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Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design

Wei Yu [a,b,c,d,*], Baizhan Li [a,b,c], Hongyuan Jia [a], Ming Zhang [a], Di Wang [a]

[a] Faculty of Urban Construction and Environmental Engineering, Chongqing University, Chongqing 400045, China
[b] Key Laboratory of Three Gorges Reservoir Region's Eco-Environment, Ministry of Education, Chongqing University, Chongqing 400045, China
[c] National Centre for International Research of Low-Carbon and Green Buildings, Chongqing University, Chongqing 400045, China
[d] State Key Laboratory of Building Safety and Built Environment, Beijing 100015, China

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ABSTRACT

Several conflicting criteria exist in building design optimization, especially energy consumption and indoor environment thermal performance. This paper presents a novel multi-objective optimization model that can assist designers in green building design. The Pareto solution was used to obtain a set of optimal solutions for building design optimization, and uses an improved multi-objective genetic algorithm (NSGA-II) as a theoretical basis for building design multi-objective optimization model. Based on the simulation data on energy consumption and indoor thermal comfort, the study also used a simulation-based improved back-propagation (BP) network which is optimized by a genetic algorithm (GA) to characterize building behavior, and then establishes a GA–BP network model for rapidly predicting the energy consumption and indoor thermal comfort status of residential buildings; Third, the building design multi-objective optimization model was established by using the GA–BP network as a fitness function of the multi-objective Genetic Algorithm (NSGA-II); Finally, a case study is presented with the aid of the multi-objective approach in which dozens of potential designs are revealed for a typical building design in China, with a wide range of trade-offs between thermal comfort and energy consumption.

1. Introduction

In order to obtain a better building performance, three factors need to be taken into consideration, including architectural building design, system and occupants, which also contribute to an energy efficient building. As an iterative process, building design often requires the design team to re-think about the fundamental aspects of the design. If the design of building is greatly optimized, it will become the first critical step to reduce the system capacity, which is correspondingly one of the most important characteristic to minimize the need for services. Although architectural design is an important aspect in building performance, it is not easy to tackle because of the complexity and diversity of the process. In the architectural strategic design, the site considers building form, ventilation strategy, day lighting strategy and services strategy which will influence the design effect independently or mutually. Thus, some useful tools can be used to assist optimal architectural design, such as lighting and thermal (LT) method.

Energy consumption and indoor environment are very fundamental and conflicting criteria in building design. In general, in order for the indoor environment to meet human thermal comfort as much as possible, this will ultimately lead to the increase in building energy consumption. However, the two factors need to be incorporated in the decision-making process in building design. Therefore, the building design is a multi-objective optimization problem [1].

In addition, the different stages of sustainable building design have different impact on building performance. As a result, the early design stages of project planning in the whole building design cannot be ignored, and any minor mistakes are likely to be amplified in the later process [2,3]. Generally, the design process includes the conceptual design stage, the preliminary design stage and the detailed design stage. Hence, the important parameters that affect the building performance are mainly considered in the conceptual design stage, including the shape, the orientation, the window-to-wall ratio (WWR), the interior space layout, etc. In traditional building design process, the conceptual design stage is often

* Corresponding author at: Faculty of Urban Construction and Environmental Engineering, Chongqing University, Chongqing 400045, China.
Tel.: +86 13594093200; fax: +86 023 65127815.
E-mail addresses: yuweicqu@gmail.com (W. Yu), baizhanli@cqu.edu.cn (B. Li), jiahony@outlook.com (H. Jia), 972257180@qq.com (M. Zhang), 460061097@qq.com (D. Wang).

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overlooked because it is difficult to make quantitative data analysis of an incomplete construction planning. However, the feedback information of the conceptual design stage has a significant impact in the whole project planning. Therefore, the purpose of this study is to derive optimal solutions at the conceptual design stage using the multi-objective optimization algorithm. The schematic design of the building not only makes it conducive to the improvement of indoor environment, but also helps to reduce building energy consumption. The proposed multi-objective optimization model assists designers to make effective and appropriate decisions as well as to avoid potential errors in the initial stage of building design process.

Computer simulation and GA method are two most efficient approaches and simplified methods. For computer simulation, numerous software are applicable to building design process, for example, Ecoteck, Energyplus, Doe-2, and TRNSYS. If they were successfully applied in building design process, better building thermal and energy performance will be achieved. Lighting and thermal (LT) method is one of the most established ones which can be used to predict annual initial energy consumption per square meter of floor area under some input parameters like local climate conditions, orientation of façade, area and type of glazing, etc. Although computer simulation is convenient and has greatly developed, it still has several setbacks. For this reason, it cannot adequately meet the requirement of the architects or owners in the conceptual design stage. For example, most building simulation tools were originally developed for HVAC engineers, therefore the input/output parameters and the description method of the available information are inconsistent with the architect's concept at the conceptual design stage. Also, the existing computer simulation software applications have a problem of data compatibility, applicable complexity and non-intuitive problem which largely hinder the use of computer simulation in the building design process.

Many research efforts have been undertaken to assist designers in building design optimization. Several scholars have introduced the multi-objective genetic algorithm has been introduced in the construction sector taking into account the specific objectives to guide the building design, and making the building optimization design more easier and feasible. A review of some of the optimization studies is presented below.

End-use operating energy consumption is the optimization criterion in most studies. Al-Homoud [4] and Coley [5] and Schukat studied Heating and cooling energy are covered by while Wetter [6] expanded the scope further by including lighting energy consumption into the optimization model. If the operating energy consumption is considered as the only optimization criterion, the proposed building might have more insulation and less cost-effective. To overcome this problem, several research investigations have used the life cycle cost as the performance criterion. Since designers don't consider a single criterion in the decision-making process, multi-objective optimization models have been proposed. Nielsen [7] applied dynamic programming in the multi-criteria design optimization based on the following four performance criteria: thermal load, daylight availability, construction cost and useable area. Hauglustaine and Azar [8] optimized the building envelope using genetic algorithms; that is, ten (10) criteria related to code compliance, energy consumption, and cost were considered. Wright et al. [9] applied multi-objective genetic algorithm to building thermal optimization with more emphasis on mechanical system design; Operating energy cost and occupant thermal comfort were the two performance criteria used. Similarly, in the case of maintaining indoor thermal comfort conditions, some scholars have also used multi-objective optimization algorithm to minimize building energy consumption, and have achieved satisfactory results [10–12].

From the above-mentioned review, it can be observed that the optimal solutions can be achieved under the multi-objective constraints, which illustrate that the multi-objective genetic algorithm is a feasible method for building design optimization.

The current studies, however, pay more attention on using heating or cooling system to improve the indoor thermal comfort, mainly focusing on resolving the conflict between building system energy consumption and indoor environment, without considering how to use building elements for efficient building energy consumption at the building conceptual design stage. This is regarded as an energy efficiency method. This study mainly considers the use of building passive design to improve indoor thermal environment conditions, and eliminate the factors that affect energy saving in buildings and the improvement of indoor thermal environment. This is a positive energy efficient method.

2. Multi-objective optimization method

This involves the application of an improved multi-objective genetic algorithm (NSGA-II), a simulation-based improved Back propagation network, and the Pareto solution to obtain a building design multi-objective optimization model. A case study is presented to validate the multi-objective optimization model by maintaining a wide range of trade-offs between thermal comfort and energy consumption.

The multi-objective genetic algorithm is different from genetic algorithm in that it comprehensively evaluates each objective value of optimization solutions. However, these objective values are often conflicting and as a result it is difficult to find an optimal solution for each objective. Therefore, the Pareto solution has been introduced into this study in order to obtain a set of optimization solutions to solve the problem.

2.1. Multi-objective evolutionary algorithm (NSGA-II) as the optimization engine

The genetic algorithm (GA) was developed by Holland in the 1970s. This optimization algorithm was inspired by Darwin's theory of natural selection and Mendel's theory of genetics. It is a highly parallel, random and adaptive optimization algorithm which is based on "natural selection and survival of the fittest" [13]. Genetic algorithms are initiated by selecting a population of randomly generated solutions for the problem considered. They move from the generation of one solution to another by evolving new solutions using the objective evaluation, selection, crossover and mutation operators. Generally, in the genetic algorithm the solutions are represented by a code rather than the initial variables. Typically, a solution is represented by a string of bits (also called chromosome). Each bit position is called gene, and the values that each gene represent are called alleles. Nowadays, with the development of computer technology, the GA has been extensively used in many areas, pattern recognition, image processing, neural network, optimal control etc., [14]. The GA has also been applied in several building studies, including online optimization [15], optimization of HVAC system controls [16] and optimization of green building design [17]. In these studies, it has been proven that GA is very efficient even with non-differentiable functions, and in comparison with the baseline situation it has shown significant improvements in the optimization result.

A specific class of GA, multi-objective evolutionary algorithm (MOEA), is based on Pareto-dominance, which enables the algorithm to simultaneously optimize all the objectives. The complexity of MOEA is that there is a competitive relationship between each objective function, that is, when one of the objective functions achieves better results the others optimization results may not be realistic. Therefore, the optimal solution is often not the only one, but a set of optimal solutions which do not have mutually dominated relationship, that is, the non-dominated front. The algorithm employs the Pareto (front) which is used to calculate the fitness of each solution (solutions of equal rank having equal fitness).

This paper adopted the non-dominated-and-crowding sorting genetic algorithm II (NSGA-II), developed by Deb [18]. This algorithm uses a specific population sorting approach, which is firstly based on dominance, and then on a crowding distance computed for each individual. Due to this selection process, both convergence and spreading of the solution front are ensured, without requiring the use of external population. NSGA-II is capable of maintaining the population diversity and avoid the loss of excellent individuals at small computation, and there is no need to set some parameters of algorithm (such as the σ_{share} and σ_{mate} in MOGA). NSGA-II is recognized as one of the most efficient MOEA.

2.2. Objective of fitness function–back propagation neural network combined with genetic algorithm

There are many factors that affect building energy consumption. These include transparency ratio (%), building form factor, orientation, optical and thermo-physical properties of the materials used in building envelope etc. These factors have nonlinear coupling impact on building energy consumption. Therefore, dynamic computing is the main energy analysis method in the process of building efficiency design. Due to the complexity of the dynamic computing process, it is difficult for the general engineer staff to master it. In general, most of the commercial dynamic modeling programs are time-consuming, especially when it comes to providing the results annually. Furthermore, the cost of these programs is prohibitive for small research establishments. Therefore, there is a need for alternative approaches to perform this task. As a result, the alternative approaches must have high accuracy and computational speed which can greatly simplify the design optimization process and reduce design optimization time in building energy efficiency. The recently developed technology, artificial neural network (ANN) could offer such an alternative approach [19].

Therefore, ANN is used to establish the multi-objective prediction model and the Genetic algorithm for optimizing the ANN is used to improve the prediction accuracy. Dorsey et al., [20] designed a genetic adaptive neural network training (GANNT) algorithm and shown that the GA also worked well for optimizing the ANN. The GANNT algorithm is different from other genetic search algorithms because it uses real values instead of binary representations of the weights. In this paper, the genetic algorithm is adopted for training the BP network. The genetic algorithm is utilized to optimize the BP network's weight or threshold. Fig. 1 illustrates a simple outline of the GA used in this paper [21].

3. The multi-objective optimization model in building sustainable design

3.1. The multi-objective optimization model

3.1.1. Components of the optimization model

The components of the optimization model are presented in the following order: variables, constraints, and objective functions. The model concentrates on building conceptual design because of its importance in determining the performance of both energy consumption and of indoor thermal comfort. The same methodology could be applied later to a large scope covering other building systems such as heating, ventilation, and air conditioning system.

- *Variables*: In this study, the buildings are limited to a rectangular shape with a known total floor area. Table 1 shows the defined variables with their corresponding names.
- *Constraints*: Building envelope-related variables are aimed at taking advantage of energy efficient design. Based on China's current building energy efficiency system [22,23], the constraints of variables are summarized in Table 1.
- *Objective functions*: Since the purpose of this study is to assist designers to achieve comfort-energy efficiency building design, both energy consumption and thermal comfort are selected as the two objective functions to be optimized using the optimization model.

The annual energy consumption of the building is calculated by Energyplus. In this study the expected air conditioning system load, maintaining the thermostat Setpoint between 18 °C and 26 °C throughout the year is used instead of annual energy consumption.

The metric used to assess thermal comfort is the percentage of thermal comfort hours throughout the year, representing the number of hours at indoor temperature between 18 °C and 26 °C divided by 8760 h.

3.1.2. Optimization model framework

In this study, the genetic multi-objective optimization algorithm has been used to select and optimize possible design based on the prediction of energy consumption and indoor thermal comfort performance, and obtaining the optimal solution. As a result, the designer needs to limit the range of input variables and then take full advantage of the computer to comprehensively compare the different solutions. The optimization framework of this study is summarized in Fig. 2.

First a model of the model building was created in Energyplus and validated using measured data. Using this model, a database of cases was created and used to train and validate the GA–BP network. After training and validation, the GA–BP performed fast evaluations of the building performance, with a good accuracy and without simplifying the problem. Finally, NSGA-II was run by using the GA–BP to evaluate the potential solutions.

3.2. GA–BP multi-objective predicting model

3.2.1. Obtaining the samples for GA–BP prediction model

The samples are chosen by following principles: enough samples, accurate samples, representative samples, and uniform distribution of samples. Therefore, the model building for this study is typical three-storey residential buildings [24,25] in Chongqing, China. The floor height is 2.8 m; and the floor area of each household is approximately 90 m^2, which is the average household floor area in Chongqing. Fig. 3 shows the plan view of the model building.

A computer model of the house was developed in Energyplus. The energy consumption and indoor thermal comfort performance in Energyplus simulation was obtained when one of the 14 variables (building floor area, building story, orientation, shape coefficient, wall heat transfer coefficient, wall thermal inertia index, roof heat transfer coefficient, roof thermal inertia index, window heat transfer coefficient, area ratio of window to wall for east, west, south, north direction) changed individually. For example, when the remaining variables were unchanged, the results can be obtained when the wall heat transfer coefficient changed from 0.8 W/(m^2 K) to 2.0 W/(m^2 K). As a result, the other data can be obtained when the other variables change individually. 100 sets of data as the training samples and 44 sets of data were selected as the testing samples for the GA–BP network according to the characteristic of BP network's generalization capability, and also based on these simulation data.

In order to improve the accuracy and convergence rate of the GA–BP network model, the training and testing samples' data must

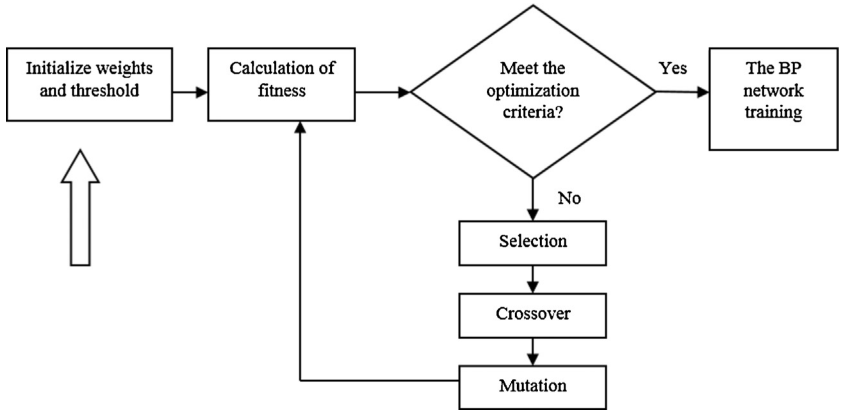

Fig. 1. Genetic algorithm for optimizing the BP network's weight or threshold.

Table 1
Constraints of variables used for optimization.

The category of variables	Variables	Unit	Range
Building design	Layout plans	None	A typical layout plan in Chongqing, China
	Orientation	Deg.	−180–180
	Shape coefficient	None	≤0.45
	Floor area	m^2	Set a specific value before optimization (in this study set as 600)
	Stories	Layer	In this study set as 3
	North window–wall ratio	None	$0.2 \le r \le 0.35$
	South window–wall ratio	None	$0.3 \le r \le 0.50$
	East window–wall ratio	None	$0.04 \le r \le 0.35$
	West window–wall ratio	None	$0.02 \le r \le 0.25$
Envelope design	Wall heat transfer coefficient	$W/(m^2 K)$	$0.34 \le k \le 2.8$
	Wall heat inertia index	None	$1.5 \le D \le 4.0$
	Roof heat transfer coefficient	$W/(m^2 K)$	$0.3 \le k \le 2.8$
	Roof heat inertia index	None	$1.5 \le D \le 4.0$
	Window heat transfer coefficient	$W/(m^2 K)$	$1.6 \le k \le 6.0$

be normalized. The normalization method is described in the following equation. x_i is samples' input or output parameter value, $\bar{x}_i$ is a real number between 0 and 1.

$$\bar{x}_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad i = 1, 2, \ldots, m \tag{1}$$

3.2.2. Design of the BP neural network

Hsu [26] found that a three-layer BP neural network can solve random function's fitting and approximation problem. As a result, a three-layer BP neural network is adopted in this paper.

The number of the hidden nodes is calculated by empirical formula [27], and the training results show that the network error is minimum when there 13 hidden neural nodes.

According to the model's input and output parameters, we can obtain the BP neural network's structure: 14-13-2. A schematic diagram of the three-layer feed forward neural network architecture is shown in Fig. 4.

3.2.3. Selection of the training parameters

The BP neural network training parameters settings are: the target training mean squared error of $1e-5$; the training function of train lm; the learning rate of 0.5, and max epoch of 2000 [28,29].

Therefore, the genetic algorithm parameters settings are: the population of 70; the selection rate of 0.06; the mutation function of non-Unit Mutation with the parameter {2 gen 3}; the crossover function of arithXover with the parameter {20}; the gen of 700 [30].

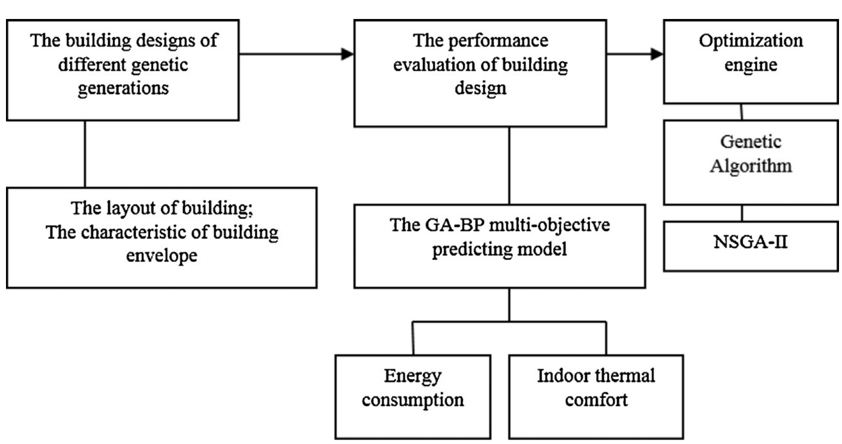

Fig. 2. The building design optimization model framework.

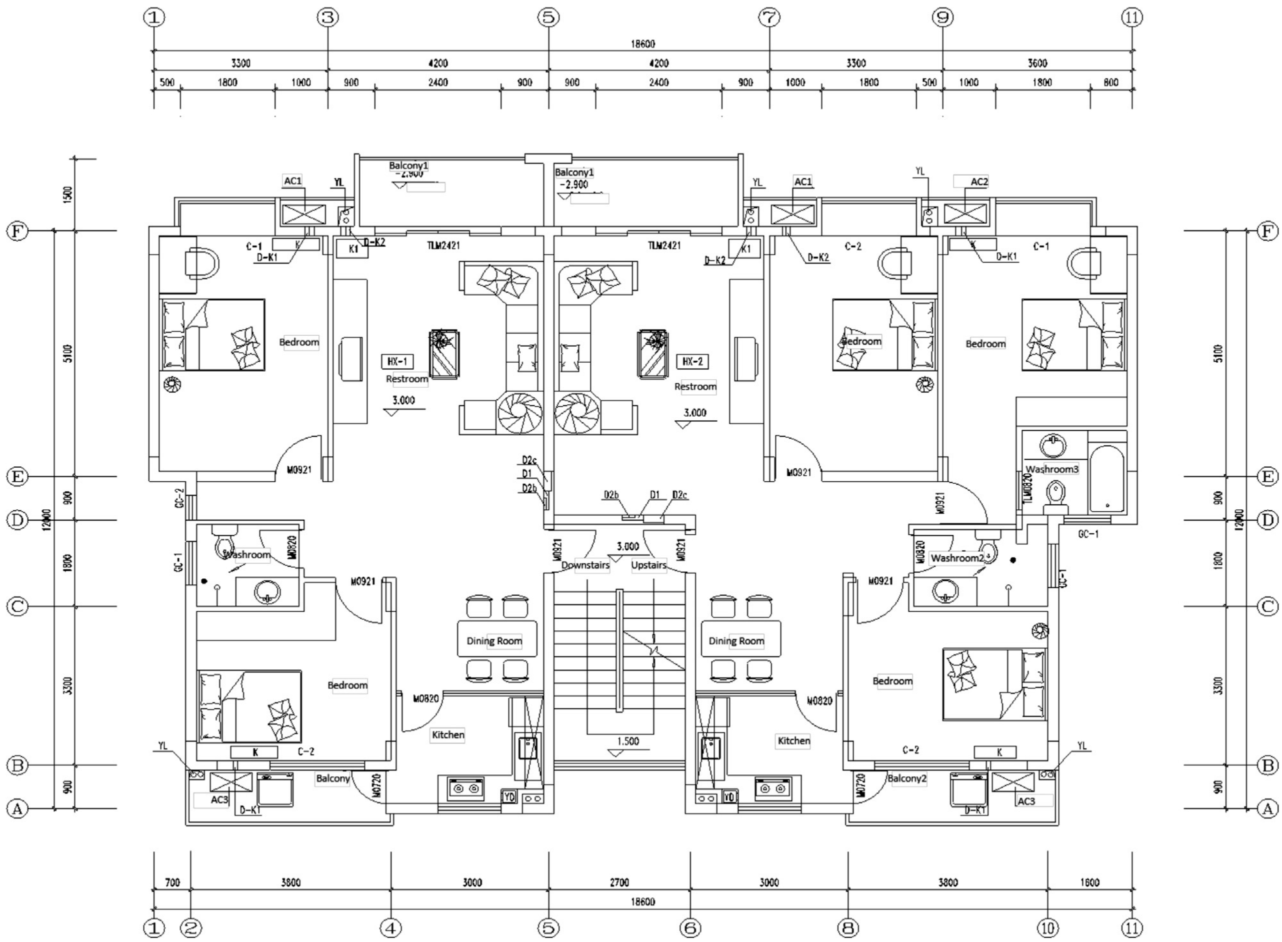

Fig. 3. The plan view of the model building.

3.2.4. Analysis of the GA–BP network model's predicted results

The normalized data have been used for training and testing the GA–BP network. The GA–BP network is trained repeatedly with the training times n of 87 and the mean square error of 1e − 005, then the network is convergent and the training stops, as shown in Figs. 5 and 6 shows that the GA–BP network' results and actual results have a high degree of liner fitting, which illustrate the achievement of the desired requirements of GA–BP network model through the samples training.

The results predicted by the GA–BP network shown in Fig. 7 indicate high accuracy. This is because the maximum relative errors of the predicted energy consumption and indoor thermal comfort are 1.7%, while performance has and 2.1%, respectively. Therefore, this proves the fact that the GA–BP neural network gives satisfactory

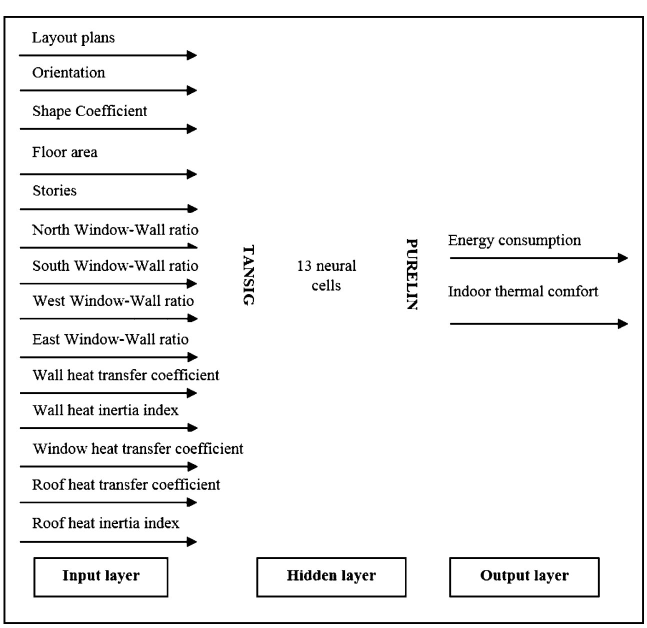

Fig. 4. The BP network model.

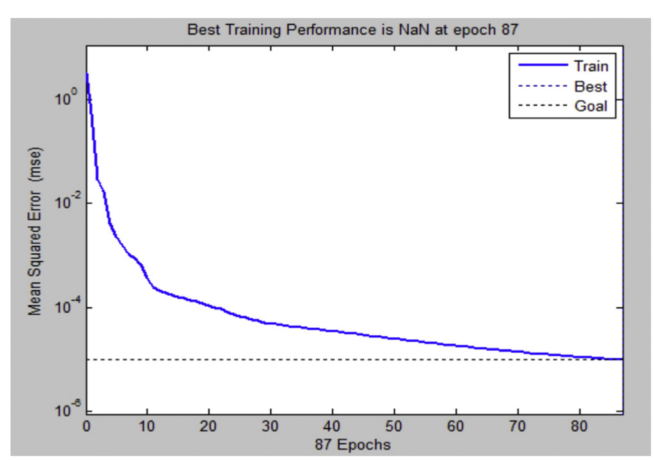

Fig. 5. The performance of GA–BP network training.

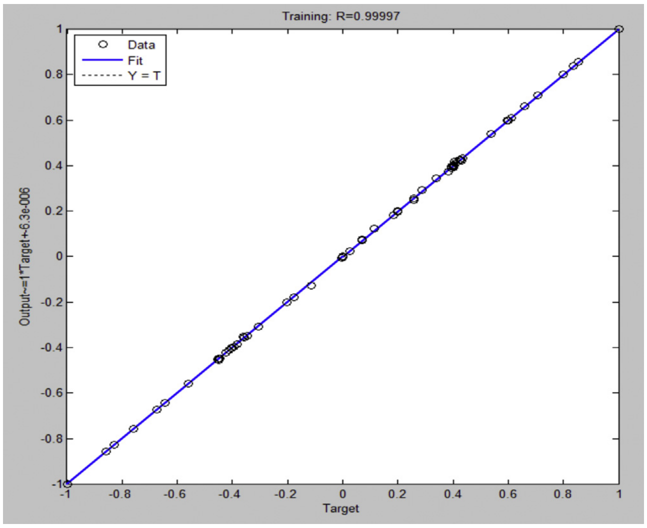

Fig. 6. The liner fitting between GA–BP network's training results and actual results.

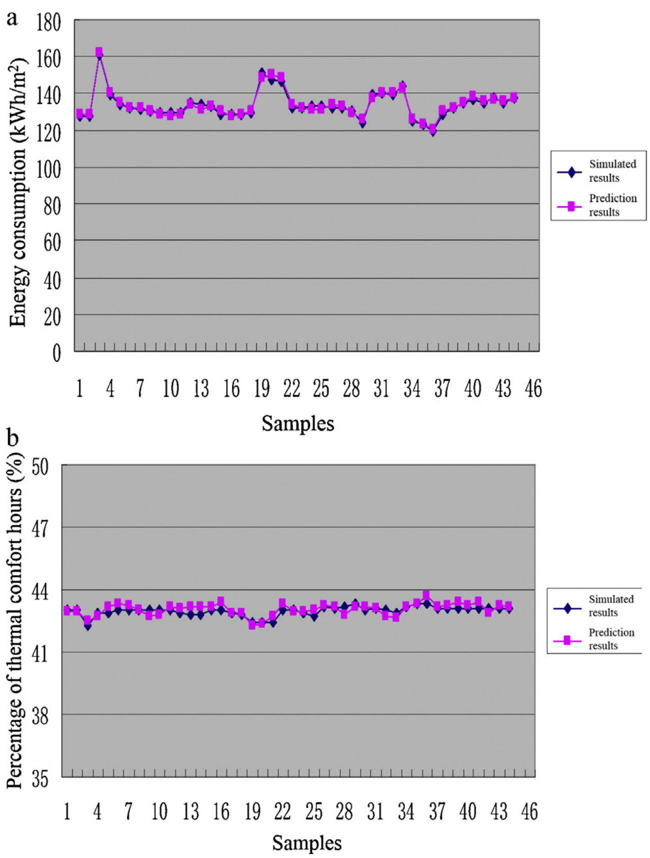

Fig. 7. (a) A comparison of the predicted results and simulated results of the GA–BP network (energy consumption). (b) A comparison of the predicted results and simulated results of the GA–BP network (the percentage of thermal comfort hours).

results with a deviation of 3.3% and successful prediction rate of 95.3–98.7%.

As a result of the high local optimization ability to combine with the genetic algorithm, BP algorithm is good at global optimization and can assist in avoiding the local optima, and get the global optima quickly. The evaluation of the results of energy consumption and indoor thermal comfort predicted by GA–BP network model show higher accuracy, and further extending analysis of this model is possible through adopting a multi-objective optimization.

3.3. NSGA-II design for multi-objective optimization model

The NSGA-II design was approximated using Matlab software.

3.3.1. Selection of NSGA-II parameters

In this paper, NSGA-II was run with the default parameters of the algorithm as summarized in Table 2.

3.3.2. Program design of NSGAII

The core elements of genetic algorithm are the parameters coding, initial population setting, design of fitness function, design of genetic operation, and control parameters setting. There are two ways for parameters encoding, which include binary encoding and floating point encoding. This paper selected the floating point encoding method.

The genetic algorithm does not use external information in the evolutionary process, but only based on the fitness function, and uses each fitness value of population for search optimization. Therefore, the fitness function in this paper is GA–BP network, and the GA–BP network's objective functions are the fitness value, energy consumption and indoor thermal comfort.

$$\text{Fitness function}: \quad \text{eval} = \text{sim}(\text{net}, \text{sol});$$

The GA–BP network's simulation function 'sim' calls the trained network 'net', and then calculate the 'eval' value of the individual 'sol'.

Multi-objective optimization can be described as finding a set of design variables $X = (x_1, x_2, \ldots, x_n)^T$ to assist the objective functions to obtain minimum value. However, in this study, these two objective functions are energy consumption and indoor thermal comfort. Through the multi-objective optimization, energy consumption is minimized and the percentage of indoor thermal comfort hours is maximized. Therefore, it is needed to transform the objective function to optimize the problem of indoor thermal comfort, and consider the individual fitness as non-negative value. As a result, the critical-method is used to transform the indoor thermal comfort objective function.

$$\text{Fit}(f(x)) = c_{\max} - f(x), \quad f(x) < c_{\max}$$

The $C_{\max}$ is the maximum value of $f(x)$.

Due to the fact that the maximum percentage of indoor thermal comfort hours is 1, the objective function of indoor thermal comfort can be transformed as follow:

$$\text{eval}_{\min} = 1 - \text{eval}$$

So that the multi-objective functions can be described as follow:

$$f(1) = \text{eval}(1, :); \quad \% \text{ the fitness function of energy consumption}$$

$$f(2) = 1 - \text{eval}(2, :); \quad \% \text{the fitness function of indoor thermal comfort}$$

4. A case study of building design multi-objective optimization model

In order to test the accuracy and practicality of the building design multi-objective optimization model, the model building in Section 3.2.1 is used as an example for optimization analysis. The multi-objective optimization model is used on a trial basis to determine an optimal solution which will not only be critical to energy saving in buildings, but also help to improve the indoor thermal environment. Therefore, prior to optimization, the layout and area of this model building is described in Section 3.2.1. Then, the optimal solution is found for the other 12 variables.

Table 2
NSGAII parameters.

Population size	Crossover probability	Mutation type	Mutation probability	Distribution indices	Termination criterion
100	0.9	Polynomial	0.05	20 in both cases	700

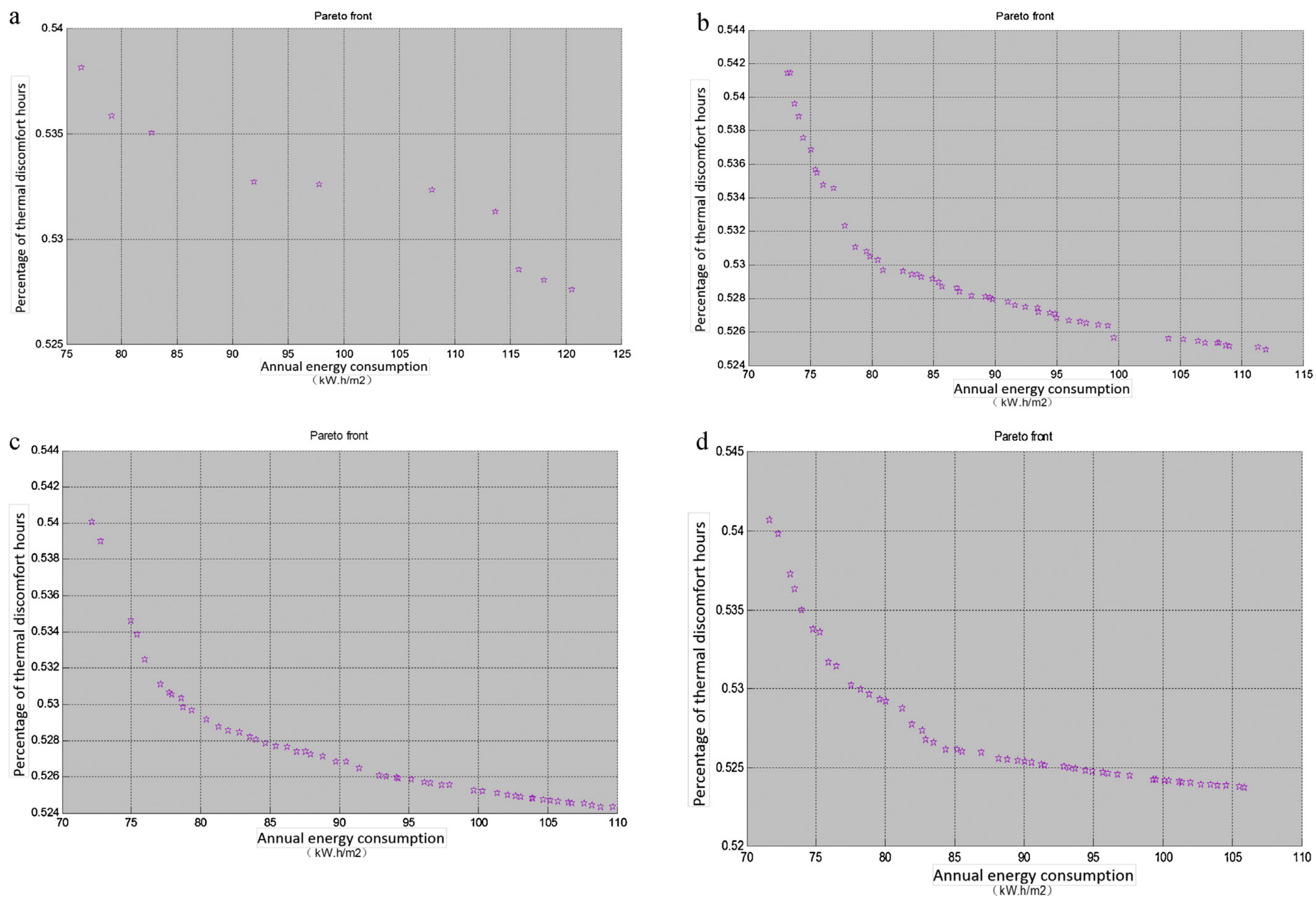

Fig. 8. (a) The distribution of initial population. (b) The distribution of the fiftieth population. (c) The distribution of the one hundredth population. (d) The distribution of the 318th population (the end of the optimization).

Based on the established multi-objective optimization model, the NSGA-II is used as the optimization algorithm to enhance the design variables of the model building. The optimization process is shown in Fig. 8.

Fig. 8 shows the optimization process. The initial population evolved from generation to generation with gradual convergence, and finally preserving a steady-state. The randomly generated initial population is displayed in Fig. 8(a). After the 50th generation the population converged by the smaller evolutions as given in Fig. 8(b). Apparently when the population evolves to the 100 generations, it converged close to the optimal solution given in Fig. 8(c).

When the population evolve to the 318 generations, the average change of Pareto solution is less than the setting value ($1e-4$), as given in Fig. 8(d). At the end of the optimization, the individuals of entire population are uniformly distributed into the set of optimal solutions and the border per individuals has been well reserved. Hence a successful multi-objective optimization is achieved, as displayed in Fig. 8, alone with each point corresponding to a Pareto optimal solution, which are not better or worse between each Pareto optimal solution. As a result, designers can choose the optimum design solutions according to their actual needs.

The analysis in Fig. 8 shows a smaller change in the percentage of indoor thermal comfort hours (less than 3%) in the process of building design multi-objective optimization. This also means there is a slight change in indoor thermal comfort performance with varying natural ventilation building designs. As result, the Pareto solution which has minimum building energy consumption is selected as the optimal solution design, and the model building design is improved according to the optimal solution's design variables range as given in Table 3.

The above optimal adjustment is applied to the model building design. The energy consumption and indoor thermal comfort of improved building design are calculated by Energyplus. The results are compared to the Pareto optimal solution as well as given in Fig. 8.

Table 4 shows that the relative errors between Pareto optimal solution and simulated results in Energyplus are small. This indicate that the energy consumption and indoor thermal comfort performance can be accurately predicted by the building design multi-objective optimization model, which illustrates that the model can be used in actual building design optimization. Furthermore, the multi-objective optimization model makes it possible

Table 3
The optimal adjustment of model building design.

Number	The improvements
1	Change the building orientation between 0° and 172°, which will change the building orientation from north to south(make south window-wall ratio the most)
2	Minimize the west and east window-wall ratio; reduce the north window–wall ratio to an appropriate amount, namely change the east, west and north window–wall ratio with 0.04, 0.02 and 0.2, respectively To meet the indoor day lighting requirements, the south window-wall ratio can be 0.35 as the model building set
3	Change the wall heat transfer coefficient 1.96 W/m^2 K with 0.5 W/m^2 K
4	Change the wall heat inertia index 3.03 with 3.93
5	Change the roof heat transfer coefficient 2.71 W/m^2 K with 0.5 W/m^2 K
6	Change the roof heat inertia index 1.76 with 3.41
7	Change the external window heat transfer coefficient 5.1 W/m^2 K with 1.8 W/m^2 K

Table 4
A comparative analysis of Pareto optimal solutions and simulated results in Energyplus.

Building designs	The base design	The improved design
Energy consumption (kW h/m^2) (the prediction value of GA–BP network)	141.68	71.51
Energy consumption (kW h/m^2) (the simulation value of Energyplus)	138.98	72.63
The relative error between prediction and simulation value (%)	1.91	1.57
Percentage of indoor thermal comfort hours (%) (the predicting value of GA–BP network)	44.2	45.7
Percentage of indoor thermal comfort hours (%) (the simulation value of Energyplus)	43.1	44.8
The relative error between prediction and simulation value (%)	2.49	1.97

to achieve the goal of energy efficiency building design as well as meeting the requirements of indoor thermal comfort. From Table 4 it can also be observed that the improved building design's energy consumption is reduced by nearly 50%, but the percentage of indoor thermal comfort hours is increased by 1.5%. The optimal solution of energy consumption is minimum whether calculated by multi-objective optimization or Energyplus. This indicates an achievement of the purpose of building optimization design.

5. Conclusions and further research

In the pursuit of a sustainable society, the improvements of environmental performance in buildings have a critical impact. It is essential to have suitable tools available at the conceptual design stage to assist designers to find efficient alternative designs. This paper proposed multi-objective optimization model that can be used to determine optimum or near optimum building designs for given conditions. This paper described the combination of an artificial neural network (ANN) and multi-objective evolutionary algorithm.

First, this study introduced the Pareto solution and proposed the NSGAII as a theoretical basis of the building design multi-objective optimization model.

Second, the Genetic algorithm is used to optimize the ANN in order to improve the prediction accuracy, and a more accurate GA–BP network has been derived for the energy consumption and indoor thermal comfort prediction. The GA–BP network was trained and tested using simulation results. The database of the case was created using Energyplus. The GA–BP network provided acceptable approximations of the simulation results, with the average relative errors for total energy consumption and the percentage of indoor thermal comfort hours below 1.7% and 2.1%, respectively. The GA–BP network was then implemented in NSGA-II to enable fast evaluations.

Finally, the optimization results of the building design multi-objective optimization model for the case study show significant improvements of the energy performance, and insignificant improvement of indoor thermal comfort performance. Furthermore it can be observed that the relative errors for the Pareto optimal solution and simulated results in Energyplus are relatively small, illustrating that the energy consumption and indoor thermal comfort performance can be accurately predicted by the building design multi-objective optimization model, and the model can be used in actual building design optimization.

The prediction results suggest that the building design multi-objective optimization model is an effective tool for building optimization design. However, the evaluation results of fitness function from the GA–BP network are accurate or not highly dependent on the training samples, which mean that there is need for extensive testing or simulation data for training samples of each building type or building form. As a result, future studies need to consider improving the database of different buildings for the extensive use of the building design multi-objective optimization.

Conflict of interest statement

The authors declare no conflict of interest.

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