Optimization of Triple-Glazed Windows with Anti-Infrared Properties Based on BP Neural Network and Genetic Algorithm

Runguo Chen

School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Beijing, 100876, China

1415327394@bupt.edu.cn

**Abstract.** This study addresses the energy-saving needs of buildings in hot regions by proposing a triple-glazed window thickness optimization method based on a back propagation (BP) neural network and a genetic algorithm, aiming to reduce the transmission of solar energy above the 700nm wavelength band and decrease indoor cooling energy consumption. By constructing an optical model for triple-glazed windows to generate datasets, the nonlinear relationship between glass thickness and light transmittance was fitted using a BP neural network. With the global search capability of the genetic algorithm, the optimal combination of glass thicknesses was successfully found: L1 =7.36mm, L2 = 4.04mm, and L3 = 4.94mm, resulting in a reduction of approximately 48.52% in light energy transmission above the 700nm wavelength band. This study confirms the effectiveness of combining BP neural networks and genetic algorithms for glass selection in architecture, offering theoretical support and new insights into nonlinear optimization. Although limited by data and structure, future research and model optimization are expected to improve performance.

# INTRODUCTION

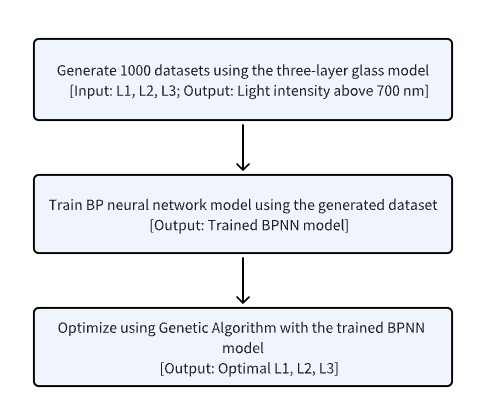
In the context of increasing global energy shortages and climate change, energy conservation and emissions reduction have become increasingly crucial. The IPCC AR6 report indicates that building emissions account for 40% of total greenhouse gas emissions, making building energy efficiency a key pathway to achieving emissions reduction goals [1]. Among building components, windows exhibit the lowest energy efficiency, causing approximately 40% of energy loss [2, 3]. In hot summer regions, designing window glasses appropriately to minimize the amount of sunlight entering the room can help lower indoor temperatures, reduce air conditioning usage, and thus achieve energy savings.

To optimize the performance of multilayer films and enhance their properties, such as thermal insulation, numerous studies have been conducted. Pan et al. proposed a new method to reduce scattering losses in high-reflection coatings by optimizing the interfacial electric field intensity distribution without changing the spectral reflectance. They designed three different high-reflection coating structures, and the coating achieved an angle-resolved scattering (ARS) value of 0.001 sr⁻¹ at 632.8 nm [4]. Cho et al. used artificial neural network models to analyze the properties of ITO/Al/ITO multi-layer films and found that increasing Al film thickness or annealing temperature decreased sheet resistance. They then applied a genetic algorithm to achieve a maximum figure of merit of 12.28×10⁻⁴ X⁻¹ [5]. Yue et al. introduced a simulated annealing particle swarm optimization (SAPSO) method based on surface plasmon resonance (SPR) phase detection, which demonstrated higher accuracy and faster convergence in extracting thickness and optical constants from multi-layer films compared to the PSO method [6]. Zhang et al. utilized a particle swarm optimization (PSO) algorithm to optimize visible transmission and NIR reflection in multilayer films for transparent-heat reflective windows. They designed a five-layer TiO2/Ag/TiO2/Ag/TiO2 structure, achieving 87% visible transmittance and 95% NIR reflectance [7]. Jiang et al. proposed a deep reinforcement learning-based method for multi-layer optical thin film optimization. Their deep Q network (DQN) effectively optimized complex multi-layer thin-film structures, with an 8-layer solar absorber reaching 94.55% absorption [8]. Fukada et al. employed machine learning to design multi-layer films by learning experimental procedures from chemical literature, creating a tool that can predict untrained film structures [9]. These studies highlight the significant potential of optimization algorithms in enhancing the performance of multi-layer films.

Although there has been extensive research on multi-layer film design, relatively fewer studies focus on optimizing multi-layer glass thickness to reduce specific wavelength solar light transmission. This study will address this gap by focusing on the optimization of triple-glazed window thickness under summer heat conditions. Using back propagation (BP) neural networks combined with genetic algorithms, the study aims to optimize glass thickness to minimize the transmission of solar light in wavelengths greater than 700nm. The subsequent sections of this paper will elaborate on the optimization process based on BP neural networks and genetic algorithms, discussing and analyzing the optimization results to validate the feasibility and practicality of using neural networks to replace complex physical models for global optimization.

# METHODS

This study employs BP neural networks and genetic algorithms for optimization, aiming to design triple-glazed window thicknesses to minimize solar light transmission at wavelengths above 700nm. The optimization process is illustrated in Figure 1. Each dataset is created by randomly selecting the thickness of each glass layer within the range of 3 mm to 10 mm. Then, an optical model is employed to calculate the transmitted light intensity above 700 nm based on these thicknesses, which serves as the output of the dataset. The process involves generating 2000 such datasets with a three-layer glass model to predict light intensity above 700 nm, training a BP neural network on these datasets, and then using a genetic algorithm with the trained model to optimize the layer parameters (L1, L2, L3).



**Figure 1.** Optimization Flowchart (Original)

## Triple-Glazed Optical Model

To meet the energy-saving needs of buildings in hot summer conditions, this study constructs a simplified triple-glazed optical model for simulating and optimizing glass thickness. The triple-glazed structure consists of three layers of glass and two air gaps. The relative dielectric constant of the glass is 3.9, with thickness ranging from 3mm to 10mm. This study only considers vertical incidence, i.e., the angle of incidence is 0°. This model simplifies the number of glass layers and air gaps, reducing computational complexity and facilitating rapid optimization calculations for glass thickness.

The optical model for triple-glazed windows is based on wave optics principles, considering multiple reflections and transmissions between glass and air layers. Incident light intensity follows the AM1.5G standard solar spectrum, which accounts for radiation characteristics after passing through the atmosphere. The formula for calculating light transmittance is as follows:

The reflection rate of the glass is

(1)

where is the refractive index of the glass, derived from , where is the dielectric constant of the glass. is the refractive index of light in a vacuum. The transmittance of a single layer of glass is:

(2)

where , is the thickness of the glass, and is the incident light wavelength. The final transmitted light intensity is:

(3)

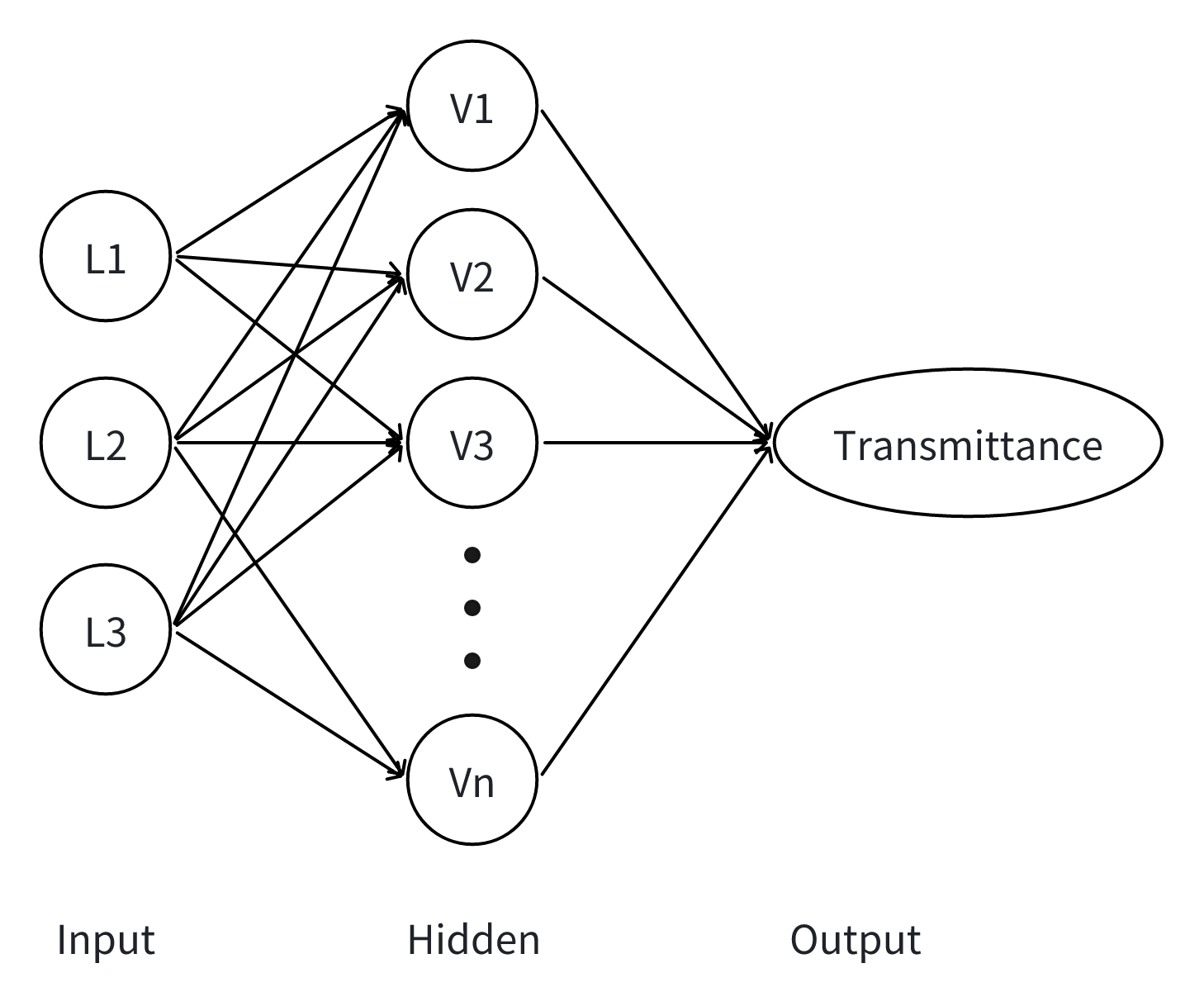
where is the incident light intensity, and 𝑇ₙ is the transmittance of the nth layer of glass.

This study uses the model to randomly generate 2000 sets of data (input as the thickness of the three layers of glass, output as the normalized total transmitted light intensity above 700nm) as the dataset for the BP neural network.

This document was prepared using the AIP Conference Proceedings template for Microsoft Word. It provides a simple example of a paper and offers guidelines for preparing your article. Here we introduce the paragraph styles for Level 1, Level 2, and Level 3 headings. Please note the following:

## BP Neural Network Construction

The BP neural network has strong nonlinear fitting ability. Through multi-layer neurons and activation functions, it can learn and fit complex nonlinear relationships. Its backpropagation algorithm constantly adjusts weights to accurately capture the nonlinear input-output relationship, showing great nonlinear fitting ability in many practical problems. The BP neural network consists of an input layer, a hidden layer, and an output layer, as shown in Figure 2. The number of input layer nodes is 3, corresponding to the thicknesses of the three layers of glass (L1, L2, L3), with values ranging from 0.003 to 0.010. The hidden layer uses the Sigmoid function as the activation function to effectively handle nonlinear problems [10]. The number of output layer nodes is 1, representing the normalized transmittance above 700nm. The learning rate is set to 0.1 to balance training speed and stability; the number of training cycles is set to 1000 to ensure the network has sufficient opportunities to learn data features and converge; the target error is set to 0.001, and the training process terminates early when the prediction error reaches this threshold to prevent overfitting; the training function uses the Levenberg-Marquardt algorithm, combining the advantages of gradient descent and Newton's method for fast convergence and excellent global optimization capabilities.



**Figure 2.** Structure of Neural Network (Original)

During the training of the BP neural network, the simulated dataset is used for training, with each set of data containing the thickness of the three layers of glass as input and the corresponding normalized transmittance as output. Through forward propagation, the network output is calculated, and the error between the output and the true value is backpropagated into the network, adjusting network parameters using gradient descent to minimize prediction errors.

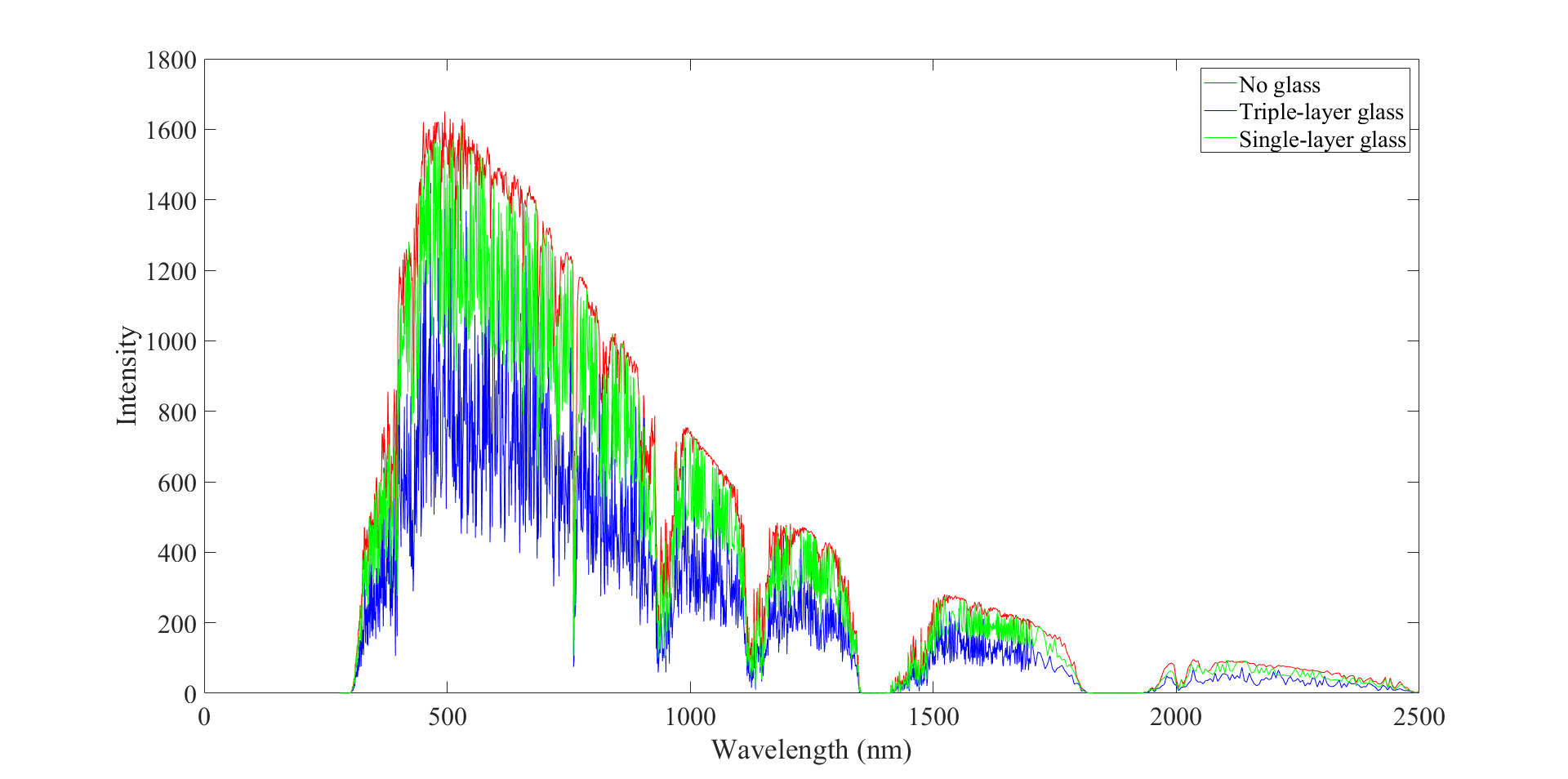
## Genetic Algorithm Optimization

The genetic algorithm is a global optimization algorithm based on natural selection and genetic mechanisms, including basic steps such as population initialization, selection, crossover, mutation, and fitness evaluation.

In this study, the genetic algorithm optimizes the minimum value of the BP neural network's output layer, i.e., the total transmittance above 700nm. The specific implementation steps are as follows: first, a group of random combinations of triple-glazed window thicknesses is generated as the initial population, with each thickness ranging from 3mm to 10mm, and the population size is set to 100. Next, each individual is input into the trained BP neural network, calculating the normalized transmittance above 700nm as the fitness value, to minimize this value.

# RESULTs

After training, the determination coefficient (R²) of the BP neural network reached 0.9815, indicating good fitting of the training data. Ultimately, the optimized triple-glazed window thicknesses are L1 =7.36mm, L2 = 4.04mm, and L3 = 4.94mm. This glass combination reduces the transmitted light intensity above 700nm by approximately 48.52%, significantly decreasing the energy entering the room. As shown in Figure 3, the red curve represents no glass, the green curve represents single-layer glass, and the blue curve represents triple-layer glass. The horizontal axis of Figure 3 denotes wavelength, and the vertical axis indicates light intensity. Overall, the transmittance of triple-layer glass is lower than that of single-layer glass across most wavelengths, particularly in the near-infrared band, where it demonstrates a stronger ability to block thermal radiation. This indicates that triple-layer glass has a more significant advantage in terms of thermal insulation.



**Figure 3.** Optimized Transmitted Light Intensity vs Incident Light Intensity Curve (Original)

The optimized triple-layer glass combination demonstrates superior performance in reducing infrared transmittance, as evidenced by the data in Table 1. Compared to single-layer glass (3 mm), which exhibits a transmitted light intensity of 3.85 (19.73% attenuation), the optimized triple-layer design achieves a transmitted intensity of 2.47, corresponding to a 48.52% infrared attenuation rate. This represents a 35.8% improvement in infrared blocking relative to single-pane glass. Even against the random triple-layer combination (transmitted intensity = 2.51, 47.65% attenuation), the optimized structure delivers an additional 1.59% reduction in transmitted energy. The results underscore the critical role of thickness optimization in balancing optical and thermal performance for energy-efficient glazing systems.

**TABLE 1.** Comparison of Transmitted Light Intensity for Different Glass Structures (Original)

|  |  |  |
| --- | --- | --- |
| **Glass Type** | **Transmitted Light Intensity (>700nm)** | **Infrared Attenuation Rate** |
| No glass | 4.79 | 0% |
| Single-layer glass(3mm) | 3.85 | 19.73% |
| Random triple-layer combination (7.04mm,8.52mm, 5.75mm) | 2.51 | 47.65% |
| Optimized triple-layer combination | 2.47 | 48.52% |

# DISCUSSION

In practical building energy-saving designs, adopting the triple-glazed window thickness combination determined by this optimization scheme can effectively reduce the incident energy in the near-infrared band, significantly lowering indoor cooling loads and achieving energy-saving and consumption-reduction goals. When physical models become too complex or even impossible to construct due to increased variables, datasets can be constructed to train neural networks, enabling the combination of neural networks and genetic algorithms for optimization as an alternative to complex physical models. This method can not only address complex multi-variable optimization problems but also continuously iterate and optimize models through feedback from experimental data, gradually enhancing prediction accuracy and practical application effects.

Despite the achievements of this study, some limitations remain. First, the number of experimental data samples is limited, primarily focusing on the single variable of glass thickness. Second, the structure of the BP neural network is relatively simple, leaving room for improvement in fitting the more complex rules of light propagation. Additionally, the study does not sufficiently consider dynamic factors during actual glass usage, such as aging and the long-term impact on light transmission. Future research will aim to expand the sample size and incorporate more factors affecting light transmission, such as glass composition and environmental conditions, to build a more comprehensive input dataset. Simultaneously, there will be attempts to introduce more advanced deep learning architectures, such as convolutional neural networks, whose powerful feature learning ability can more effectively handle the complex relationships in the optimization of the thermal insulation performance of three-layer glass, for further enhancement of model performance and adaptability [11]. Continuous iteration of experimental verification and model optimization is expected to facilitate the implementation and continuous improvement of the optimization scheme in practical applications.

# CONCLUSION

The study focuses on the energy-saving needs of buildings in hot summer regions, successfully developing an optimization method based on BP neural networks and genetic algorithms to precisely optimize triple-glazed window thicknesses. This innovative solution effectively reduces the transmission of solar energy above the 700nm wavelength band, significantly lowering indoor cooling energy consumption. Through model training with simulated datasets and leveraging the global search capability of genetic algorithms, the optimal glass thickness combination was obtained: L1 =7.36mm, L2 = 4.04mm, and L3 = 4.94mm. This combination dramatically reduces light energy transmission above the 700nm band by approximately 48.52%, showcasing significant optimization effects.

This study provides solid theoretical support for glass selection in architectural design, significantly reducing air conditioning loads by minimizing near-infrared light energy incidence, effectively promoting the realization of building energy-saving goals. Furthermore, it broadens the scope of solving complex nonlinear optimization problems, possessing important theoretical value and broad application prospects.

However, the study's dataset mainly focuses on glass thickness and ignores glass composition, surface treatment, and environmental factors. Its neural network structure is also simple. Future research should expand the sample size, introduce more variables, and try advanced deep learning architectures.

# REFERENCES

1. S. Kar, N. S. Kumar and A. Bhatia, "Use of Genetic Algorithm to Optimize Energy Efficiency, Construction Cost, and Daylight in Building Design," in *Third International Conference on Sustainable Energy, Environment and Green Technologies,* IOP Conference Series: Earth and Environmental Science 1279, (IOP Publishing, Bristol, 2023), pp. 012029.
2. M. Tarantini, A. D. Loprieno and P. L. Porta, Energy **36**, 2473-2482(2011).
3. X. Chen and Y. Gu, Energy and Buildings **304**, 113838(2024).
4. Y. Pan, W. Yang, A. Tian et al., Optics & Laser Technology **145**, 107520(2022).
5. E. N. Cho, P. Moon, C. E. Kim et al., Expert Systems with Applications **39**, 8885-8889(2012).
6. C. Yue, Z. Qin, Y. Lang et al., Optics Communications **430**, 238-245(2019).
7. K. Zhang, Z. Chen, J. Guo, Renewable Energy **237**, 121913(2024).
8. A. Jiang, O. Osamu and L. Chen, Scientific Reports **10**, 12780(2020).
9. K. Fukada and M. Seyama, Scientific Reports **12**, 930(2022).
10. J. Li, J. Cheng, J. Shi and F. Huang, "Brief introduction of back propagation (BP) neural network algorithm and its improvement," in *Advances in Computer Science and Information Engineering,* Advances in Intelligent and Soft Computing 2, edited by D. Jin et al. (Springer, Berlin, Heidelberg, 2012), pp 553-558.
11. B. Liu, Y. Cao, Y. Gan et al., "Convolutional Neural Network (CNN) for Building Energy Efficiency Analysis, Prediction, and Real-time Adjustment Strategies," in *2023 11th International Conference on Information Technology: IoT and Smart City (ITIoTSC),* (IEEE, 2023), pp. 262-267.