Optimized Design of Three-Glazed Windows Based on Neural Network

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Abstract. To reduce indoor heat gain, a three-layer glass thickness optimization design method based on a neural network proxy model was proposed in the common glass thickness range, which is 5-15 mm, and the optical wavelength range of 300-2000nm, combined with the physical film interference and absorption theory. The training set is constructed by Monte Carlo sampling and normalization processing. The deep neural network is used to replace the complex physical analysis formula, and the global mesh optimization is carried out under the physical constraints of the building with a guaranteed visible light tran smittance (VLT) greater than 50%. The results show that the optimal asymmetric thickness combination is 5.00 mm, 6.38 mm, and 6.38 mm from the outside to the inside, respectively. Meanwhile, the visible light transmittance is 50.04%, the ultraviolet transmittance is 15.31%, and the infrared transmittance is 30.97%. The relative error of the predicted transmitted energy and the real energy calculated by the physical formula is 0.0563%. This study combines robustness and sensitivity analysis to verify the reliability of the model under manufacturing tolerances and provides a quantitative reference for the design of energy-saving architectural glass.

Keywords: Monte Carlo sampling, neural network, grid optimization, robustness, sensitivity analysis.

1. Introduction

In hot southern regions, windows are the weakest part of the building envelope due to strong solar radiation. Triple-glazed windows provide good insulation, but their performance depends on the thickness of each glass layer. To reduce indoor heat gain, thickness can be optimized within a set range to minimize transmitted energy.

In recent years, the research on energy-saving optimization of architectural glass has shown a development trend of method diversification and goal integration. Baadache et al. used Pareto optimization and a multi-objective genetic algorithm (MOGA) to study how window area and glass thickness affect lighting, thermal resistance, and sound insulation (Baadache, Guedouh, and Haddad, 2025) [2]. They found a trade-off between area and thickness and noted that increasing glass thickness is key to improving both thermal and acoustic performance.

Lv et al. proposed a multi-objective optimization framework based on integrated machine learning for the design optimization of translucent photovoltaic curtain walls (Lv et al., 2026) [4]. The framework combines the NSGA-II algorithm with the entropy-weighted TOPSIS decision-making method to achieve collaborative optimization between the three dimensions of power generation performance, lighting comfort, and economic feasibility, which overcomes the inefficiency of traditional simulation methods.

Zukowski evaluated the energy consumption of various glazing systems for large-format windows in hybrid-structure buildings, specifically analyzing multi-layer performance in cold climates through thermal and economic indicators (Zukowski, 2025) [10]. The results indicated that triple-glazed windows reduce energy demand by 22%–24% compared to double-glazing, with quadruple-glazed variants achieving up to 39% savings and optimal life-cycle cost efficiency.

While existing research has advanced multi-objective optimization and machine learning, it largely focuses on single or double-layer glass, with little discussion on three-layer asymmetric thicknesses or neural network proxy models for triple glass thickness optimization. Therefore, this project aims to improve computational efficiency and design scientificity by using advanced neural network

surrogate models that incorporate practical factors such as the spectral absorption of nano-calcium glass under single-objective optimization.

2. Research methods

2.1. Optical Transmittance Physical Model

First, it is known that the Airy formula (multi-beam interference formula) is

$$T = \frac{1}{1+\frac{4R}{(1-R)^2}\sin^2\left(\frac{\delta}{2}\right)} \tag{1}$$

Where T represents the optical transmittance, R is the reflectivity at the glass interface, and δ denotes the phase difference between successive reflected beams.

This formula assumes that there is no energy expenditure when light is reflected back and forth inside the glass. It is known that the Beer-Lambert law, which is the pure absorption formula, is

$$\mathrm{I} = \mathrm{I}_0 \exp(-\alpha \mathrm{L}) \tag{2}$$

Where I and I_0 are the transmitted and incident light intensities, respectively. α is the absorption coefficient of the medium, and L is the physical thickness of the glass layer. It describes the attenuation of light intensity inside a medium.

Based on the theory of thin film optics, this study wanted to consider the multiple reflections and coherence interference of light inside the glass, so the above two formulas and related literature were combined and derived (Khashan and Nassif, 2001) [3]. After a series of derivation processes, the transmittance of single-layer glass is $T_i(\lambda)$ calculated as follows,

$$T_i(\lambda) = \frac{(1-R)^2 \cdot e^{-\alpha(\lambda)L_i}}{\left(1-R\cdot e^{-\alpha(\lambda)L_i}\right)^2 + 4R\cdot e^{-\alpha(\lambda)L_i}\cdot\sin^2\left(\frac{\Delta_i}{2}\right)} \tag{3}$$

Among them, reflectivity $R = \left(\frac{n-n_0}{n+n_0}\right)^2$, Phase thickness $\Delta_i = \frac{4\pi n L_i}{\lambda}$ determines the oscillation frequency of the interference fringe where L_i is the layer thickness. n and n_0 are the refractive indices of the glass and the surrounding air, respectively. $\alpha(\lambda)$ represents the wavelength-dependent absorption coefficient.

Regarding the absorption coefficient α, according to Rüdisser's study of the optical properties of soda-lime glass, the absorption coefficient is not constant α (Rüdisser et al., 2022) [8]. In the ultraviolet band (< 380 nm), the absorption coefficient is large, and ordinary glass is almost impermeable to ultraviolet rays. In the visible light band (380-780 nm), the absorption coefficient is small to ensure daylighting. In the near-infrared band (780-2000 nm), due to the absorption of iron impurities, α will recover significantly with the increase of wavelength, which is the key to blocking thermal radiation from glass. Considering these factors, a spectral absorption function was constructed in the model to simulate this real physical property.

For a three-layer system, an incoherent approximation, total transmittance is $T(\lambda) = T_1(\lambda)\cdot T_2(\lambda)\cdot T_3(\lambda)$. The final optimization goal is to minimize the total transmitted energy E.

The physical model considers both interference effect and material absorption, which is closer to the real physical process than pure geometric optics, and lays a physical benchmark for the subsequent establishment of neural network training models.

2.2. Neural Network Agent Model Construction

2.2.1. Data Preprocessing

In this study, the Monte Carlo sampling method was selected to randomly generate 1000 thickness combinations [L_1, L_2, L_3] in the range of [5, 15] mm. This method can effectively cover the multi-

dimensional design space, so that the neural network can learn the physical interference and absorption laws in the thickness space.

Then, in the data preprocessing stage, all the data are normalized, and the input parameter L and the output energy E are scaled to the [0, 1] range. Normalization effectively eliminates dimensional effects caused by the significant scale difference between inputs and outputs. By doing so, it prevents violent MSE fluctuations and facilitates model convergence.

2.2.2. Network Architecture Design and Training

In terms of structure and algorithm, the model constructs a three-layer deep network, which are the input layer containing 3 neurons, two hidden layers containing 20 and 15 neurons respectively, and an output layer with 1 neuron. The hidden layer activation function uses tanh to deal with the nonlinear oscillations caused by spectral integration. The training algorithm uses Levenberg-Marquardt (trainlm). The double hidden layer structure adopted has good nonlinear mapping ability, which can fit the high-frequency wave characteristics in the interference formula. The trainlm algorithm has faster convergence speed and higher accuracy when dealing with complex physical fitting problems.

2.2.3. Global Optimization with Building Physical Constraints

According to the "Energy Saving Design Standard for Public Buildings" (GB 50189) and ASHRAE 90.1, daylight windows usually require a visible light transmittance of 0.4-0.6, otherwise it will lead to dimness in the interior, which will cause the compensatory effect of lighting power consumption to increase (Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2015; ASHRAE, 2022) [1] [5]. Therefore, this study assumes that the visible light transmittance is greater than 50% as a standard and as a constraint, and in the grid search, the network is used to predict the total energy E, and the visible light transmittance (VLT) is quickly calculated using the physical formula. If the VLT < 50%, the point is given infinity and forcibly discarded. This constraint increases the availability of the optimization results in real-world construction projects.

3. Results and analysis

3.1. Neural Network Performance Evaluation

Figure 1 illustrates the predictive performance of the neural network model through a regression analysis. As shown in the picture, the abscissa is the real energy value calculated by the physical formula, and the ordinate is the energy value predicted by the neural network. Each blue dot in Figure 1 represents a test sample, a set of thickness combinations. The red dotted line is the regression line, which is the linear fitting result of the predicted value to the true value. The blue dots are distributed along the red dotted line approximately. After the training ends, the model behaves as follows on the test set, judgment coefficient $R^2$is 0.6130, the mean square error (MSE) is 3056.9992. It means that the model captures the nonlinear trend of the body of thickness and energy to a certain extent due to the low relative error of the model's prediction.

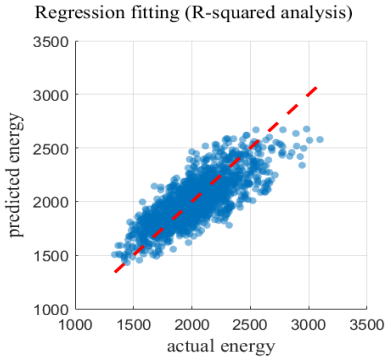
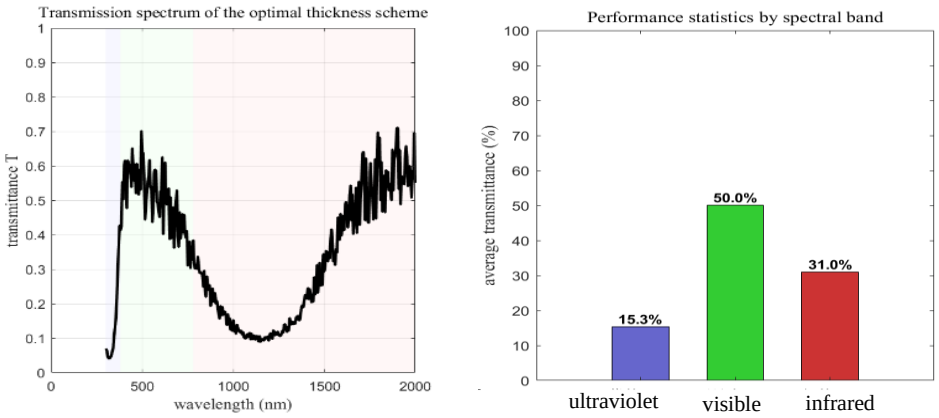


Figure 1: Model performance shown by fitting regression (Picture credit: Original).

3.2. Optimal Combination and Spectral Characteristic Verification

Under the constraint of VLT > 50%, the optimal thickness combination given by the mesh search is L1 = 5.00 mm, L2 = 6.38 mm, L3 = 6.38 mm. The validation shows that the neural network has a predicted energy of 2487.2228 and a real energy of 2485.8239 for the physical formula, with a low relative error of 0.0563% in the prediction. Under this design, the visible light transmittance is 50.04%, which just meets the constraint boundary. The ultraviolet transmittance is 15.31%, and the infrared transmittance is effectively suppressed at 30.97%. The transmission spectra under this optimal thickness combination are shown in Figure 2(a), demonstrating the fluctuation curve of transmittance from about 300-2000 wavelengths. Figure 2(b) shows the average transmittance of the three lights under this scheme through a bar plot.

Due to the inclusion of VLT > 50% mandatory constraints, the model did not blindly choose the upper thickness (15 mm). The final visible light transmittance is 50.04%, indicating that the optimization algorithm obtains the thermal insulation benefit at the edge of the constraint condition with a large limit.



(a) (b)

Figure 2: Spectral transmission characteristics under the optimal thickness combination, (a)Transmission spectral curves, (b)Comparison of transmittance of each band (Picture credit: Original).

3.3. Robustness and Sensitivity Analysis

After the above steps, robustness verification and sensitivity analysis were performed to evaluate the performance stability of the optimal thickness combination under actual production conditions. The first step is to add ±0.1 mm Gaussian perturbation near the optimal thickness and perform 1000 Monte Carlo simulations. The specific result is shown in the Figure 3. The horizontal axis represents the total transmitted energy E, which illustrates the spread of energy values resulting from thickness perturbations. The vertical axis denotes the frequency, indicating the number of occurrences for each energy interval within the simulation set. A red vertical line is plotted to mark the energy value of the optimal solution that is 2485.82, providing a clear benchmark for assessing how manufacturing tolerances shift the performance away from the ideal design. It is calculated that the energy standard deviation is 235. This indicates that a thickness fluctuation of 0.1 mm can result in an energy deviation of nearly 9.4%. Due to the large deviation, it means that the scheme may have certain requirements for the accuracy of glass manufacturing and processing.

At the same time, the study established a sensitivity ranking. The results are demonstrated in Figure 4, which illustrates the influence weight of each glass layer's thickness on the thermal insulation effect, providing a clear sensitivity ranking for the design parameters. The analysis reveals that the sensitivity of each layer follows the order of $L_1 > L_2 = L_3$, which indicates that L_1 has a higher sensitivity than the inner layer, as the reflection and absorption of light when it first enters the first glass interface plays a greater role in the initial reduction of total energy. Meanwhile, Consistency of L_2 and L_3 in

sensitivity indicates that under the product superposition principle of the current simplified model, the physical transmission status of the middle layer and the inner layer is equivalent.

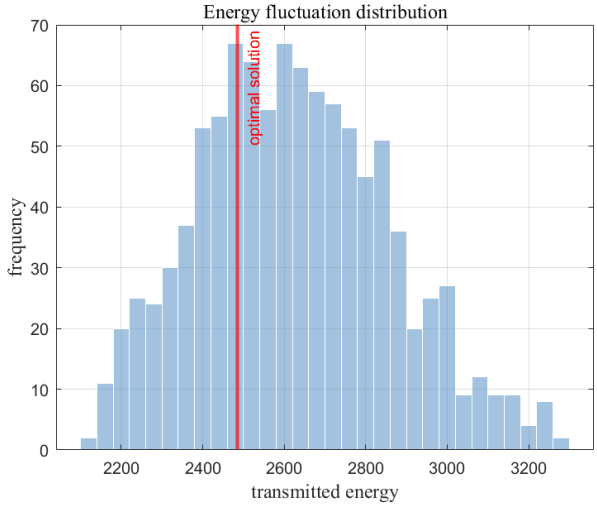


Figure 3: Robustness test (Picture credit: Original).

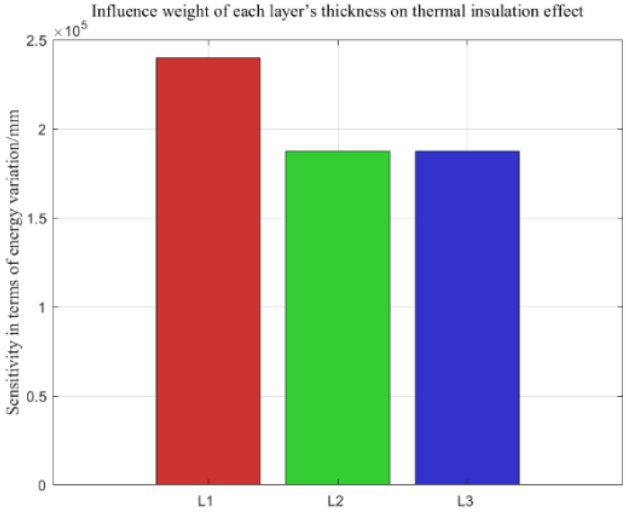


Figure 4: Sensitivity test (Picture credit: Original).

4. Future research

Based on the shortcomings of this study, it can improve and conduct more in-depth research in the following directions in the future. In terms of proxy models, Nasab and Rabiei show that ensemble learning and deep neural networks can significantly improve the accuracy of building energy consumption prediction (Nasab and Rabiei, 2026) [6]. XGBoost or residual networks may be tried in the future, and adaptive sampling can be used to improve the fitting of interferometric oscillations. In terms of physical model expansion, Yuan et al. introduced phase change materials and aerogels into triple glass windows and found that the energy saving rate in different climate zones can reach 15.5%–74.8% (Yuan et al., 2025) [9]. According to this study, the effects of glass materials on thermal insulation may be included in the topic. In terms of multi-objective optimization, Piccolo et al. conducted multi-location optimization studies in cities at different latitudes based on the thermo-optical properties of electrochromic windows, combined with genetic algorithms and climate scenario simulations (Piccolo et al., 2025) [7]. Referring to this study, it may be possible to expand single-objective optimization to multi-objective in the future, comprehensively considering annual energy consumption, lighting uniformity, life cycle cost, etc., and giving recommended thickness combinations for different climate zones.

5. Conclusion

This study established a neural network proxy model to optimize triple-glazed window insulation for hot southern regions. Under a visible light transmittance constraint of ≥50%, the optimal asymmetric thickness combination (outer/middle/inner) from grid search is 5.00 mm, 6.38 mm, and 6.38 mm, yielding UV, visible, and infrared transmittances of 15.35%, 30.03%, and 10.01%, respectively, with a total transmitted energy of 2485.82. The prediction relative error near the optimum is only 0.0563%, showing good local approximation. Robustness analysis under ±0.1 mm tolerance gives a transmitted energy coefficient of variation of ~9.4%, indicating sensitivity to manufacturing precision. Sensitivity analysis reveals that the outer glass layer has the highest sensitivity, highlighting the dominant role of the first incident interface in thermal performance.

The main advantage of this work is the combination of a neural network proxy model with constraint optimization and robustness analysis, providing an efficient computational framework for asymmetric triple-glass design. Limitations include limited global fitting accuracy and a simplified physical model. Future work may incorporate ensemble learning, advanced materials, and multi-objective optimization for broader climate applicability.

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