Prediction, comparison and analysis of comfort level and energy consumption of a passively remodeled dwelling based on BP neural network computation

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Abstract. Many ordinary dwellings are not well built in the vast rural areas of China, with poor comfort level and high energy consumption. The China Resources Charity Foundation funded the renovation of more than 200 farmhouses. Compared with the BP neural network model established with the measured data, the BP neural network model established with the simulated data can more quickly estimate the energy saved by the renovation measures of rural dwellings and the improved indoor environment, which is very necessary for the government and enterprises to make decisions to help. In this paper, one of the renovated houses (No. 285) was selected for tracking measurement before and after renovation to obtain real indoor environment and energy consumption data. Simulation software (DesignBuilder) was used to simulate the other 36 renovated houses in order to train the BP neural network model. The energy consumption of No. 285 was calculated by using the trained BP neural model, and the calculated results were compared and analyzed with the simulated data and measured data. Results show that the BP neural network model after training is better than the simple energy consumption simulation software in energy consumption prediction, but there are still errors from the actual measurement values. Regardless of software predictions or actual measurements, the results show that the renovation measures have indeed exerted a very positive impact. As to the overall trend, the software predictions are the same as of the actual measurements, and the variance of day and night temperature variance and the annual extreme values are greatly reduced.

1. Introduction

Energy consumption has become an important social issue in China. In recent years, a large number of energy-saving building practices have been carried out in China, including various types of public buildings, such as gymnasiums, libraries and office buildings. However, the prediction and research of residential building energy consumption have more potential for energy saving, especially in China, a country with a large population. In China, the main forms of residential buildings are divided into two types: one is dwelling house in the city, and the other is single house in the countryside. At present, the research on residential building energy consumption mainly focuses on urban dwelling house, and some achievements have been made. Due to poor construction conditions and imperfect public facilities, single houses distributed in rural areas have a serious waste of energy, which should be paid more attention to.

The prediction and research of building energy consumption are helpful to reduce building energy consumption. However, the energy consumption of buildings is a complex issue. Different climatic environments, building types, construction methods, materials used to maintain structures, orientation of buildings, cooling requirements and other factors have a significant impact on the energy consumption of buildings.

At present, the research methods of building energy consumption can be roughly divided into two kinds, physical modeling method and data prediction method [1]. Physical modeling methods rely on thermodynamic rules for detailed modeling and analysis. Common software includes DesignBuilder, EnergyPlus, eQuest, and Ecotect. The software calculates building energy consumption based on detailed
building and environmental parameters, such as construction details, operating time, heating, ventilation and air conditioning (HVAC) design information and climate information [2]. However, some of the detailed data may not be available to users, which can lead to a decrease in prediction accuracy. Instead, the data algorithm method is based on a large number of operations of existing data and uses the reasoning of mathematical model to predict future energy consumption. In contrast, it is more efficient and operable. In recent years, with the constant modification of software parameters and the continuous evolution of algorithm methods, the two energy consumption calculation methods have different advantages in different buildings.

In China, residential buildings can be roughly divided into urban aggregative housing and rural detached housing. Compared to urban housing, rural housing usually needs to be self-sufficient in heating, power supply and water supply. However, the countryside in China is usually backward. The ordinary rural houses are badly built and the thermal environment is often neglected, with no any insulation for walls. Backward architectural cognition and unskilled construction skills make these houses with poor comfort level but high energy consumption.

Unfortunately, these backward villages are often located in the most scenic areas, and inefficient energy use can wreak havoc on the beautiful landscapes. Therefore, the energy-saving reconstruction of these houses can not only improve the living comfort of farmers, but also protect the beautiful environment.

To achieve fast and reliable building energy conservation prediction, we must rely on the computational method, namely the meta-model method. Meta-model, or agent model, refers to the agent model calculated based on the computer model, which simulates more complex design variables with a large amount of known building data. Compared with prediction models, the prediction calculation of meta-models is faster. Common meta-models include Adaptive Regression Splines (MARS), Kriging (KG), radial basis function (RBF), artificial neural network (ANNs) and support vector Regression (SVR) [7].

There is no optimal meta-model technology, but the accuracy of prediction results depends on the most suitable technology selection and technical input, and ANNs model is still the most commonly used building energy consumption prediction technology. In many studies, ANNs model has shown excellent performance, providing a regression coefficient (R) higher than 0.9 in most cases, which is more accurate than many physical, statistical and regression methods [15]. It is worth noting that ANNs model is the most commonly used alternative model for building performance simulation (BPS), because it has stable and satisfactory performance in solving large problems [7]. Neural networks are especially suitable for studying problems with the influence of large variables, such as this study.

An ANN (see Ref. [16] for details) is a processing data system that learns the relationship between inputs and outputs by studying recorded data, obtained from the original model. It is a network of computation units, called neurons, which are connected by weighted links (called synaptic connections or synapses), over which information is transmitted and manipulated. Each neuron receives input data from the previous ones by means of synapses, handles these data and combines them through a transfer function so as to generate output data that are sent to the following neurons. The network learns from provided inputs and outputs (coming from the original model) by means of training. In particular, this is an iterative procedure that aims to properly set the weights of the synaptic connections by minimizing a certain parameter, such as the sum of squared errors (SSE) or the root mean squared error (RMSE) [12] [13].

The performance of an ANN significantly depends on input and output data, as well as its architecture and parameters, which must be set carefully [17]. The ANN model used in this study is a feed-forward MLP, composed of three layers and thus with only one hidden layer. The number of hidden neurons is detected by means of ‘trial-and-error’. This parameter highly affects the ANN performance: when it increases, the training data set error decreases at the cost of compromising the model generalization ability. The network is trained with Levenberg-Marquardt back-propagation algorithm coupled with Bayesian regularization. A sigmoidal function for the hidden layer and a linear function for the output layer are used as transfer functions. The training is stopped when the RMSE stabilizes or the maximum number of epochs, set equal to 1000 as in Ref. [15], is reached. Then, the network is tested on a second sample of input and output data by considering the coefficient of regression (R) and the distribution of the relative error between the ANN outputs and the original model targets as performance indicators.
China Resources Charitable Foundation is a charitable organization of China Resources Group. Every year, companies and employees of China Resources Group make donations to the foundation, and the annual fund of about RMB 100 million Yuan is used to improve the living environment of poor rural residents. In 2013, China Resources Charitable Foundation funded the renovation of rural houses in three natural villages of WuDian Town, JinZhai District, AnHui Province to improve the living environment of farmers. In consideration of durability and economy, the renovation mainly adopts the method of passive building energy saving instead of the addition of active equipment.

This paper selected one house (No. 285) of the modified houses as the study case. The indoor environment parameters and energy consumption in a year were recorded through the field measurement, the measured data were compared with the annual simulation results obtained by the energy consumption simulation software and the data calculation result using BP network, and then the result was used to improve the energy saving prediction, so as to predict the energy saving potential of the local rural house more accurately.

Simulation data which input BP neural network are used to quickly know the value of renovation measures to improve the indoor environmental quality of rural houses and reduce energy consumption. This rapid estimation helps local governments formulate renovation measures. In addition, most rural houses are built by villagers themselves, which has a lot of irrationality and randomness, and both construction and use exist at the same time. The houses are in the process of constant change for a long time, and it is necessary to keep the basic construction situation of the houses stable for a long time according to field measurement. The measured data for a long time cannot accurately reflect the actual situation of rural buildings.

2. Methodology

No. 285 house is located in Gutang Village, Wudian Town, Jinzhai County, Anhui Province, which is 175 kilometers away from the provincial capital Hefei. Jinzhai’s climate is subtropical monsoon climate characterized by hot and rainy summers and gentle and less rainy winters. The Gutang Village is located in the depths of the Dabie Mountain, effected by the mountain microclimate, and there is large temperature difference in the morning and evening with high humidity: the average temperature is 33 ℃ in the summer, and the average temperature is - 1 ℃ in winter.

No. 285 is a three-layer house with flat roof, which is one of many detached houses along the street of Gutang Village. The left and right walls are connected with other houses. No. 285 covers an area of 140.89 m² in total, with the use space mainly on Layers 1 and 2, including a living room, two bedrooms, one kitchen and one dining room. No. 285 has a poor construction quality. The wall is a single-layer red brick wall with a thickness of 240 mm, the windows are made of aluminum alloy single-layer glass, the roof deck is 150-mm concrete single-layer floor, and all enclosures have simple structures and maintenance functions and do not have any insulation and energy saving measures. The interior decoration is simple with only
painting of the wall surface, and there is no insulation measures such as suspended ceiling.

No. 285 is mainly used by a couple around 50 years old. The couple make a living by farming and do some small handicrafts. They are basically at home except in the busy farming seasons, so the housing usage rate is very high. The couple has a son who works outside all year round with his wife. They come back to live during the Spring Festival every year, which is almost negligible. The elderly couple cook three times a day. Most of the energy used for cooking is on fire, with a small amount of electricity and about 3.2 tons of coal each year. There are no cooling ways in the summer, and in the winter they rely on electric blankets (filaments heated by resistance wires) for heating. The couple said they did not feel hot in summer, but felt colder in winter. They have to heat their rooms with charcoal brazier in a month or so in winter.

According to the construction situation of No. 285 house and its use characteristics, the energy-saving transformation was carried out to reduce its energy consumption and improve the indoor living environment. The renovation methods include: 1. Wall renovation: add 100-mm thick polystyrene board insulation on the basis of the original wall, and externally brush the thermal mortar; 2. Window renovation: replace single-layer glass with double-layer hollow glass, and replace aluminum alloy window frame with plastic steel window frame with better tightness; 3. Kitchen renovation: use electrical appliances instead of open fire.

To accurately record the indoor environment of No. 285 before and after the renovation, the air temperature and humidity recorder was installed in the main space of the farmhouse.

The air temperature and humidity recorder is a HOBO U10-003 type temperature and humidity data collector produced by Onset. The recorder can be used to monitor and record the temperature and relative humidity in the indoor environment, and can be widely used for monitoring people's indoor environmental comfort.

Finally, the digital model of No. 285 house was built using DesignBuilder software to simulate the energy consumption and indoor environment before and after the renovation. The envelope setting parameters before renovation are shown below.

| Table 1. Opaque exterior parameters of envelope summary before renovation. |
| --- | --- | --- | --- | --- |
| Construction | Reflectance | U-Factor with Film (W/m2-K) | U-Factor without Film (W/m2-K) | Gross Area(m2) | Net Area(m2) |
| Block1 | 150mm brick | 0.30 | 2.297 | 3.500 | 105.70 | 93.17 |
| Block2 | 150mm brick | 0.30 | 2.297 | 3.500 | 128.43 | 115.09 |
| Block3 | 150mm brick | 0.30 | 2.297 | 3.500 | 127.01 | 120.3 |

| Table 2. Exterior fenestration parameters of envelope summary before renovation |
| --- | --- | --- | --- | --- |
| Glass Construction | Glass Area(m2) | Frame Area(m2) | Divider Area (m2) | Area Opening of One Opening (m2) |
| Block1 | single-layer | 4.86 | 0.65 | 0.15 | 5.66 |
| Block2 | single-layer | 7.59 | 0.77 | 0.19 | 8.55 |
| Block3 | single-layer | 4.09 | 0.59 | 0.14 | 4.82 |

After renovation, the U-Factor with Film was set as 0.337 W/m2-K, and the U-factor without Film was set as 0.355 W/m2-K in opaque exterior. In exterior fenestration, the glass U-factor was set as 3.835, the glass solar heat gain coefficient (SHGC) was set as 0.768, and the glass visible transmittance was set as 0.744. In HVAC system, the thermostat setpoint temperature at peak load is 24 °C in the sensible cooling and 22 °C in sensible heating. The calculated design load is 10116 kWh in the sensible cooling and 9241 kWh in sensible heating of total three zones.

In Ref. [18], the implementation of simulation-based large-scale uncertainty/sensitivity analysis of building energy performance (SLABE) has allowed to qualify the existing building stock, which constitutes the examined category, by defining 46 characteristic parameters related to thermal energy demand for space conditioning and thermal comfort. These parameters are related to geometry, thermal envelope, building operation and type of in-room terminals for space conditioning. Based on the actual situation of rural houses in Jinzhai, we have sorted out 34 parameters, as shown in Table 3.
Table 3. Characteristic parameters of the existing building stock taken from Ref. [16].

| Geometry      | p1           | Orientation (angle between North axis and building North) |
|---------------|--------------|---------------------------------------------------------|
|               | p2           | Area of each floor (m2)                                  |
|               | p3           | Form ratio                                              |
|               | p4           | Floor height (m)                                        |
|               | p5           | Window to wall ratio: South                             |
|               | p6           | Window to wall ratio: East                              |
|               | p7           | Window to wall ratio: North                             |
|               | p8           | Window to wall ratio: West                              |
|               | p9           | Number of floors                                        |
| Envelope      | p10          | Type of window glasses                                  |
|               | p11          | Type of window frames                                   |
|               | p12          | Clay (floor) thickness (m)                              |
|               | p13          | Clay (floor) thermal conductivity (W/m K)               |
|               | p14          | Clay (floor) specific heat (J/kg K)                     |
|               | p15          | Expanded clay (roof) thickness (m)                      |
|               | p16          | Expanded clay (roof) thermal conductivity (W/m K)       |
|               | p17          | Expanded clay (roof) specific heat (J/kg K)             |
|               | p18          | External bricks' (walls) thickness (m)                  |
|               | p19          | External bricks' (walls) thermal conductivity (W/m K)    |
|               | p20          | External bricks' (walls) specific heat (J/kg K)         |
|               | p21          | Floor block thickness (m)                               |
|               | p22          | Floor block specific heat (J/kg K)                      |
|               | p23          | Internal bricks' (walls) thickness (m)                  |
|               | p24          | Internal bricks' (walls) thermal conductivity (W/m K)    |
|               | p25          | Internal bricks' (walls) specific heat (J/kg K)         |
|               | p26          | Roof block thickness [m]                                |
|               | p27          | Roof block thermal conductivity (W/m K)                 |
|               | p28          | Roof block specific heat (J/kg K)                       |
| Operation     | p29          | People density (people/m²)                              |
|               | p30          | Artificial light load (W/m²)                            |
|               | p31          | Infiltration rate (h⁻¹)                                 |
| HVAC          | p32          | Heating set point temperature (°C)                      |
|               | p33          | Cooling set point temperature (°C)                      |
| Energy        | p34          | total energy                                            |

To train the BP neural network model more accurately, 69 other houses were measured in the village, No. 213-284. These houses vary widely in construction, from original rammed earth structure to multistory brick structure built in recent years. For training a model more similar to No. 285, we selected the above 69 houses surveyed and selected 36 houses of 39 households for detailed mapping, including the size, construction and use of the buildings. According to the mapping results, we use DesignBuilder simulation software to build the digital models. Using software simulation results and mapping statistical results, the information summary of the 36 houses were completed.

Rural housing has a small scale, simple and crude construction, simple use condition, and no too many parameters for input, so the calculation time of BP neural network is very short.

3. Results
According to the information in figure 2, the BP neural network model was built. According to BP neural network theory and operation steps, the prediction of building energy consumption is realized by programming in MATLAB.

- **Data import and normalization**
  Firstly, the data T was imported with the output of numeric matrix type. Input data and output data were determined, 26 groups (70%) of the 36 groups of data were randomly selected as training data and the rest as test data, and then the normalization processing to the data was carried out.
Set up BP neural network
BP neural network was constructed and parameter configuration was set. The number of iterations (epoch=1000). Learning rate lr = 0.1; the target goal = 0.00004;

Test the training model
Test the model with the remaining 30% data, and output the graph of network results.

The BP neural network was ended by the 8th generation, and the gradient was 0.00461. The best performance occurred in the 6th generation, with a performance value of 0.0658. The calculation results are shown in figure 4: it can be seen from the figure that the fitting degree of BP model for training data is very good, reaching 0.99777, and it is generally considered that R < 0.05 is a small error. However, the fitting degree of test data is poor, only 0.55947, with a comprehensive performance of 0.81519, which cannot provide very accurate prediction.

DesignBuilder software simulation results show that before modification, 8791 kWh of electricity is used in summer and the total energy is 13171 kWh.

Using the BP neural network model and the information of mapping, the energy consumption of No. 285 was calculated. The calculation procedure is the same as that in the test of BP neural network model. Firstly, input data were loaded and normalized, then the BP neural network model was used for calculation, and finally the results were anti-normalized. The final calculation result of No. 285 is 13911 (kWh).

Results show that before the modification, 3220 kWh of electricity and 3.2 tons of coal are used in summer, equal to 13300 energy, but after the modification, 4203 kWh of electricity and 2.4 tons of coal are used in winter, equal to 11763 energy.

| No. 285 Total energy | Simulation | BP neural net work | Measurement |
|----------------------|------------|--------------------|-------------|
|                      | 13864      | 13911              | 14122       |
4. Conclusions
The BP neural network model after training is better than the simple energy consumption simulation software in energy consumption prediction. This means that the BP neural network model based on simulated data is suitable for rapid estimation of energy saving in rural houses, which is helpful for the government to formulate specific policies to help. Compared with the simulation of rural housing by single energy consumption software, the calculation of energy consumption by adding BP neural network training model is more accurate. There are still errors from the actual measurement values, mainly because the quality of the houses actually built is not perfect, especially the rural houses, and there will be some differences between the actual usage and the software simulation. In addition, the data show that the fitting degree of the trained BP neural network model is not very ideal, which may be related to the insufficient amount of data. Some houses that are quite different from other houses contribute points farther from the fitting curve.

Regardless of software predictions or actual measurements, the results show that the renovation measures have indeed exerted a very positive impact. As to the overall trend, the software predictions are the same as the actual measurements, and the variance of day and night temperature and the annual extreme values are greatly reduced.

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