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Research paper

Analysis of building energy efficiency optimization design effectiveness based on multi-objective optimization algorithm

Wei Guo[1], Yaqiong Dong[2]

Abstract: With the increasing attention of society to sustainable development and environmental friendly design, building energy saving design has become a research hotspot. In this paper, a method combining multi-objective optimization algorithm and neural network backpropagation strategy is proposed to solve the problem that traditional design methods are difficult to balance multi-objective. By dividing the architectural design problem into multiple sub-problems, each sub-problem corresponds to a design objective, and applying multi-objective optimization technology, the global optimization is realized. The experimental results show that the error of energy consumption prediction model is almost 0, while the error of daylighting prediction model is between 0 and 5, and the average error is about 3. The correlation coefficients of all models exceeded 0.9845, highlighting the excellent performance of neural networks in forecasting accuracy. The BP neural network showed good convergence in 2800 to 3000 iterations, further demonstrating the high efficiency of the method in energy consumption and daylighting prediction. The research not only provides a scientific and feasible strategy for building energy efficiency optimization design, but also enhances its scientific value and practicability through the display of quantitative results.

Keywords: building energy efficiency, environmental adaptive design, multi-objective optimisation, neural networks, pareto optimization

[1]MSc., Henan University of Urban Construction, School of Management, Pingdingshan, China, e-mail: guoweivip@outlook.com, ORCID: 0009-0005-6821-6865
[2]MSc., Henan University of Urban Construction, School of Management, Pingdingshan, China, e-mail: dongyaqiong@163.com, ORCID: 0009-0001-5498-4661

1. Introduction

The problem of global energy consumption and environmental pollution is becoming a global challenge. As one of the main areas of energy consumption, the importance of energy-saving design is becoming more and more prominent in the building industry [1]. According to statistics, the energy consumed by buildings during their life cycle accounts for a considerable part of the total energy consumption in the world, and has a significant impact on the environment [2]. Therefore, building energy efficient design is not only related to energy efficiency, but also directly affects the sustainability of the environment and the improvement of human life quality [3]. However, the traditional architectural design methods often face great challenges in the face of multi-objective and multi-variable optimization problems. These goals may include energy efficiency, cost-effectiveness, indoor comfort, environmental impact, etc., and they may conflict with each other, complicating finding the optimal solution during the design process [4]. At present, the existing methods such as hybrid genetic algorithm, improved ant colony optimization algorithm and distributed parallel genetic algorithm have made some progress, but there are still some problems such as slow convergence and easy local convergence [5]. On the other hand, multi-objective optimisation is a method to deal with multi-objective problems, which decomposes a complex multi-objective problem into several relatively simple sub-problems [6]. And training neural networks is usually done by continuously adjusting the weights through back propagation algorithm to minimise the gap between the network output and the actual objective [7].

As the global climate continues to change, the importance of energy efficient building design is becoming more and more significant. Yue and Jia designed a three-dimensional model of urban landscape based on Structure from motion algorithm and simulated the landscape signals by autocorrelation function. The results show that the application value of different categories of green building materials in urban 3D landscape design is different [8]. Andiyan proposed a harmonious development between the main functions of office buildings and the environment, aiming to analyse the building's response to environmental issues under the application of the green building concept. The results show that the green building concept can continue to be used to solve the environmental problems of buildings [9]. Zhou et al. selected a green office building in a city as an example, and obtained the indoor environmental quality through on-site measurements, and obtained the user's satisfaction with the building through questionnaires. The experimental results show that the level of energy use in this green office building is much less than the constraints of the national standard [10]. Almeida et al. experts selected green and non-green buildings of the university with similar characteristics to compare energy use and simulate the interactions between the occupants and the systems in the building, with the aim of analysing the impact of occupants' behaviour in terms of energy use. The results of the study show that the occupants' influence on the energy performance of the building is about 72%, which can provide a reference for the design of green buildings [11].

On the other hand, multi-objective optimisation algorithms as a class of computational methods for solving problems involving multiple conflicting objectives. Hamsaveni et al. have proposed a multi-objective optimisation] algorithm aimed at solving the problem of wavelength allocation and shortest path identification in WDM networks. The study is able to analyse the optimal routing paths of the nodes as well as the available wavelengths at each moment in time, thus reducing the system burden [12]. Wang et al. proposed a multi-objective optimization algorithm based on a multi-area division sampling strategy integrating a genetic algorithm and a differential evolutionary algorithm to cope with the standard flexible job shop scheduling problem. The results of the study show that the model and algorithm have achieved remarkable results and have potential applications in solving other similar problems [13]. Anh et al. propose an optimal energy management method for optimal thermoelectric hybrid isolated microgrids using intelligent optimization techniques. Experimental results show that the improved multi-objective particle swarm optimization algorithm has 1 better performance [14]. Chen et al. proposed a control optimization method based on multi-objective optimization algorithm to solve the problem that it is difficult for existing control optimization methods to take into account all performance indicators of three control systems at the same time. The results show that the method is feasible and effective [15].

In summary, the current research on building energy efficiency has been greatly developed, but at present there are still problems such as slow] convergence speed and easy local convergence. In order to achieve a balance between multiple objectives in building design, improve design efficiency and performance, while ensuring the optimal balance of energy efficiency, environmental sustainability and user experience in buildings under different climatic conditions, the study proposes a building energy efficiency design method based on multi-objective optimisation algorithm. By decomposing the complex building design problem into multiple sub-problems and applying the multi-objective optimisation technique to deal with it, and introducing neural network back propagation to improve the efficiency of the optimisation process. The innovation of this research is that the multi-objective optimisation technique takes into account energy consumption, comfort and other indicators to achieve the global optimal solution, and back propagation quickly approximates the objective function to accelerate the convergence of the optimisation algorithm and improve the search efficiency. This research is divided into four parts. The first part introduces the research background, problems and solutions of building energy efficiency design optimisation. The second part introduces the building energy-saving design optimisation method combining multi-objective optimisation algorithm and neural network. The third part designs a comparative experiment for performance testing of building energy-saving design optimisation. The fourth part summarises the research method, analyses the experimental results, and puts forward the shortcomings and outlook of the method.

2. Building energy efficiency optimization considering multi-objective and PCNN

Energy-efficient optimal design of buildings based on multi-objective optimisation algorithms aims to achieve the optimality of building systems considering multiple objectives such as energy efficiency, indoor comfort and environmental impact. Through this approach, the study is expected to find the set of Pareto optimal solutions under different design variables and constraints, thus achieving a balance between energy efficiency, environmental sustainability and user experience of the building.

2.1. Building energy saving optimization design based on Pareto optimal solution

Different climate regions around the world, such as tropical, temperate and cold zones, have unique climate characteristics, including temperature fluctuations, precipitation patterns, humidity levels and solar radiation intensity. These factors directly affect a building's energy needs, including heating, cooling, lighting and ventilation. To achieve this, the study combines climate data analysis and building energy consumption simulations. Research took into account factors such as building form, orientation, material selection and layout, which interact with climate characteristics to determine the building's energy efficiency [16]. This paper selects an improved multi-objective particle swarm optimization (MOPSO) algorithm, which finds Pareto optimal solution set by maintaining a group of particles to iteratively search in the search space of multiple targets. Its general idea and technical process are shown in Fig. 1.

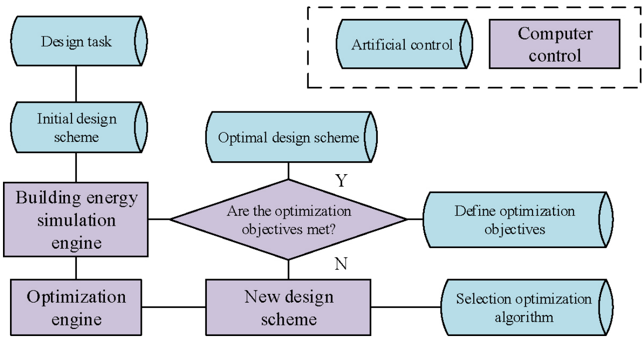

Fig. 1. Overall idea and technical process of building energy efficiency optimisation design

In Fig. 1, the technical process includes the establishment of building energy consumption model, the definition of design variables and constraints, the selection and application of optimisation algorithms, as well as the final obtainment of the Pareto optimal solution set based on multi-objective optimisation, which leads to the best balance in the case of multiple objectives. Optimisation problems are divided into two categories: single-objective and multi-objective. Single-objective problems have only one objective function and are usually common in building energy efficiency design [17]. Multi-objective problems involve two or more objective functions and are relatively difficult to solve because there are often conflicts between different objectives [18]. Methods for solving multi-objective problems include the primary objective method, the linear weighted sum method, and Pareto optimality. Among them, the computational expression of linear weighted sum method is shown in Eq. (2.1) [19].

$$\min_{x \in X} \sum_{i=1}^{n} w_i f_i(x) \tag{2.1}$$

In Eq. (2.1), $f_i(x)$ and w_i denote the objective function and its weight coefficients for the i respectively, and X denotes the feasible space for optimisation. The number of objective functions is denoted by n. On the other hand, for single-objective optimisation algorithms, their performance evaluation indexes are stability, effectiveness, speed, coverage, robustness and convergence. The method of evaluating the robustness of an algorithm is to change the parameters several times, record the optimal solutions under different settings, and calculate the standard deviation of their objective function values. The smaller standard deviation indicates the better robustness of the algorithm, the specific calculation is shown in Eq. (2.2) [20].

$$\text{Rob} = \sqrt{\frac{\sum_{i=1}^{n}\left(\frac{\sum_{i=1}^{n} f_i}{n} - f_i\right)^2}{n}} \tag{2.2}$$

In Eq. (2.2), Rob denotes the metrics for evaluating the robustness of the algorithm, the value of the objective function of the optimal solution found by the algorithm in the first i run is denoted by f_i, and n denotes the total number of runs. Convergence is the accuracy of the optimisation algorithm in approaching the optimal solution. The evaluation method is to determine the convergence stage of the algorithm and calculate the standard deviation of the objective function value of the solution at that stage, the formula is shown in Eq. (2.3) [21].

$$\text{CON} = \sqrt{\frac{\sum_{i=b}^{t}\left(\frac{\sum_{i=b}^{t} f_i}{n} - f_i\right)^2}{t-b+1}} \tag{2.3}$$

In Eq. (2.3), CON denotes the metric for evaluating the convergence of the optimisation algorithm, t denotes the number of all solutions searched in the optimisation run, and the solution searched at b is the optimal solution searched by the optimisation. The effectiveness of a multi-objective optimisation algorithm is assessed by considering the Pareto optimal set generated and the time cost required [22]. In order to eliminate the unit differences between different optimal design objectives, each objective vector of the Pareto solution is first converted to a normalised value using the maximum-minimum normalisation method, and then the values of each evaluation metric are calculated based on these normalised values, which are standardly calculated as shown in Eq. (2.4) [23].

$$F_i^j = \frac{f_i^j - f_{\min}^j}{f_{\max}^j - f_{\min}^j} \tag{2.4}$$

In Eq. (2.4), F_i^j denotes the normalised value of the j objective corresponding to the i solution, and f_i^j denotes the actual value of the j objective corresponding to the i solution. $f_{\max}^j$ denotes the actual maximum value of the j-th objective obtained by the algorithm in the optimisation process, and $f_{\min}^j$ denotes the actual minimum value of the j-th objective obtained by the algorithm in the optimisation process. In studying the optimal design of buildings for energy efficiency, in addition to evaluating the algorithm efficacy, special attention needs to be paid to the potential failure scenarios. In a given optimisation problem, if the optimal solution obtained by an algorithm is sufficient to meet the user's accuracy requirements, it can be considered as a satisfactory solution. The quality of the optimal solution can be measured by calculating the relative difference in the objective function value between it and the true optimal solution, which is given in Eq. (2.5) [24].

$$\delta = \frac{|f' - f^*|}{f^*} \times 100\% \tag{2.5}$$

In Eq. (2.5), f' and f^* represent the objective function value of the optimal solution obtained by the algorithm and the objective function value of the real optimal solution, respectively. Successful optimisation run means that the algorithm finds a satisfactory solution in a finite time, and the success rate is the ratio of the number of successful runs of the algorithm in multiple runs to the total number of runs, which is calculated as shown in Eq. (2.6) [25].

$$\beta = \frac{N_{\text{success}}}{N_{\text{all}}} \times 100\% \tag{2.6}$$

In Eq. (2.6), N_{all} denotes the total number of optimisation runs, while N_{success} denotes the number of successful optimisation runs among them. To study the use of the analytical method to calculate the energy consumption of a building, a physical calculation model that can accurately reflect the actual working condition of the building is first determined. In this regard, a physical calculation model based on EnergyPlus was chosen as the theoretical basis for the analytical method [26]. The total energy consumption of the building at a certain moment $tQ_{\text{all},t}$ can be basically calculated as the sum of the energy consumption of the HVAC system, lighting, electrical equipment, and other related energy consumption, the specific expression of which is shown in Eq. (2.7) [27].

$$Q_{\text{all},t} = Q_{\text{sys},t} + Q_{\text{lights},t} + Q_{\text{equip},t} + Q_{\text{others},t} \tag{2.7}$$

In Eq. (2.7), $Q_{\text{sys},t}$, $Q_{\text{lights},t}$, $Q_{\text{equip},t}$ and $Q_{\text{equip},t}$ represent the energy consumption of HVAC equipment, lighting equipment, appliance-related energy and other related energy, respectively. In recent years, neural networks have made significant progress in multi-objective optimisation of building performance. By utilising deep learning techniques, the complex non-linear relationships of building systems can be effectively captured. Combined with multi-objective optimisation algorithms, the ability of neural networks to synergistically optimise building energy consumption, comfort and other multifaceted objectives has been enhanced. Therefore, the study proposes a multi-objective optimisation method for building performance based on neural networks, and Fig. 2 demonstrates the research framework of the method.

In Fig. 2, the study firstly needs to perform the determination of performance objectives, then the design of parameter space, followed by parameter and performance mapping, and then the selection of tools and platforms. Generally traditional performance mapping usually uses simulation methods with high accuracy. The neural network mapping method is used for performance evaluation by inputting the building design parameter data and obtaining the evaluation results through the mathematical operation of the neural network model [28]. The model is trained based on the data set obtained from research or simulation, and can be reused after the training is completed, and the performance evaluation results are quickly obtained through simple operations, and the specific performance mapping comparison is shown in Fig. 3.

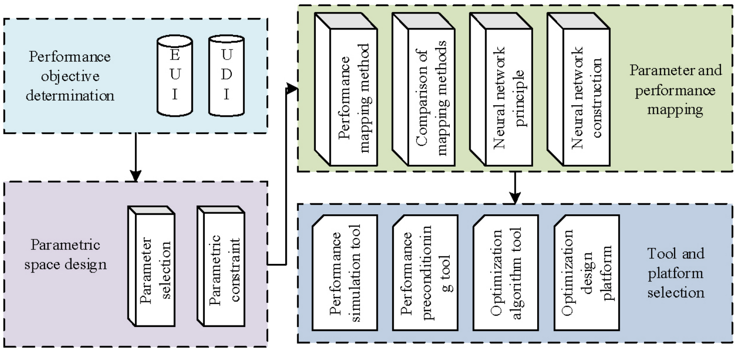

Fig. 2. Research framework of multi-objective optimisation method of building performance based on neural network

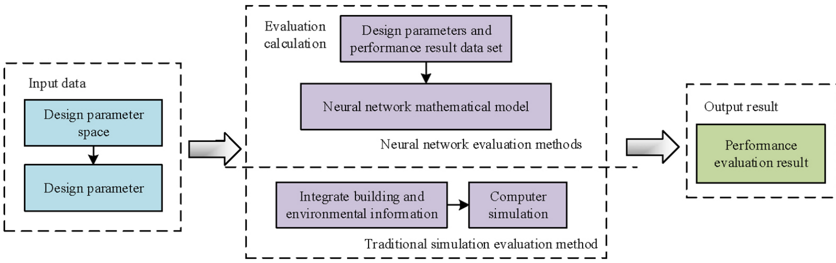

Fig. 3. Comparison of core steps of performance mapping methods

In Fig. 3, there is a clear difference between the traditional performance mapping approach and the neural network approach in terms of the core steps. The traditional approach relies heavily on simulation techniques to obtain a performance assessment through refined modelling and numerical calculations.

2.2. Multi-objective optimization design based on BPNN

In order to improve the efficiency of the optimization process, backpropagation neural network (BPNN) is introduced. Through iterative training, the network can predict building performance quickly and accurately [29]. Meanwhile, in order to reveal the correlation between form and performance, designers are able to adjust building features more accurately to meet various requirements and goals and to improve the overall performance of the building, the training of the mapping model of building form and performance is crucial. In the study, the process is accomplished through neural network training, utilizing the corresponding morphology and performance datasets. The training consists of three steps: structure design, dataset generation and training validation [30]. In BPNN, tansig (hyperbolic tangent S-type) and Purelin (linear) are two commonly used transfer functions. tansig function is usually used in the hidden layer, and its output ranges between [–1, 1], which has the property of nonlinearity, which is helpful for the network to learn the complex nonlinear relationship [31,32]. Whereas Purelin function is usually used in the output layer and its output is directly equal to the input, which is very suitable for linear mapping, especially in regression problems. In this case, the mathematical expression for the net input value of the BPNN at the j-th neuron is shown in Eq. (2.8) [33].

$$S_j = \sum_{i=1}^{x} w_{yi} \cdot x_i + b_j = W_j X + b_j \tag{2.8}$$

In Eq. (2.8), x_i denotes the input of the neuron in the input layer, b_j denotes the threshold value, and the connection weights of the j neuron in the latter layer to the i neuron in the former layer are tabulated by w_{yi}; S_j denotes the net input. The study further obtains the output of y_j, which is the output of the j-th neuron, through the excitation function, which is given in Eq. (2.9) [34].

$$y_j = f(S_j) = f\left(\sum_{i=1}^{x} w_{yi} \cdot x_i + b_j\right) = f(W_j X + b_y) \tag{2.9}$$

In Eq. (2.9), $f(\cdot)$ denotes the hull function. Backpropagation (BP) network learning is a backpropagation algorithm that allows the neural network to continuously adjust the connection weights to adapt to the mapping relationship between inputs and outputs. In training, the network calculates the error between the output and the target through forward propagation, and then gradually adjusts the weights to minimize the error through backpropagation [35]. Fig. 4 shows the BP neural network learning process, i.e., the network topology diagram.

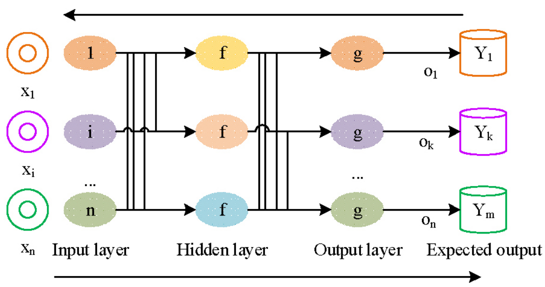

Fig. 4. Topology of BP neural network

In Fig. 4, the BPNN algorithm consists of two stages: forward propagation and back propagation. In forward propagation, the input data passes through the neuron network, generating the output and calculating the error by comparing it with the actual target. In backward propagation, the error is propagated backwards through the network, and the connection weights are adjusted by gradient descent to gradually learn the mapping relationship between the input and the output, and continuously iteratively optimize the network performance. In forward ship, the input expression of the j-th node of the hidden layer is shown in Eq. (2.10) [36].

$$\text{input}_{j=} \sum_{i=1}^{x} u_{ji} x_i + y_j \tag{2.10}$$

In Eq. (2.10), x_i denotes the input value of the input layer, y_j denotes the deviation value of the implied layer, and u_{ji} denotes the connection weights between the nodes of the input and implied layers. The expression of the output value of the j-th node of the implied layer is shown in Eq. (2.11) [37].

$$\text{out}_j = f(\text{input}_j) = f\left(\sum_{i=1}^{x} u_{ji}x_i + y_j\right) \tag{2.11}$$

In Eq. (2.11), out_j denotes the output value of the j node of the implicit layer. The input of the k-th node of the output layer is shown in Eq. (2.12) [38].

$$\text{input}_k = \sum_{j=1}^{q} v_{kj}C_j + b_k = \sum_{j=1}^{1} v_{kj} f\left(\sum_{i=1}^{n} u_{ji}x_i + y_j\right) + b_k \tag{2.12}$$

In Eq. (2.12), $f(x)$ denotes the transfer function of the implicit layer, v_{kj} denotes the weights between the nodes of the implicit layer and the nodes of the output layer, and b_k denotes the threshold value of the nodes of the output layer; where $i = 1, 2, 3, \ldots, n$, $j = 1, 2, 3, \ldots, q$, $k = 1, 2, 3, \ldots, m$. The output value of the k-th node of the output layer is shown in Eq. (2.13) [39].

$$O_k = g\left(\text{input}_k\right) = g\left(\sum_{j=1}^{q} v_{kj}C_j + b_k\right) = g\left(\sum_{j=1}^{q} v_{kj} f\left(\sum_{i=1}^{n} u_{ji}x_i + a_j\right) + b_k\right) \tag{2.13}$$

In Eq. (2.13), $g(x)$ denotes the transfer function (output layer) and O_k denotes the output of the output layer node. a_j denotes the deviation value of the hidden function. The standard algorithm for network weight adjustment is based on the error gradient descent method. First, the specific calculation in Eq. (2.14) is used by calculating the error table between the desired output and the actual output of each sample [40].

$$E_p = \frac{1}{2}\sum_{K=1}^{L} (T_k - o_k)^2 \tag{2.14}$$

In Eq. (2.14), T_k denotes the desired output. From this, the global error is calculated in Eq. (2.15) [41].

$$E = \frac{1}{2}\sum_{P=1}^{P}\sum_{K=1}^{L} (T_k^p - o_k^p)^2 \tag{2.15}$$

Through multiple rounds of cycling, the study continuously adjusted parameters such as the learning rate so that the backpropagation network gradually converged to achieve the desired training goal.

3. Performance verification of building energy efficiency multi-objective optimization algorithm

This study focuses on the impact of building morphological changes on space loading using a morphological parametric dataset containing 200 sets of data obtained from a parametrically constrained monolithic space by mF version 2023 software and Latin hypercube sampling method. The performance target datasets corresponding to the evaluation results of morphological parameters and daylighting and energy performance are obtained by Ladybug+Honeybee version 2023 simulation tool on Grasshopper platform. The simulation method is used to gain insight into the effects of building morphological changes on daylighting and energy performance, and a neural network prediction model is constructed using the Matlab R2021a toolbox.

3.1. Optimization analysis of building energy efficiency for climate change

Fig. 5 shows the mean square error of the energy consumption and daylighting prediction models for typical climate regions such as Shanghai, Beijing, Harbin, Guangzhou and Kunming.

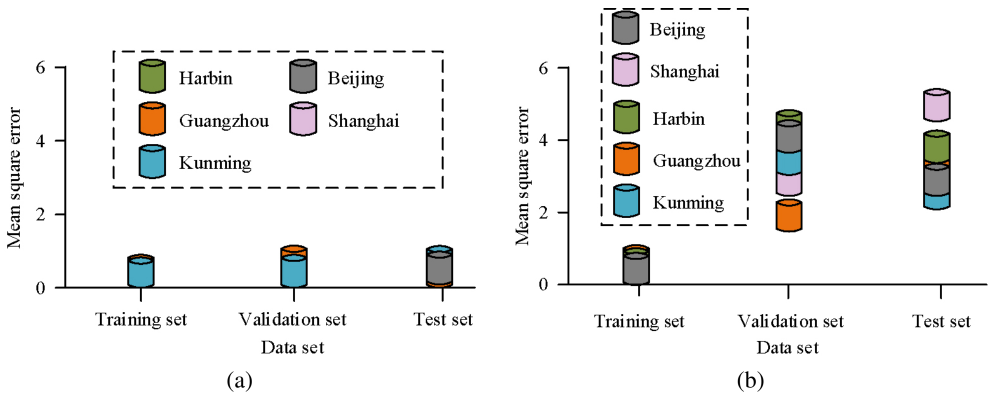

Fig. 5. Mean square error of neural network in typical climatic regions; (a) Energy consumption, (b) Daylighting

In Fig. 5, Fig. 5a shows the mean square error of the energy consumption prediction model for a typical climate region, and it can be observed that the energy consumption prediction model mean square error is low, basically close to 0. Fig. 5b shows the mean square error of the daylighting prediction model for a typical climate region. It can be observed that the lighting prediction model mean square error, the minimum is 0, the maximum is not more than 5, and the average is around 3. Fig. 6 illustrates the evolution of the size of the Pareto solution set per generation for different climate zones.

According to Fig. 6a, the number of optimal solutions in Harbin varies greatly at about 31 and 36 generations of optimization, and the number of optimal solutions gradually tends to stabilize after about 31 generations of optimization. According to Fig. 6b, the maximum

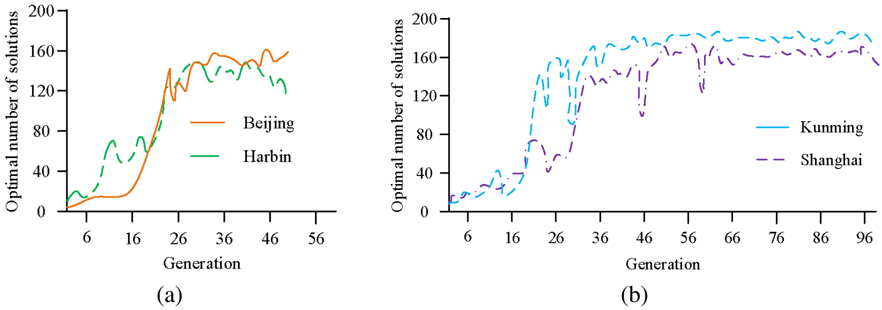

Fig. 6. Each represents the number of optimal solutions in each generation of the city; (a) Number of optimal solutions per generation in Harbin and Beijing, (b) Number of optimal solutions per generation in Shanghai, Kunming and Guangzhou

number of optimal solutions in Shanghai is 180, and the number of optimal solutions gradually tends to be stable after about 31 generations of optimization. To verify the optimization effect, the study conducted comparative experiments focusing on energy consumption and lighting performance. Ten samples from each of the entire parameter space and the Pareto solution set were selected for performance comparison. Through the statistical analysis of the sampling and performance data of feasible solutions in different climate zones, the performance improvement in Beijing and Shanghai climate zones was derived, see Fig. 7.

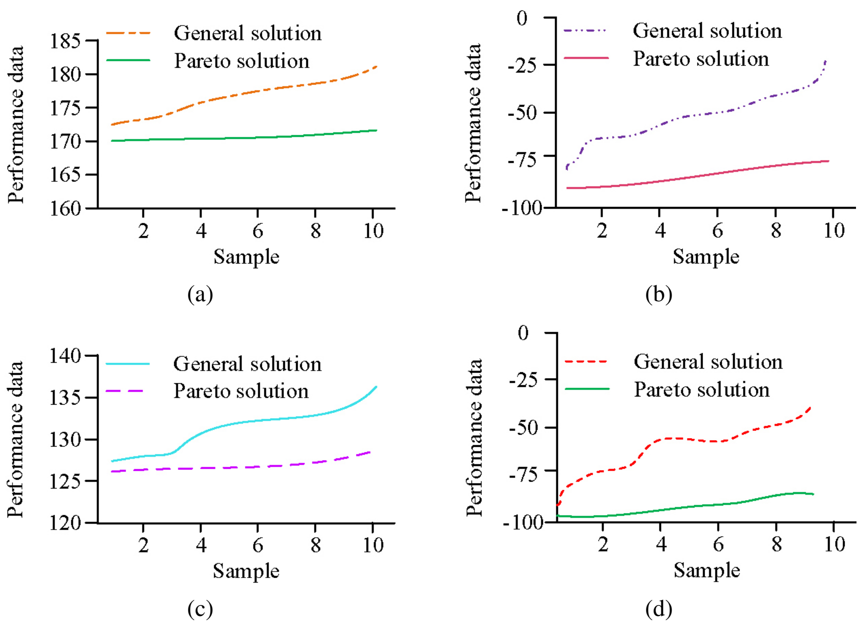

Fig. 7. Improved lighting and energy performance; (a) Energy consumption in Beijing, (b) Beijing daylighting, (c) Energy consumption in Shanghai, (d) Shanghai daylighting

According to Fig. 7a, in Beijing energy consumption, the pareto solution is around 170, while the general solution is as low as 175 and as high as 183. According to Fig. 7b, in Beijing light harvesting, the pareto solution is around –75, while the general solution is as low as about –175 and as high as about –20. According to Fig. 7c, in Shanghai energy consumption, the pareto solution is around 127. According to Fig. 7d, the pareto solution is around –77 in Shanghai daylighting. After the multi-objective optimization, the energy consumption and daylighting performance of the building are significantly improved.

3.2. Performance analysis of building energy efficiency optimization based on BPNN

In order to compare the performance of the method used in the study with other methods, the study further uses generative adversarial network, convolutional neural network to do comparison with the experimentally proposed BPNN to record the convergence changes, the results are shown in Fig. 8.

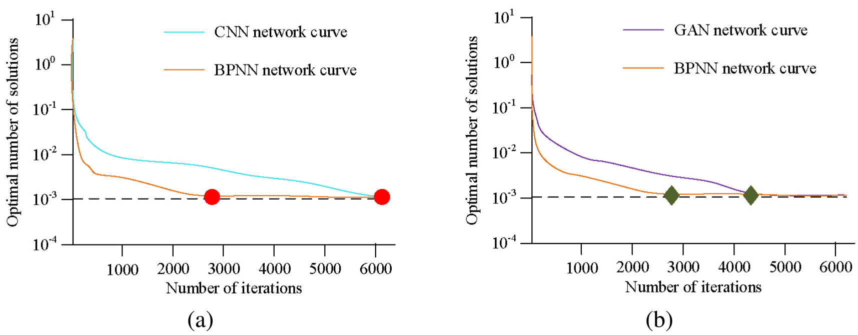

Fig. 8. Comparison of convergence results; (a) Convergence curve of BPNN network and GAN network, (b) Convergence curve of BPNN network and GAN network

In Fig. 8a, BPNN starts to show a convergence trend at about 3000 iterations, while convolutional neural network needs close to 6000 iterations before it starts to converge smoothly. In Figure 8b, the BPNN has shown good stability at about 2800 iterations, compared to about 4500 iterations needed to generate adversarial networks to achieve a similar stable state. This shows that BPNN not only converges quickly during training, but also reaches a stable solution earlier, which is a significant advantage for application scenarios that require fast prediction and optimization calculations. The study further analyses the error decline rates of the original BP network and the optimized network (denoted as GA-BP below). Fig. 9 illustrates the comparison of the error drop rate results for the original BP network and the GA-BP network.

According to the comparison results of Fig. 9a and Fig. 9b, it is obvious that there are significant differences in the number of iterations when the two networks reach the target value. It takes 100 iterations for BPNN to reach the target value for the first time, while the optimized GA assisted BP network shows a faster convergence rate, reaching the target value after only 51 iterations.

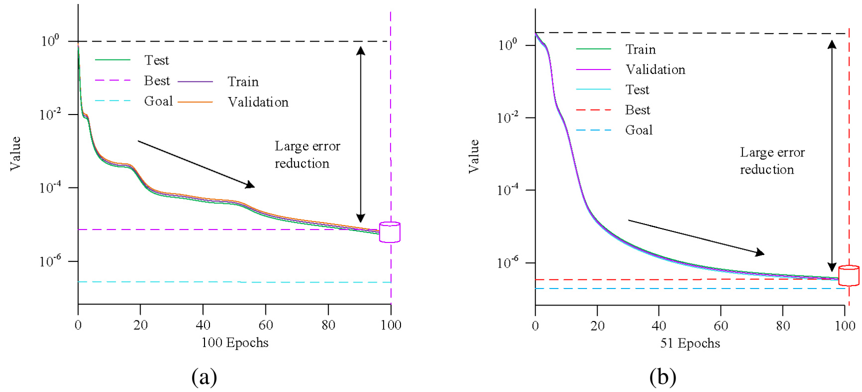

Fig. 9. Error decline rate results of the original BP network and optimised GA_BP network; (a) BP neural network error reduction diagram, (b) Optimized BP network error reduction diagram

4. Conclusions

In the current era of growing concern about climate change and resource scarcity, the building industry bears a huge responsibility for energy consumption and environmental impact. To cope with this challenge, building energy efficiency has become a crucial aspect in design and construction. Based on this, the study proposes an optimal design of buildings for energy efficiency based on a multi-objective optimisation algorithm and analyses its potential in improving design effectiveness. The results show that the multi-objective optimization method can achieve high accuracy of energy consumption prediction model in typical climate regions, and the error is close to zero, while the average value of daylighting prediction model is controlled within 3, although there are some errors. The correlation coefficient of neural network training is higher than 0.9845, showing excellent prediction accuracy. BP neural network showed good convergence in 2800 to 3000 iterations, demonstrating the efficient performance of the method in energy consumption and daylighting prediction. Through the comparison experiment, the optimization effect of this method in energy consumption and daylighting performance is remarkable, which is superior to the traditional method and other existing algorithms. The modified optimization method is suitable for building design in different climate regions, and can adapt to the uncertainties brought by global climate change, providing flexible and adjustable solutions for building energy conservation design. Although the methods in this study perform well in several aspects, there is still room for improvement. For example, the algorithm parameters are further optimized to improve the application efficiency of the algorithm on larger scale problems. Consider combining the methods of this study with other advanced technologies, such as machine learning, big data analysis, etc., to explore deeper optimization strategies for building energy efficiency. It is expected that the findings of this study will stimulate more research on building energy efficiency and environmental adaptive design, and jointly promote the development of the construction industry in a more efficient and environmentally friendly direction.

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