. *Optics and Laser Technology*, 2021, 142, 107180.
- [10] Rao, A.; Lee, J. Machine learning assisted optimization in engineering design: Recent progress and challenges. *Engineering Applications of Artificial Intelligence*, 2022, 113, 104995.

- [11]Yang, X.; Sun, W.; Zhao, J. Surrogate modeling for engineering design optimization: Methods and challenges. *Engineering Applications of Artificial Intelligence*, 2020, 95, 103898.
- [12]Zhang, H.; Chen, W. Interpretability of machine learning models in engineering design: A review. *Structural and Multidisciplinary Optimization*, 2021, 64, 3457-3478.



© 2025 by the author(s); licensee International Technology and Science Publications (ITS), this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (<http://creativecommons.org/licenses/by/4.0/>)