Developing a heating and cooling demand prediction model for residential buildings in the cold climate zone of China

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Abstract. The performance-oriented design method requires that architects should have the ability to calculate the energy performance of the design solutions and improve the design scheme accordingly. However, energy simulation is complex and time-consuming, which hinders architects to perform the optimization. The study aims to deduce a forecasting model and develop a simple tool for the energy demand of high-rise residential buildings in the cold climate zone of China. Firstly, a representative of residential building in cold climate zone was selected as the prototype. Then sensitivity analysis was conducted to identify significant variables. Finally, Multiple Linear Regression and Multilayer Perceptron methods were used to obtain the prediction models. The tool, based on statistical analysis and without modelling interface, is easy to assist architects to calculate the heating and cooling demand at schematic design stage.

1. Introduction

Energy efficiency in buildings has been one of the key topics of Sustainable Development Goal 7 “affordable and clean energy” [1]. Since IEA Annex 30, whose theme is “bringing simulation to application”, simulation in building energy efficiency design has been highlighted. More than 400 energy simulation tools have been developed over the last 50 years [8]. However, most simulation tools are not able to adequately provide feedback at the early design stage [2]. The main reason is that the majority of existing tools are only able to simulate with all of the detailed input information [3]. The excessive requirement of technical knowledge is another important factor that thwarts architects’ attempts to integrate the optimization with the design process [4]. Furthermore, Hollberg A [6] think 20 seconds to 3 minutes for one simulation is so long in an iterative analysis that evolutionary algorithm is required to reduce optimization duration. Tian Z [8] reviewed seven commonly used building energy optimization tools (BEOPs) and concluded that they could not adequately address architects’ needs.

For architects, they need constant feedbacks of decisions and directive information for improvements during the design process. “Accuracy” is less important compared with “intelligence”, “usability” and “interoperability” as shown in figure 1 [9], according to a survey among 230 architects. The rank order instead of the concrete and accurate values is what architects actually focus on. However, existing tools are mostly designed to calculate the results as accurate as possible, which lead to the complexity and time-consumption in simulation. As a result, these tools may miss the opportunity to quantify, rank-order and identify powerful instruments driving critical design decisions [9].
In China, there are two methods to evaluate buildings’ energy performance in Design standard for energy efficiency of residential buildings in severe cold and cold zones JGJ 26-2018. Either of them is recognized. One prescribes the maximum of U values of opaque envelope (U_o), window-to-wall ratios (WWR_o, WWR_n, WWR_we). U values of windows (U_s, U_n, U_w) and solar heat gain coefficient of windows (SHGC_s, SHGC_n, SHGC_we). The other is the benchmark, called index of heat loss of building. During the design process, architects are inclined to choose the maximum values suggested in the standard at schematic design stage even at the cost of other aspects like aesthetics. Otherwise, engineers may feel reluctant to calculate the energy performance at later stages (normally when the construction design is done) to make sure the index of heat loss of building is lower than the benchmark value. Actually, the limits to each factors in the standard is to help to realize the energy goals, and there are a number of better combinations of the values of the ten major design variables indicated in the standard (See table 2). They might be better than the combination of the maximum value of each of them.

The code-compliance-design method is not sufficient to realize energy efficiency, but it still dominates building market. Although noticeable research achievements had been made on performance-oriented methods in China, their application in practice is still hindered as being complex and time consuming.

Figure 1. Architects priorities for ranking a simulation tool.\cite{9}

Figure 2. Residential building types and shares in China.\cite{10}

This study aims to develop a simple energy demand prediction tool for the mainstream building type at early design stage in cold climate zone in China. The paper is organized in 4 sections. Section 2 presents the research method, including selecting the reference building, sampling, and sensitivity analysis. Section 3 describes sensitivity analysis results and prediction model. The last section concludes the model’s applicability, and highlights the limitations and further research.

2. Methodology
The method in this research includes three parts. First, select the reference building on behalf of typical high-rise residential buildings in cold climate zone in China. Secondly, identify significant variables. Orthogonal design is used to generate samples based on the ten design variables mentioned in Section 1. Finally, different sensitivity methods are compared.

2.1. The reference building and simplification
Design standard for energy efficiency of residential buildings in severe cold and cold zones JGJ 26-2018 allows all new buildings follow the ten maximum values mainly because the great similarity in terms of layout, functions, lighting, occupancy and even service systems, although every building is different in concrete size and internal rooms layout. Figure 3 shows the typical-floor plan of a representative building in the city of Jinan, with 24-stories and 4 households per story. In China,
residential buildings of this type, the slab-type high-rise type characterized by a rough rectangle plan, accounts for 41% of urban residential buildings as shown in figure 2 \cite{10}, and it is prevalent in cold climate zones as shown in figure 4. The main reason for the popularity is that the shape factor of the rectangle plan is small enough to reduce transmission heat sinks in winter. What’s more, it ensures a larger south facade to get more solar heat in winter, compared with the tower residence. Over spring and fall, natural ventilation is fluent, which ensures indoor comfort. Instead of applying the maximum values for the ten variables in the standard, developing a rough energy prediction model to explore better combination based on a representative building would be more reasonable and helpful. It is intended to help the designers to have a rank-order of energy saving measures at the schematic design stage rather than providing the accurate results for energy demand.

![Figure 3. The typical-floor plan of a high-rise residential building in China](image3)

![Figure 4. Climate zones in China](image4)

2.2. Sampling and Sensitivity analysis

2.2.1. Sampling. The ten design variables mentioned in section 1 are selected to perform sensitivity analysis (SA) to identify their significance. Orthogonal design, achieved by matching each level of each factor with an equal number of each level of the other factors, is applied to generate a sample for SA. The matching method in orthogonal design avoids loss of data either by plan or by accidental. In this study, there are five levels of values for each parameter as shown in table 2 and a sample of 81 combinations are generated. Afterwards, heating and cooling demand of each combination is simulated with DesignBuilder.

|                      | Average value | Standard deviation | Standard error | Confidence interval | Upper limit | Lower limit | t    | df | Sign. |
|----------------------|---------------|--------------------|----------------|--------------------|-------------|-------------|------|----|-------|
| Heating demand       | -0.186        | 0.400              | 0.731          | -0.335             | -0.036      | -2.54       | 29   |    | 0.017 |
| Cooling demand       | 0.126         | 0.209              | 0.382          | 0.480              | 0.204       | 3.30        | 29   |    | 0.003 |
| Total                | 0.598         | 0.404              | 0.734          | -0.210             | 0.909       | -0.81       | 29   |    | 0.024 |
To simplify the thermal model, all accessory zones are removed and each floor zones are lumped together according to the methodology proposed by Piccol\[4\]. Furthermore, the complex profile was converted into a rectangle one with the same floor area. A paired t test is used to quantify the difference in energy demand after simplification. As expected, Sign. is less than 0.05 as shown in table 1, which means the rectangle profile did not offer difference in essence. It also indicates that one representative building can be used to develop the heating and cooling demand model in this study.

### 2.2.2. Sensitivity analysis
Anh-Tuan Nguyen\[11\] carried out a performance comparison of nine sensitivity analysis methods using two real-world building energy models and found out that the PEAR (Pearson product-moment correlation coefficient), PCC (partial correlation coefficient), and SRC (standardized regression coefficient) could give more reliable results than SPEA (Spearman coefficient), PRCC (partial rank correlation coefficients), and SRRC (standardized rank regression coefficient). PEAR measures the linear correlation coefficient between dependent and independent variables. PCC measures the degree of association between two random variables, with the effect of a set of controlling random variables removed. SRC estimates independent variables’ significance from a regression analysis that has been standardized.

To avoid the limitation of regression-based sensitivity in terms of non-monotonic problems, Multilayer Perceptron (MLP) is used as a comparison in this study. It is a type of feed-forward neural network utilizing back-propagation for training. In this paper, PEAR and PCC are used to perform local sensitivity analysis while SRC and MLP are used to carry out global sensitivity analysis. Comparisons between different methods guarantee the reliability and validity.

### 3. Results and discussion

#### 3.1. Results of local sensitivity analysis
Results of local SA are presented in figure 5. For high-rise residential buildings in cold climate in China, figure 5 shows that the order and trend of sensitivity indices using PEAR and PCC are consistent, no matter on heating, cooling, or total demand. As shown in figure 5 (a), SHGC of all windows, WWRs, and WWR\(_{we}\) have negative correlations with heating demand while all U values and WWR\(_{a}\) have positive correlations with that. The absolute value of sensitivity indices of WWR, and SHGC, are larger than that of the largest positive variable, U value of opaque envelope. For cooling demand, figure 5 (b) shows that the negative variables, U values of all windows, have slight influence on cooling demand, with almost the smallest absolute value of sensitivity index. When it comes to the

| Variables | Symbol | Values | Units |
|-----------|--------|--------|-------|
| U value of opaque component (\(U_o\)) | W | 0.09, 0.12, 0.15, 0.18, 0.21 | W(\(m^2\)K\(^{-1}\)) |
| U value of south-facing window (\(U_s\)) | X\(_1\) | 0.8, 0.9, 1.0, 1.1, 1.2 | W(\(m^2\)K\(^{-1}\)) |
| U value of north-facing window (\(U_n\)) | Y\(_1\) | 0.8, 0.9, 1.0, 1.1, 1.2 | W(\(m^2\)K\(^{-1}\)) |
| U value of west and east-facing window (\(U_{we}\)) | Z\(_1\) | 0.8, 0.9, 1.0, 1.1, 1.2 | W(\(m^2\)K\(^{-1}\)) |
| SHGC of south-facing window (\(SHGC_s\)) | X\(_2\) | 0.2, 0.3, 0.4, 0.5, 0.6 | - |
| SHGC of north-facing window (\(SHGC_n\)) | Y\(_2\) | 0.2, 0.3, 0.4, 0.5, 0.6 | - |
| SHGC of west and east-facing window (\(SHGC_{we}\)) | Z\(_2\) | 0.2, 0.3, 0.4, 0.5, 0.6 | - |
| WWR of south façade (\(WWR_a\)) | X\(_3\) | 0.3, 0.4, 0.5, 0.6, 0.7 | - |
| WWR of north façade (\(WWR_n\)) | Y\(_3\) | 0.3, 0.4, 0.5, 0.6, 0.7 | - |
| WWR of west and east façade (\(WWR_{we}\)) | Z\(_3\) | 0.3, 0.4, 0.5, 0.6, 0.7 | - |
whole year, PEAR and PCC sensitivity index both demonstrate that SHGC, and WWR, are conducive to reduce annual energy demand, while the rest variables have positive correlations with total demand as shown in 5 (c). The comparison of sensitivity index order among figure 5 (a), (b), and (c) illustrates that ten variables have complex influence on heating, cooling and total demand. Of all ten parameters, only WWRn and Uo have positive correlations with heating, cooling and the total whereas the rest 8 variables have conflicting effect in summer and winter. However, all of them demonstrate that SHGC is the dominating variable. WWRw and Uo, the least important variable in winter and summer separately, ranks 4th and 5th over the year. Similarly, SHGCn and SHGCw, the least ones over the whole year, are perceived significant whether in summer or winter.

![Figure 5](image_url)

**Figure 5.** Local sensitivity analysis results comparison between PEAR and PCC. (a) Sensitivity factors on heating demand; (b) Sensitivity factors on cooling demand; (c) Sensitivity factors on heating and cooling demand.

3.2. Results of global sensitivity analysis

Due to the randomness, MLP is run three times. Because MLP results show significance only, SRC result, based on Multiple Linear Regression (MLR), is converted to significance. The comparison of global SA is presented in figure 6. These global sensitivity results are consistent with local sensitivity results. SHGC, is always the first and most important factor for heating, cooling and the total, even if the offset between summer and winter. WWRn and Uo are second only to SHGC, because of the accumulation of adverse effect in summer and winter. WWRw, the fourth important on the list, has so much adverse influence on cooling demand while vary little is offset by heating. The significance of the rest 6 variables, even and less important after being great offset over a year separately, is as
considerable as SHGC, totally, contributing almost 30% to energy demand. All in all, it is necessary to include all the ten variables in energy calculation model to cut down annual demand.

Figure 6. Global sensitivity analysis results comparison between PEAR and PCC. (a) Sensitivity factors on heating demand; (b) Sensitivity factors on cooling demand; (c) Sensitivity factors on heating and cooling demand. (L-Multiple Linear Regression; M-Multilayer Perceptron)

3.3. Prediction model and verification
Based on the 81 combinations, this study obtained prediction models by MLR and MLP. To verify the reliability of these models, 20 random combinations are tested. The predictive values from MLR and MLP models are compared with actual values simulated by DesignBuilder, as showed in figure 7. The results show that errors of MLP vary from -2.55% to 3.07% while those of MLR are between -2.7% and 2.0%. It is accurate enough to rank them and select the solution consistent with their design concept. The MLR model was developed into a simple tool by programming, whose interface was shown in figure 8. The comparison of the 20 combinations also highlights that the optimization is necessary to achieve high thermal performance. For example, NO.17 is nearly 30% lower than NO.15.

In response to the state-of-art of code-compliance-design method in China, the sensitivity indices help architects understand the optimization mechanism, and the tool assists them to compare the alternatives. Architects do not have to control the factors strictly, like 0.5 as window-to-wall ratio in south facade and can make a trade-off between aesthetics and thermal performance flexibly. If architects have intended values or ranges for some variables, the tool offers all possible combinations immediately.
4. Conclusion
The Design standard for energy efficiency of residential buildings in severe cold and cold zones JGJ 26-2018 is not intended to control the specific value of every variable. Architects are encouraged to explore better combinations instead of following the maximum combination. For slab-type high-rise residential buildings in cold climate zone of China, SHGC_n is the absolutely decisive variable for heating, cooling and total energy demand. WWR_n and U_n are second only to SHGC_n because of the accumulation of adverse effect in summer and winter. WWR_west, the fourth important on the list, has so much adverse influence on cooling demand while vary little is offset by heating. The significance of

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**Figure 7.** Comparison of actual and predictive values.

**Figure 8.** The Interface of the tool.
the rest 6 variables, even and less important after being great offset over a year separately, is as considerable as SHGC, totally, contributing almost 30% to energy demand.

Although the model is based on the representative building and the energy simulation is conducted with the typical weather data of Jinan, the model is also applicable to other residential buildings of this type in cold zone when compared with the fact that one maximum combination is applied to both types of residential buildings in entire climate zone. The prediction model is reliable to rank the alternatives for slab-type high-rise residential buildings at schematic design stage because accurate energy demand is not necessary.

Considering the great similarity of high-rise buildings in cold zone, the MLR model is recognized as the calculation core of the simple tool. In this case, it is not necessary to model the concrete buildings in the tool, only with input boxes of variables’ ranges and output of the all possible combinations. One deficiency is that thousands of possible combinations will be produced if the ranges of variables are not set reasonably which offer difficulty to architects to choose. The other is that the sensitivity indices are not showed in the interface. Both of them will be solved in future research.

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