Prediction and optimization of indoor thermal environment and energy consumption based on artificial neural network

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Abstract. Commercial software and simulation tools frequently used by researchers in predicting indoor thermal condition and energy consumption of a green building can ensure high precision, however, the computational process are usually time-consuming and cannot clearly and directly give suggestions for a ‘greener’ design. This paper aimed to develop a novel model based on artificial neural network (ANN) to speed up the simulation and provide optimal design solutions. Training and testing data representing design scenarios of different insulation thickness, shading coefficient, ventilation rate and their corresponding Annual Energy Demand (AED) and Uncomfortable Degree Hours (UDH) value were obtained from a numerical analysis model at first. The deduced ANN model was tested and validated, showing very high accuracy as a predictor for broad range of inputs. Relationship between design parameters and outputs were analysed and presented intuitively. The ANN results directly offered suggestions of minimizing AED and UDH, the optimum solution was to reduce ventilation and increase insulation to the limit, and reduce shading coefficient form base-case 0.5 to approximately 0.2. UDH could be lessened by 4% and AED could be reduced by nearly 29% compared to the base case design in this way.

Keywords: Artificial Neural Network, Building Performance Prediction, Optimal Design, Annual Energy Demand, Uncomfortable Degree Hours

1. Introduction

Architecture designers and engineers are keen in searching for ‘green building’ techniques, which achieve energy conservation while maintaining good living conditions at the same time.
Indoor thermal condition and energy consumption of heating, ventilation and air conditioning (HVAC) system are two crucial indicators for identifying the performance of such buildings. Researchers have developed algorithms and simulation models to predict these indicators under certain design conditions including building geometries, structures, material properties, energy-saving technologies. However, the computational process is usually time-consuming and results cannot clearly reveal the relationship and influences between input and output variables. For example, the commercial software such as EnergyPlus, DeST, TRANSYS, DOE-2, are all able to calculate the energy demand of a building with given settings, nevertheless, for decision-makers who intended to optimize building design, it is difficult to perform direct actions without run hundreds or thousands of simulations that evaluate various retrofitting scenarios [1][2]. Therefore, in practical application of green building design, we need a surrogate model that can clearly show the relationship between design factors and objectives, quickly simulate different scenarios, and precisely point out the direction of optimization.

Artificial neural network (ANN) is the most popular technique of prediction and control in the area of robotics, mathematics, physics and control [3]. It is typical artificial intelligence modelling method inspired by human brain, which simulates the relationship between inputs and outputs into complex nonlinear functions by learning from exist data [4]. The objective of this paper is to propose an ANN model that not only offer a less time-consuming method to predict annual energy consumption and comfort level for various retrofitting scenarios while achieving acceptable accuracy, but also generate a simple and straightforward demonstration of the influencing relationship between design parameters and performances, moreover, provide optimum solutions and directions for renovating buildings towards a more ‘greener’ level.

Methodology of this research is as follows: a base case that representing the most typical building design was initially simulated through the numerical analysis, Annual Energy Demand (AED) and Uncomfortable Degree Hours (UDH) were set as two outputs, generating a set of base data. Thereafter, design factors including insulation thickness, shading coefficient and ventilation rate were parameterized as inputs of the model. Different design scenarios were composed by varying the value of input variables, where in this research 1000 scenarios were tested and therefore 1000 sample datasets were obtained accordingly. These samples were used to build the ANN and to verify the accuracy. The relationship between input factors and the output indictors were investigated using the predicted datasets. Results were analyzed and intuitional figures were made to show the energy demand and comfort variation trend under different shading, insulation, and ventilation levels. Then finally optimum scenarios were suggested for certain targets, giving retrofitting proposal accordingly.

2. Building model and sample data

2.1. Base-case building model settings
The research object of this paper is a south-facing single room located on the intermediate floor of an office building. The floor plan and elevation are shown in figure 1. The building was tested under weather condition of Taiyuan, a typical city of cold regions in northern China. The hourly weather data of a whole year (8760 hours) was obtained from the meteorological database of EnergyPlus.
Figure 1. Floor plan (a) and elevation (b) of the room.

Figure 2. Numerical room model.

A base-case setting was assigned to the room model, representing the common structure, material and design parameters of a building in China. The structure and thermos-physical peripheries of the base-case envelope (including external wall, internal wall, roof, ceiling and window; doors are treated as internal wall for simplification) are shown in table 1. Heating and cooling were assumed to be achieved by a central air conditioning system.

Table 1. Thermo-physical parameters of the base-case building envelope.

| Building envelope | Components (from outside to inside) | Thickness mm | Thermal conductivity W/m·k | Density kg/m³ | Specific heat capacity J/kg·k
|-------------------|-----------------------------------|--------------|-----------------------------|---------------|-----------------------------|
| External wall     | XPS board (Insulation layer)       | 40           | 0.028                       | 25            | 1500                        |
|                   | Aerated concrete                   | 240          | 0.18                        | 1800          | 1050                        |
| Internal wall     | Reinforced concrete                | 100          | 1.74                        | 2500          | 922                         |
| Floor & ceiling   | Reinforced concrete                | 100          | 1.74                        | 2500          | 922                         |
| Window            | Insulating glass                   | 21           | -                           | -             | -                           |

2.2. Numerical model

Heat transfer process of the base-case building envelope as well as the enclosed indoor air were further analysed numerically in order to simulate the energy and thermal comfort performance of the room. Figure 2 shows the numerical model of the indoor air of the tested room. Indoor air was treated as a lumped system, ignoring the influence of latent heat change.

Heat balance equation of the air can be build based on the settings and assumptions above.

\[ Q_1 + Q_2 + Q_3 = Q_4 + \Delta Q_{\text{air}} \quad (1) \]

Where \( Q_1 \) represents the heat gain through external wall, internal wall, floor and ceiling, W; \( Q_2 \) represents solar radiation through window, W; \( Q_3 \) represents conductive heat gain through window, W; \( Q_4 \) represents infiltration heat loss, W; \( \Delta Q_{\text{air}} \) represents heat storage and emission of air, W. Items of the heat balance equation were calculated by the following formula.

\[ Q_2 = I \cdot A_c \cdot \alpha_c \quad (2) \]
\[ Q_3 = A_c \cdot k_c \cdot (T_{\text{air}} - T_{\text{out}}) \quad (3) \]
\[ Q_4 = 0.278 \cdot \rho_{\text{air}} \cdot c_{p,\text{air}} \cdot V_t \cdot (T_{\text{air}} - T_{\text{out}}) \quad (4) \]
\[ \Delta Q_{\text{air}} = \rho_{\text{air}} \cdot c_{p,\text{air}} \cdot V_{\text{air}} \cdot \frac{\partial T_{\text{air}}}{\partial \tau} \quad (5) \]
Where $T_{air}$ and $T_{out}$ represents the indoor air temperature and outdoor colligate temperature, respectively. $K$ is the solar radiation intensity per unit area, $W$; $A_c$ is the area of window, $m^2$; $\alpha_c$ is the transmittance of window, which is 0.58 in this case; $k_c$ is the heat transfer coefficient of window, $W/(m^2 \cdot K)$; $\rho_{air}$ is density of indoor air, $kg/m^3$; $c_{p,air}$ is the specific heat capacity of indoor air, $J/(kg \cdot K)$; $V_{air}$ is volume of the room, $m^3$; $V_l$ is the air infiltration rate, $m^3$. $T^r_{air}$ represents the indoor air temperature at time $\tau$, $K$.

Specifically for $Q_1$, since the thermal storage of opaque building envelope (including wall, ceiling and floor) was considered and the heat transfer process was regarded as one-dimensional unsteady state heat conduction problem, equal-space finite element method with was employed to discretize the heat transfer governing equations of these opaque structures, obtaining a series of equations about the temperature value of each mesh. FORTRAN programming was carried out, the Tridiagonal Matrix Algorithm (TDMA) method was used for resolving the equations (discretized equations of opaque building & heat balance equation of the lumped indoor air). Under given boundary and initial conditions, temperature distribution along the thickness direction of building envelope as well as the temperature of indoor air at each time point can be obtained finally.

2.3. Determination of objectives and variables

Two final indicators, namely Annual Energy Demand (AED) and annual Uncomfortable Degree Hours (UDH) were designated as the objective. In summer cooling season, cooling load and summer uncomfortable degree hours are expressed as:

$$Q_C = \int_{D_{sum}} \sum_{i=1}^{6} A_i h_{in}(T_{n,i} - T_H) + A_c k_c(T_{out} - T_H) + \rho_{air} c_{p,air} V_l(T_{out} - T_H)$$

$$I_{sum} = \int_{0}^{8760} (T_{air} - T_H)d\tau$$

where $Q_C$ represents the summer cooling load, $kWh$; $D_{sum}$ is the air conditioning working hours in summer, $h$; $A_i$ is the area of the $i$-th envelope, $m^2$; $h_{in}$ is the convective heat transfer coefficient of the interior surface, $W/(m^2 \cdot K)$; $T_{n,i}$ is the interior surface temperature of $i$-th envelope, $K$; $T_H$ is the air conditioning working temperature, i.e. the upper temperature limit of comfort, 26 $^\circ C$ in this study. $I_{sum}$ represents summer uncomfortable degree hours, $h^\circ C$, which is the product of duration when temperature exceed upper comfort limit among all 8760 hours in a year and the superfluous degree.

Similarly, in winter heating season, heating load and winter uncomfortable degree hour are:

$$Q_H = \int_{D_{win}} \sum_{i=1}^{6} A_i h_{in}(T_L - T_{n,i}) + A_c k_c(T_L - T_{out}) + \rho_{air} c_{p,air} V_l(T_L - T_{out})$$

$$I_{win} = \int_{0}^{8760} (T_L - T_{air})d\tau$$

where $Q_H$ represents the winter heating load, $kWh$; $D_{win}$ is the heating hour in winter, $h$; $T_L$ is the heater working temperature, i.e. the lowest comfortable temperature in winter, 18$^\circ$C. $I_{win}$ represents the winter uncomfortable degree hours, $h^\circ C$.

Annual Energy Demand $Q_{year}$ and annual Uncomfortable Degree Hours $I_{year}$ is then calculated as follows.

$$Q_{year} = Q_C + Q_H$$
\[ I_{year} = I_{sum} + I_{win} \]  

Three design factors were considered as the variables, including insulation layer thickness, overall shading coefficient, and air change rate.

### 2.4. Sample data establishment

The range of the selected influential input variables were chosen according to practical conditions and 10 values were tested for each variable, as shown in table 2. 10 values for each variable consist into 1000 cases in total, representing the 1000 sample design scenarios studied in this research. All these cases were simulated according to the numerical model in Section 3.3, the corresponding values of AED and UDH were obtained and presented below.

**Table 2.** Sample data range.

| Categories   | Names                              | Description             | Unit | Base-case value | Sample data range            |
|--------------|------------------------------------|-------------------------|------|----------------|------------------------------|
| Inputs       | \( x_1 \)                          | Shading coefficient     | 1    | 0.5            | 0.1-1, interval 0.1          |
| Inputs       | \( x_2 \)                          | Air change rate         | 1    | 4              | 2-20, interval 2             |
| Inputs       | \( x_3 \)                          | Insulation layer thickness | mm  | 40             | 10-100, interval 10         |
| Outputs      | \( y_1 \)                          | Annual energy demand    | kW h  | 24268.77       | 17001.68-74443.08           |
| Outputs      | \( y_2 \)                          | Uncomfortable degree hours | h °C | 39795.49       | 37480.17-48918.19           |

### 3. ANN model results

#### 3.1. ANN training and validation

Based on these 1000 cases of input and output data, the ANN was constructed and trained using the ANN Toolbox of Matlab, adopting the Bayesian regularization backpropagation model. There is no strict constrain on the number of neurons in the hidden layer, however, it is important to select appropriate neuron numbers for hidden layer because too few neurons may cause under-fitting problems that resulting in large errors, while an overestimation in neuron numbers may induce unnecessary learning and overtraining problems [5]. Input layer of the ANN contains three neurons that representing the three corresponding input variable. Output layer is composed of the two objectives (i.e. AED and UDH). The neuron numbers of hidden layer were determined by a gradually searching method and as a result 10 neurons were decided. Among all 1000 cases, 70% were randomly selected as training data, which means 700 cases were used for ANN training. Convergence was considered to have achieved if the maximum epochs (1000 epochs in this model) was reached or mean squared error (MSE) was stabilized over certain iterations. For this model, as shown in figure 3(a), the ANN quickly converged after dozens of epochs, with a MSE of less than 5000, which was a satisfactory value for well-performed ANN prediction. The regression coefficients of R between the ANN predicted and numerical objectives approximately reached 1, showing very good correlations between the ANN and numerical results.
The remaining 30% cases of the sample (i.e. 300 cases) were used as validation data. The ANN predicted AED and UDH values were compared with the corresponding numerical results, showing an average relative error of 0.016% and 0.008% respectively, which demonstrates that the ANN prediction is very precise.

3.2. Prediction results and analysis

The proposed ANN model was further used as a simulation tool for predicting AED and UDH under untested design conditions. For this purpose, the range of variable values were broadened comparing with the numerical cases in this section. Theoretically speaking, the range can be expanded to any value, but as mentioned in previous sections, the tested condition already covered all common range of design parameters, we only implement ANN prediction on cases which the variation intervals of input value were more subdivided than that of the sample cases. Comparing to numerical simulation, the ANN calculation time was greatly shortened and the competitive advantage would be stronger when comparing with commercial software (EnergyPlus, DeST, etc.) simulations.

The effect of each design factor, i.e. input variable, on AED and UDH can be illustrated directly based on the prediction results. A single factor analysis was therefore carried out. When investigating one influential factor, the other two factors were set as constant base-case value in order to get rid of interference. Figure 4 shows the effect caused by shading coefficient variation on AED and UDH, with base-case air change rate of 4 and insulation thickness 40 mm. AED and UDH perform similar changing trend when shading coefficient increases from 0.1 to 1, with a slightly drop at the beginning and keep rising later on, which gives an inspiration that obsessively increase or avoid shading will both cause larger energy consumption and uncomfortable. There is an optimum shading coefficient 0.23 which minimizes the annual energy demand to 23553 kWh; optimum shading coefficient 0.26 minimizes the total uncomfortable degree hours to 38887 h°C. Practical green building design therefore requires thoroughly estimation in terms of shading.

![Figure 3. ANN training performance (a) and regression plots of ANN vs. numerical outputs (b).](image-url)
Figure 4. Shading coefficient influence on AED and UDH.

Figure 5(a) shows the effect caused by air change rate variation on AED and UDH, with base-case shading coefficient of 0.5 and insulation thickness 40 mm. The AED simply increases when air change rate varies from 2 to 20, demonstrating that HVAC energy saving can be achieved by enhance airtightness of the building and reduce ventilation. Nevertheless, the strategy cannot guarantee improvement in comfort level. Possible reason is that the weakened ventilation greatly improves comfort level in winter but brings opposite effect in summer, resulting an upward parabola shaped curve with the minimum value at about 2.8-6 ACH. Figure 5(b) shows the effect caused by insulation thickness variation on AED and UDH, with base-case shading coefficient of 0.5 and air change rate of 4. It is clear that among the three design parameters, insulation thickness shows the weakest sensitivity on AED and UDH. Better energy and comfort performance can be generally achieved by increase insulation thickness, however, the effectiveness is far less than the other two measures. The AED only drops from 24400 kWh to 24150 kWh and UDH only drops from 40000 h°C to 39600 h°C when the insulation thickness increased by ten times from 10mm to 100mm. Insulation thickness is therefore low-priority measures when conducting green building retrofitting in this case.

Figure 5. Air change rate (a) and insulation thickness (b) influence on AED and UDH.

3.3. Optimization results
From the tested cases of numerical model and ANN model, optimum solutions can be directly derived. The two objectives were set as optimization targets separately, the cases that minimize each target value were selected and listed in table 3. Number of cases tested through ANN were far greater than that through numerical, but the optimum solutions were similar, which again shows the accuracy of ANN prediction. Among all 1000 datasets tested by numerical model, minimum AED and UDH appears at same scenario, with shading coefficient 0.2, air change
rate 2 and insulation thickness 100 mm. Corresponding AED and UDH is 17001.68 kWh and 37480.17 h°C. In ANN estimated optimum scenario, the value of air change rate and insulation thickness are completely the same with that of the numerical model, reveals that reducing ventilation and increasing insulation as much as possible both improve energy and thermal comfort performance of the room. Shading coefficient slightly varies from the numerical results, which is mainly due to the difference between the scale of input variables. Cases tested in ANN are more specified and exact, for minimum AED the optimum case shading coefficient is 0.19 and for minimum UDH the value is 0.22.

Table 3. Optimum solution for two targets.

| Categories | Names | Solution A (Minimum AED) | Solution B (Minimum UDH) |
|------------|-------|--------------------------|--------------------------|
|            |       | Numerical results | ANN results | Numerical results | ANN results |
| Inputs     | $x_1$ | 0.2 | 0.19 | 0.2 | 0.22 |
|            | $x_2$ | 2 | 2 | 2 | 2 |
|            | $x_3$ | 0.1 | 0.1 | 0.1 | 0.1 |
| Outputs    | $y_1$ | 17001.68 | 17297.60 | 17001.68 | 17305.41 |
|            | $y_2$ | 37480.17 | 38157.97 | 37480.17 | 38148.63 |

Comparing to the base-case design, the energy demand of proposed optimum solution is largely decreased and the comfort level is greatly improved. The ANN model not only provides qualitative suggestions of macroscopic renovation direction, but also enables quick quantitative analysis on the improved performances. For example, based on pervious results, the energy saving rate and UDH reduction rate of the optimum case to the base case can be calculated. Base-case AED and UDH are 24268.77 kWh and 39795.49 h°C. For solution A, the calculated energy saving rate is 28.725% and UDH reduction rate is 4.115%. For solution B, 28.693% of energy is conserved and 4.138% of uncomfortable degree hours are reduced comparing to the base-case design.

4. Conclusions

This study developed an ANN model for use as a quick and convenient substitution tool for building performance simulation as well as optimal design by using 1000 datasets generated from a numerical model. The outcome demonstrates that the proposed ANN model can precisely predict the AED and UDH under given design scenarios considering the insulation thickness, shading coefficient and air change rate. The accuracy of ANN prediction was proved by the near-1 regressions coefficient $R$ of the 700 learning datasets and also the very low average relative error of 300 testing datasets.

In terms of optimal design, the ANN results show that in general, enhance airtightness and increase insulation thickness are energy-saving measures. Thicker insulation layer also improves comfort level, however the effects are weak and therefore gives low priority when conducting green building retrofitting design. Shading coefficient should be seriously assessed and find an optimum value for minimizing the AED and UDH. Ventilation rate also need to be evaluated to get a certain optimum range if the target is only lessening UDH. For all design scenarios considered in this study, the optimum solution is to reduce ventilation and increase insulation as much as possible, and adjust shading to reduce the shading coefficient form base-case 0.5 to approximately 0.2. UDH is lessened by 4% and the annual energy demand is
decreased by nearly 29% compared to the base case, showing that the conventional residential buildings of Taiyuan have a great potential of energy-saving. To conclude, the proposed ANN model performs quick and accuracy prediction capability on building performance, and significantly decreases effort on green building optimal design.

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