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Optimization of Winter Lighting Performance of Triple-Glazed Windows Based on Neural Networks

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Abstract:
With the escalating global energy crisis and the introduction of dual carbon targets, building energy conservation has become a key issue for China's sustainable development. Triple-glazed windows, due to their excellent thermal insulation and light-transmitting potential, are widely used in modern energy-efficient buildings. This study aims to explore the optimal solution for the combination of three glass thicknesses using advanced intelligent optimization algorithms, in order to maximize solar energy utilization during cold winters. The study first established an accurate optical model based on the Transfer Matrix Method (TMM), and then used this physical model to generate a large-scale dataset to train a feedforward neural network surrogate model that can efficiently predict the transmission performance of glass. Finally, by combining the differential evolution algorithm, the optimal thickness combination that maximizes transmittance was successfully found within the vast design space. This study provides a rapidly achievable intelligent optimization path for the optical design of low-energy building envelopes.

Keywords: Neural network, TTM, Incident energy

1. Introduction

With the intensification of the global energy crisis and the proposal of the "dual carbon" target, building energy conservation has become a key issue for China's sustainable development [1]. Building energy consumption accounts for a significant proportion of total social energy consumption, and windows and doors, as weak links in the building envelope, are particularly prone to energy loss. Improving a building's natural lighting and passive heat gain capacity is crucial for reducing winter heating load and enhancing indoor thermal comfort. Triple-glazed windows have been widely used in modern energy-efficient buildings due to their excellent thermal insulation and light-transmitting potential [2]. Traditional glass designs often rely on experience or standard specifications, failing to fully explore their performance potential under specific climatic conditions.

Early research focused on exploring the effects of different structural parameters on the light transmittance and thermal insulation performance of glass through

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experiments and theoretical analysis. For example, Liu et al.(2020) conducted an experimental study comparing the solar energy transmission radiation of triple-glazed double-cavity energy-saving glass with that of ordinary single-layer glass, and confirmed the superiority of triple-glazed glass in controlling solar radiation transmission [3]. Wang et al.(2022) used the CFD-thermal bridge coupling model to confirm that, under the condition of the same total thickness, increasing the number of glass layers can reduce the overall heat transfer coefficient of the window by 12–18%, which significantly improves the thermal insulation performance [4]. In the field of building energy conservation, Karaguzel et al.(2020) used the GenOpt-EnergyPlus joint platform to simultaneously optimize the window-to-wall ratio and glass type of the building envelope, achieving a 9.7% reduction in life cycle cost and an 11.4% reduction in annual operating energy consumption, demonstrating the economic effectiveness of intelligent algorithms in engineering-scale optimization [5]. Existing studies are mostly single-objective optimizations and rarely use the standard solar spectrum.

This study utilizes neural networks to optimize the thickness of three layers of glass (L1, L2, L3) to maximize the energy incident on the interior within the 300-2000 nm wavelength range of sunlight. The innovation lies in using neural networks to optimize the thickness of the three layers of glass, constructing an efficient surrogate model that avoids the enormous computational overhead caused by repeated calculations in traditional physical models during the optimization process.

2. Theoretical Foundations and Model Building

The AM1.5 standard solar spectral data used in this study were obtained from the ASTM G173-03 standard published by the National Renewable Energy Laboratory (NREL) in the United States [6]. The ASTM G173-03 standard provides two types of spectral data: AM1.5G (Global) and AM1.5D (Direct). Fig. 1 shows the wavelength on the horizontal axis, in nanometers, covering a broad range from 280 nm to 2000 nm, including the three main bands: ultraviolet (UV), visible, and infrared (IR). The vertical axis represents irradiance, measured in watts per square meter per nanometer, with values ranging from 0 to 1.7. The curve rises rapidly from 300 nm, then begins to decline at 480 nm, with lower values appearing at 720 nm, 940 nm, 1130 nm, 1380 nm, and 1870 nm.

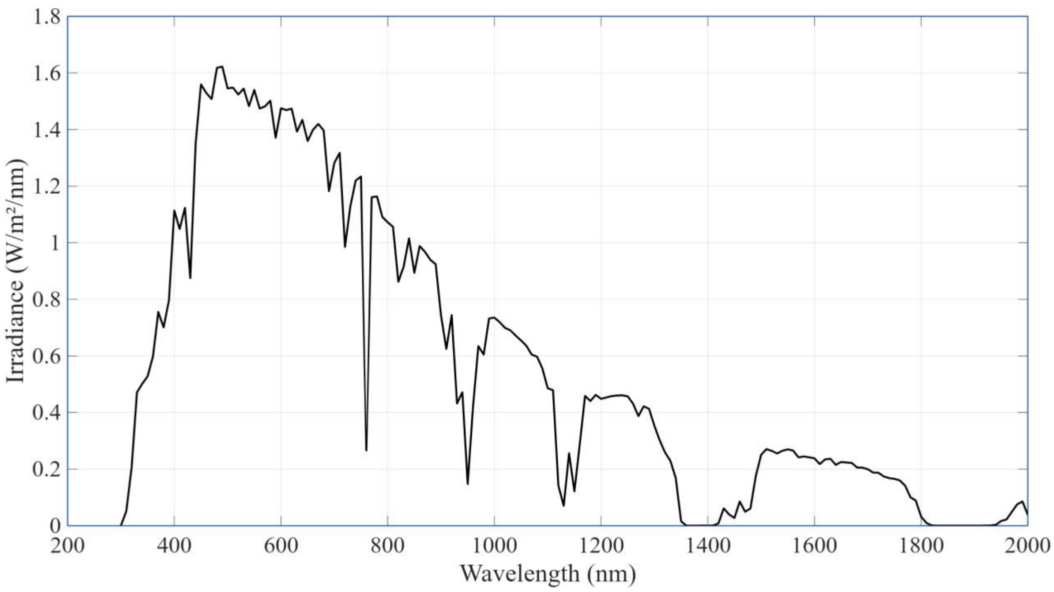

Fig. 1 Standard solar spectral data (Photo/Picture credit: Original)

2.1 Method for Calculating the Incident Energy Integral

To quantify the total solar energy entering the room under different combinations of glass thicknesses, it is necessary to integrate the glass transmission spectrum with the AM1.5G solar spectrum. Let the AM1.5G spectral irradiance incident on the glass surface be $I_{AM1.5}(\lambda)$ (unit: W/m²/nm), and the total spectral transmittance of the triple-glazed glass under perpendicular incidence conditions be Then the total power transmitted into the room per unit area of glass P_{in} (unit: W/m²) can be calculated using the following formula:

$$P_{in}=\int_{\lambda_{min}}^{\lambda_{max}} I_{AM1.5}(\lambda)\cdot T(\lambda)d\lambda \tag{1}$$

In this study, the integration wavelength range λ_{min} to λ_{max} was set to 300 nm to 2000 nm to cover the vast majority of solar radiation energy. Since the spectral data are discrete, numerical integration methods, such as the trapezoidal rule or Simpson's rule, are typically used in practical calculations. The specific steps are as follows: Read AM1.5G spectral irradiance data $I_{AM1.5}(\lambda_i)$ within the wavelength range of 300-2000 nm, at intervals of 1 nm or 5 nm, from the standard data file provided by NREL. For a given combination of three glass thicknesses (L1, L2, L3), calculate the spectral transmittance $T(\lambda_i)$ corresponding to each wavelength point λ_i using the transfer matrix method (TMM). Divide the integration interval into several smaller intervals, each with a width of $\Delta\lambda$. Within each smaller interval, approximate the product of incident energy and transmittance as the area of a small rectangle or trapezoid, and then sum all the smaller areas. For example, using the trapezoidal rule, the total energy can be approximated as:

$$P_{in}\approx\sum_{i=1}^{N-1}\frac{1}{2}\left[I_{AM1.5}(\lambda_i)T(\lambda_i)+I_{AM1.5}(\lambda_{i+1})T(\lambda_{i+1})\right](\lambda_{i+1}-\lambda_i) \tag{2}$$

Here, N is the total number of wavelength data points. This method transforms a complex integration problem into a summation problem that is easily processed by a computer, thus providing accurate and quantifiable objective function values for subsequent neural network optimization.

2.2 Modeling the Optical Properties of Three-Layer Glass

This study uses ordinary sodium-calcium-silicon float glass as the base material for triple-glazed windows. This type of glass is widely used in buildings. Its refractive index is about 1.52, and its extinction coefficient is close to zero in the visible light band, but it has certain absorption characteristics in the near-infrared region. The optical constants of glass are the key parameters that determine its transmission, reflection, and absorption performance. Taking into account the limitations of conventional building applications and production processes, this study sets the thickness optimization range to 3 mm to 10 mm [7].

2.3 Transfer Matrix Method (TMM) Principle

TMM constructs the feature matrix of each layer and multiplies the matrices of each layer to obtain the total transmittance and reflectance of the entire system [8]. For a multilayer film system consisting of N media, light enters from the incident medium (air, $n_0\approx 1$) with a refractive index of n_0, passes through N glass layers with a thickness of d_j and a refractive index of n_j, and finally enters the substrate medium (indoor air, which can also be regarded as air, $n_s\approx 1$) with a refractive index of n_s. The overall characteristic matrix M of the entire system is the product of the characteristic matrices of each layer:

$$M=I_{01}\cdot L_1\cdot I_{12}\cdot L_2\cdots I_{(N-1)N}\cdot L_N\cdot I_{Ns} \tag{3}$$

Where L_j is the propagation matrix of the j-th glass layer, describing the phase change of light within that layer. $I_{(j-1)j}$ is the transmission matrix at the interface between the ($j-1$)-th and j-th layers, describing the reflection and transmission of light at the interface. For the case of perpendicular incidence (incident angle $\theta=0$), the form of these matrices can be simplified. The propagation matrix L_j of the j-th glass layer is:

$$L_j=\begin{pmatrix} e^{-i\delta_j} & 0 \\ 0 & e^{i\delta_j}\end{pmatrix} \tag{4}$$

Where δ_j is the phase thickness of the j-th glass layer, given by the following formula:

$$\delta_j=\frac{2\pi}{\lambda}n_j d_j \tag{5}$$

Here, λ is the wavelength of light in a vacuum, and n_j and d_j are the refractive index and physical thickness of the j-th glass layer, respectively.

The interface transfer matrix $I_{(j-1)j}$ describes the interface effect from a medium with refractive index n_{j-1} to a medium with refractive index n_j. For perpendicular incidence, it takes the form:

$$I_{(j-1)j}=\frac{1}{2n_{j-1}}\begin{pmatrix} n_{j-1}+n_j & n_{j-1}-n_j \\ n_{j-1}-n_j & n_{j-1}+n_j\end{pmatrix} \tag{6}$$

By calculating the total matrix $M=\begin{pmatrix} m_{11} & m_{12} \\ m_{21} & m_{22}\end{pmatrix}$, the reflection coefficient r and transmission coefficient t of the entire system can be obtained:

$$r=\frac{m_{21}}{m_{11}}(7),t=\frac{1}{m_{11}} \tag{7}$$

Finally, the reflectivity R and transmittance T are respectively:

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$$R = |r|^2 \ (9), T = \frac{n_s}{n_0}|t|^2 \quad (8)$$

Since both the incident and substrate media in this study are air, the transmittance formula is simplified to:

$$T = |t|^2 \quad (9)$$

In multilayer glass systems, the light transmission process is far more complex than in single-layer glass. By precisely designing the thicknesses L1, L2, and L3 of the three glass layers, the transmittance of light at different wavelengths can be controlled, resulting in more constructive interference in the energy-concentrated bands of the solar spectrum (such as visible and near-infrared light), thereby maximizing the total incident energy. The transfer matrix method (TMM) is an ideal tool for accurately calculating this complex interference effect.

2.4 Neural Network Optimization Model

This study uses a neural network (NN) as a surrogate model [9]. By training on a dataset consisting of three inputs (glass thickness) and one output (indoor incident energy), the neural network is able to learn the complex nonlinear mapping relationship between the two. Once trained, this well-trained neural network can serve as a fast and efficient „black box" function evaluator, replacing the physical model that originally required numerous spectral integral calculations. This offers a significant advantage in the optimization process, as optimization algorithms (such as genetic algorithms and particle swarm optimization) typically require tens of thousands of function evaluations. If the physical model were called every time, the computational cost would be prohibitively high.

The structural design of a neural network is crucial for achieving an effective agent. A typical feedforward neural network consists of an input layer, one or more hidden layers, and an output layer. For this problem, the input layer will contain three neurons, corresponding to the thickness L_1, L_2, L_3 of the three glass layers. The hidden layers will have 20 neurons. The output layer will have only one neuron, representing the calculated total incident energy E inside the room.

2.5 Dataset Generation and Preprocessing

The performance of neural networks is highly dependent on the quality and quantity of training data. Therefore, a comprehensive and representative dataset must be generated before training. The dataset generation process is as follows: the value of L_1, L_2, L_3 is set to be in the range of [3, 10] mm. Then, uniform sampling is performed within this three-dimensional parameter space to generate a series of thickness combinations L_1, L_2, L_3. For each thickness combination, the total incident energy E in the 300-2000nm solar spectrum range is calculated using the above formulas (2) and (11). This process requires iterating through all wavelengths, multiplying the spectral irradiance of the AM1.5 standard solar spectrum by the total transmittance of the three layers of glass at the corresponding wavelength, and then integrating over all wavelengths to obtain the total energy. Ultimately, we will obtain a set of data pairs, in the form of $[(L?, L?, L?)?, E?]$, where $i = 1, 2, ..., N$ and N are the total number of samples. 70% of the dataset will be used for training, 15% for validation, and 15% for testing.

2.6 Model Training and Validation

Fig. 2A shows the distribution of prediction errors. The horizontal axis represents prediction error, and the vertical axis represents the quantity. The specific values for R^2, RMSE, and MAE are also given.

Fig. 2B is a scatter plot of the actual values versus the predicted values. The horizontal axis represents the actual values, and the vertical axis represents the predicted values. The better the model performs, the closer the scatter plot will be to the y=x curve.

As shown in Fig. 2, R^2 = 0.7955, RMSE = 0.0613, and MAE = 0.0471. The prediction error is below the engineering tolerance, and the accuracy is significantly improved compared to the traditional multiple linear models.

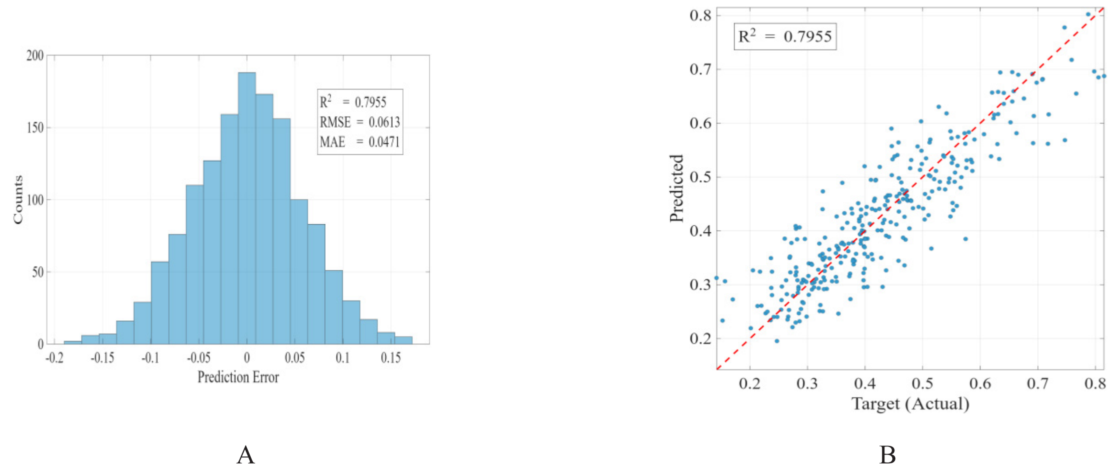

Fig. 2 Prediction error distribution and Prediction vs actual values (Photo/Picture credit: Original)

3. Optimization Scheme and Results Analysis

The core optimization objective of this study is to maximize the total solar radiation energy entering the room through the triple-glazed windows. This objective function is a highly nonlinear function, the value of which depends on the combination of the thicknesses of the three glazing layers L_1, L_2, L_3 and the spectral transmission characteristics of the entire system.

Specifically, the objective function E_{total} is defined as the integral of the product of the standard AM1.5G solar spectral irradiance $I_{AM1.5}(\lambda)$ and the total spectral transmittance $T(\lambda)$ of the three-layer glass system in the wavelength range of 300-2000 nm:

$$E_{total}(L_1, L_2, L_3) = \int_{300nm}^{2000nm} I_{AM1.5}(\lambda) \cdot T(\lambda; L_1, L_2, L_3) d\lambda \tag{10}$$

Here, $T(\lambda; L_1, L_2, L_3)$ is precisely calculated using the transfer matrix method (TMM), and it is itself a complex function of wavelength and three thickness variables. Therefore, the optimization problem can be formulated as: finding a set of L_1, L_2, L_3 values within a reasonable thickness range such that E_{total} reaches its maximum value. This maximization problem will be solved efficiently by combining a neural network surrogate model and a global optimization algorithm.

3.1 Neural Network Optimization Process

Having obtained a neural network surrogate model capable of efficiently predicting transmittance, the next step is to use this model to find the optimal combination of thicknesses for the three-layer glass that maximizes transmittance. This is a typical single-objective optimization problem, where the objective function is to maximize the transmittance $T(L_1, L_2, L_3)$ predicted by the neural network. Considering that the glass thickness L_1, L_2, L_3 is limited to the range of 3 mm to 10 mm, this is a continuous optimization problem with boundary constraints. In this study, the differential evolution algorithm is used for optimization [10]. Differential evolution is a population-based stochastic search algorithm, belonging to the category of evolutionary algorithms. It simulates the process of natural selection to perform an efficient global search in the solution space, making it particularly suitable for complex optimization problems with nonlinearity and multiple peaks, and it is less prone to getting trapped in local optima. First, the objective function is defined. Since optimization algorithms typically find the minimum value of a function, and the objective of this algorithm is to maximize transmittance, the objective function is defined as the negative value of the transmittance predicted by the neural network. Next, the boundaries of the optimization variables are defined, ensuring that the search process always operates within a reasonable physical range. Finally, the optimization process is initiated. The algorithm automatically initializes a population of candidate solutions and iteratively improves the quality of the solutions through operations such as mutation, crossover, and selection until the convergence condition is met.

3.2 Optimization Result Visualization and Anal-

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For each scheme, the total spectral transmittance is calculated using the TMM model and integrated with the AM1.5G solar spectrum to obtain the total indoor incident energy E_{total}.

The final optimization result is (L1, L2, L3) = (3.5mm, 3.4mm, 3.6mm).

Fig. 3 compares the total incident energy of standard-thickness triple-glazed glass with that of optimized triple-glazed glass, increasing it by 1.4%. Under the same solar radiation conditions, rooms using optimized-thickness glass can obtain more free solar energy, thus effectively reducing heating energy consumption in winter.

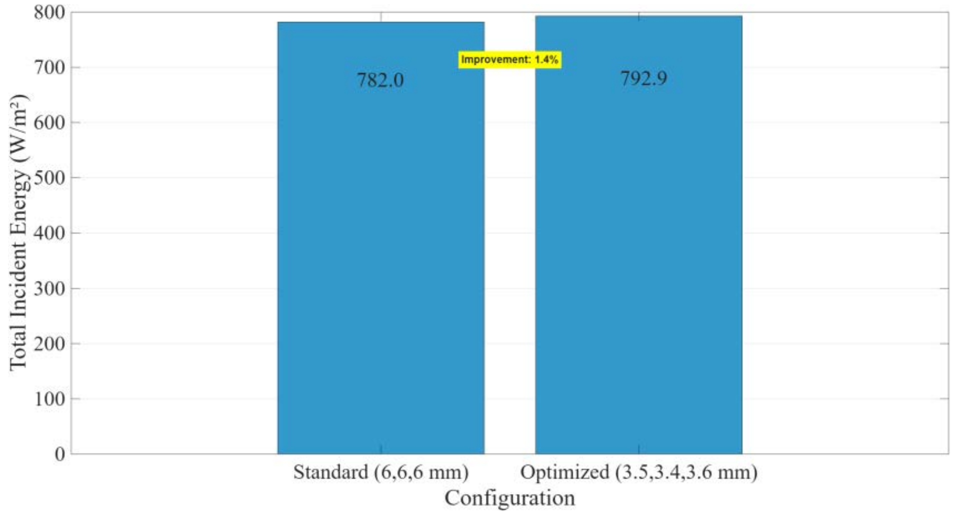

Fig. 3 Total incident energy comparison (Photo/Picture credit: Original).

Fig. 4 compares the total incident solar energy under different thicknesses. The vertical axis represents the total incident energy in watts per square meter. The bars from left to right represent the incident energy under the minimum thickness, the incident energy under the standard thickness, the incident energy under the maximum thickness, and the incident energy under the optimal thickness. By comparing these combinations, it is clear that glass that is too thin or too thick is not suitable for practical engineering. The optimized glass thickness meets the actual engineering requirements while maximizing the total incident energy.

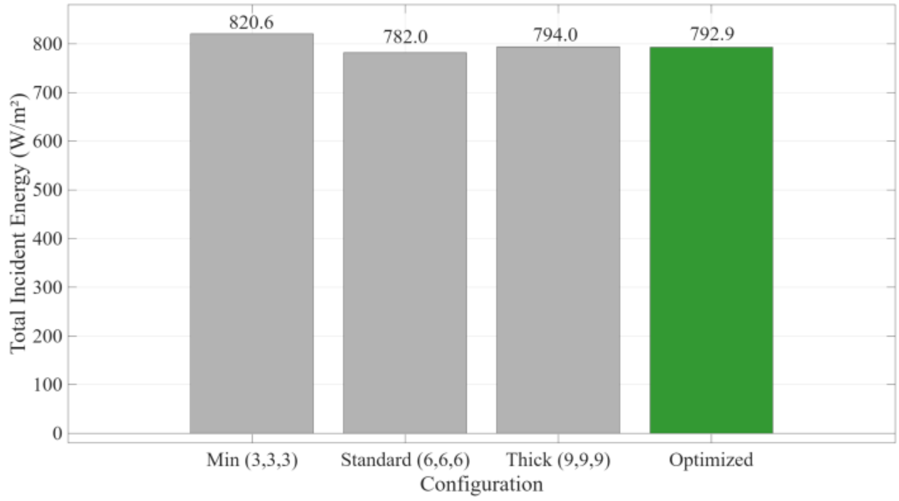

Fig. 4 Total Incident Energy for Different Configurations (Photo/Picture credit: Original).

Fig. 5 shows the transmission spectra under different conditions, with wavelength on the horizontal axis and transmittance on the vertical axis. It can be seen that the optimized transmittance spectrum is generally higher than the standard scheme across the entire 300-2000 nm range. Particularly in the visible and near-infrared bands, the transmittance curve of the optimized scheme exhibits a higher plateau, meaning more solar energy can enter the room. The oscillation pattern of the spectral curve is caused by multilayer interference. The optimized scheme, through precise control of the thickness, makes the constructive interference effect more significant in the energy-concentrated bands, thereby achieving an overall improvement in transmittance.

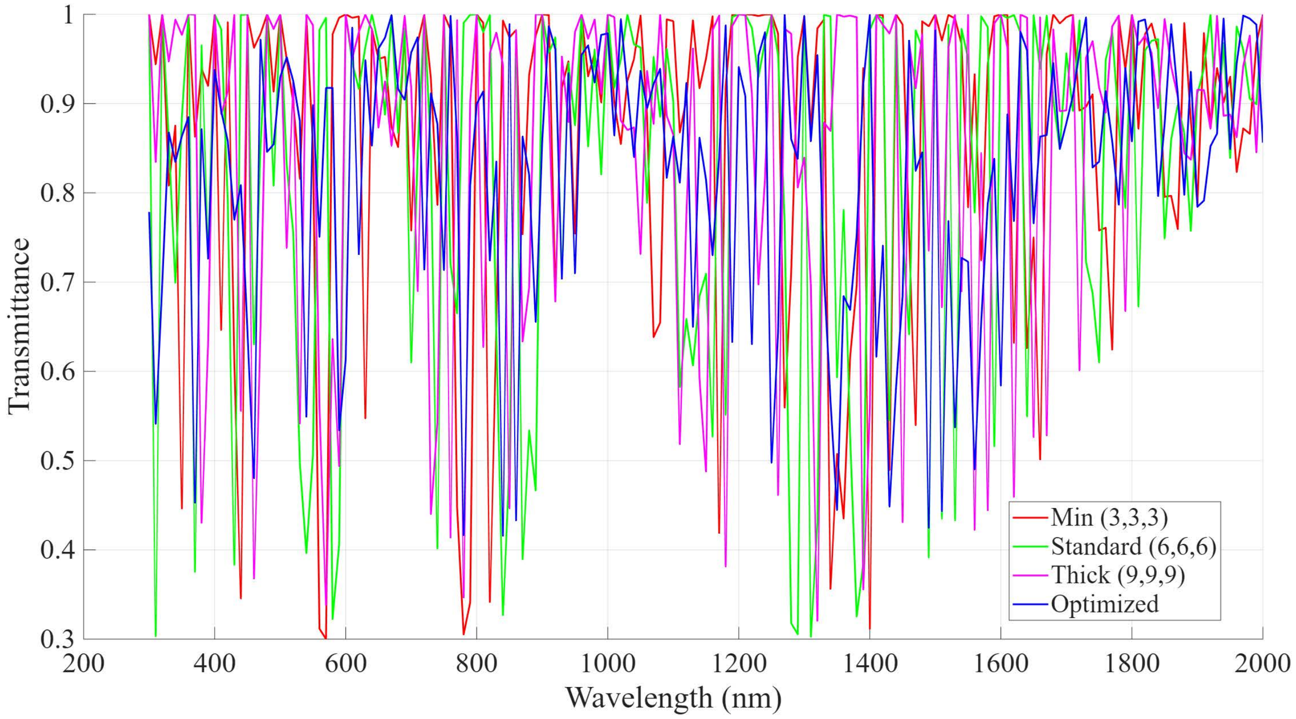

Fig. 5 TMM transmittance for different configurations (Photo/Picture credit: Original).

4. Conclusion

This study combines neural networks and the transfer matrix method (TMM) to optimize the thickness of triple-glazed windows to maximize indoor solar thermal gain. The results show that TMM can accurately simulate the interference and reflection effects of light in multi-layered glass, outperforming traditional simplified models; the constructed neural network surrogate model has high prediction accuracy ($R^2 = 0.7955$), significantly improving optimization efficiency. The optimal thickness combination obtained through the differential evolution algorithm can improve transmission energy by 1.4% compared to the uniform thickness scheme. This study still has many shortcomings. For example, the refractive index is simplified as a constant, neglecting dispersion and absorption; only normal incidence is considered without accounting for angular variations throughout the year; the optimal thickness combination has not been empirically verified; the objective function focuses solely on solar transmittance, overlooking intensity, acoustics, and cost; and the resulting solution is based on static geometry, without exploring the potential for dynamic regulation such as electrochromism.Future research will introduce more accurate material models, dynamic incidence angle simulation, annual energy consumption analysis, and more performance indicators. It will also explore integration with smart materials such as electrochromic materials to develop dynamically controlled smart window systems.

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