Coupling Effect of Building Design Variables on Building Energy Performance

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Abstract. This study provides in-depth analysis of design variables and their interactions in typical office buildings in hot summer and cold winter areas in China, revealing the complex effects of these factors on energy consumption. A combination of tree Gaussian process and linear regression are used to establish a more comprehensive and accurate energy consumption model, which is more practical than the traditional linear regression model.

Keywords: China; model; energy consumption.

1 INTRODUCTION

With the booming development of the global economy, building energy consumption has become one of the hot spots of social concern. Especially in the hot summer and cold winter areas, office buildings, as an important building type, their energy consumption problem is more prominent. Energy consumption level is directly related to the rational utilization of energy resources and the sustainable development of the environment. Therefore, a thorough study of the influencing factors of building energy consumption and the complex relationship between design variables is crucial to develop effective energy management strategies and promote the development of building energy saving technologies [1-3].

However, the building system is a highly complex system that contains numerous interrelated design variables, such as heating setting temperature, window heat transfer coefficient, air penetration, etc. The interaction between these design variables is often overlooked in traditional analysis methods, while modern architectural design needs more comprehensive and in-depth research. The objective is to meticulously examine the impact of various design parameters and their interrelated influence on the energy usage of standard office structures, utilizing a combination of TGP analysis along with a multivariate linear regression model [4-6].

M. Ali et al. (eds.), *Proceedings of the 2024 International Conference on Urban Planning and Design (UPD 2024)*, Advances in Engineering Research 237,
https://doi.org/10.2991/978-94-6463-453-2_2

2 METHODOLOGY

Methodologically, we first applied TGP to the analysis of parametric interaction effects, and then applied a multiple linear regression model to consider the interaction effects to reveal the potential relationship between design variables and energy consumption [7]. The application of gradual regression method and Bayesian information criterion makes the model more accurate and reliable. Through 180 simulation results, we verified the performance of the model and propose a series of design suggestions on the energy optimization of office buildings in hot summer and cold winter areas [8].

2.1 Model Variable

We selected a series of key design variables, covering multiple aspects of building envelope and human behavior, with specific results shown in Table 1.

Table 1. Ten distinct design elements along with their respective input probability distributions.

variable	abbreviation	scope	date format	unit
Cooling set-point temperature	& Turks and the Caicos Islands	24–28	around-the-clock	°C
Heating set value temperature	thorium	18–22	around-the-clock	°C
The ratio of window to wall	Water-water reactor	20–80	around-the-clock	Sand wall window
Power density of equipment	equip	10–20	around-the-clock	W/m^2

2.2 Modeling

To construct a realistic and representative model, we selectedTo construct a realistic and representative model, we selectedstory office building as the basis a simulation tool developed by the Lawrence Berkeley National Laboratory in the United States, to run extended simulations using the typical annual meteorological data of Ningbo city.

We designed a model of a 12-story square office building with central symmetry, encompassing both interior and exterior spaces facing east, south, west, and north. Each floor has a construction area of 400 square meters, with the building reaching a total height of 36 meters and a gross area of 4800 square meters. The outdoor rooms measure 5 meters in depth and 3 meters in height. The detailed structure of the model is depicted in Figure 1.

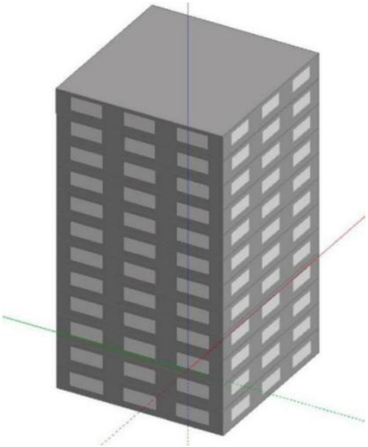


Fig. 1. Typical office building model.

We sampled and combined the variables by selecting continuous variables and discrete variables, and employing the Latin hypercube sampling technique (LHS). This ensures a uniform distribution of the variables in the parameter space, avoiding the redundancy in the simulations [9].

Through this simulation process, we obtained a diverse combination of building design parameters to more fully and accurately explore the energy consumption characteristics of office buildings in hot summer and cold winter regions. This comprehensive approach helps to deeply understand the influence of design variables on energy consumption, and provides a scientific basis for optimizing building design. The research process is shown in Figure 2.

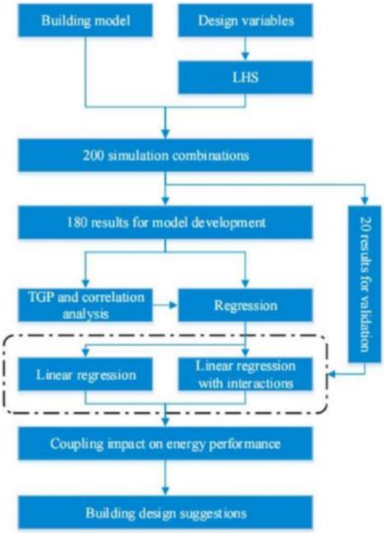


Fig. 2. Research process.

2.3 Methods for the TGP Sensitivity Analysis

To grasp the attributes of nonlinear and dynamic regression models, the tree-structured Gaussian process (TGP) sensitivity analysis technique was adopted. TGP integrates the strengths of Gaussian processes with decision trees, exhibiting robust adaptability to intricate challenges like high dimensionality, limited sample size, and non-linearity.

Methods and steps:

1. Model construction: TGP is employed to construct models grounded on the sampling plan variables and energy consumption data. TGP is able to handle nonlinear kinetic models, making it more accurate for modeling complex systems.

2. Sobol's sensitivity analysis of the method: The Sobol's method was applied to conduct the sensitivity analysis of the TGP model results. By calculating the contribution of each parameter to the energy consumption, it reveals the trend of variable influence on the model output [10].

Sensitivity indicators:

1. Main effect (Si): measures the ratio of the overall output variability resulting from a single variable. The larger the index, the greater the variable has on the model output.

$$Si = Var(E[y \mid xi]) / Var(y) \tag{1}$$

2. Sum of effects (Ti): assesses the proportion of the model output variance to the overall output variability attributable to the interaction between each parameter and other variables. Similarly, the larger the index, the more significant the interaction between the variables.

$$Ti = E[Var(y \mid x - i)] / Var(y) \tag{2}$$

Analysis procedure:

Evaluation of the contrast between primary and aggregate effects enables the deduction of the interactive coupling impacts among variables. These indicators not only provide insight of the effects of individual variables, but also reveal complex relationships between parameters in the system, providing deep insights into optimizing energy consumption. Compared with conventional methods, TGP sensitivity analysis has higher computational efficiency and adaptability and is a powerful tool for studying complex systems.

2.4 Regression Analysis of Building Energy Consumption and Design Variables

For an in-depth exploration of the correlation between building energy consumption and design parameters, multiple linear regression models were employed, which includes two scenarios accounting for main and interactive coupling effects.

Model expression:

$$y(x_1,x_2,\ldots,x_n)=\beta_0+\beta\sum_{i=1}^{n}x_i+\in \tag{3}$$

Stepwise regression technique: This approach integrates the forward and backward selection procedures. It verifies the statistical significance of the independent variables introduced into the model, eliminating those that are insignificant. Furthermore, the application of shellfish

Utilizing the Bayesian Information Criterion (BIC) to ascertain the variables permitted for inclusion in the model, to prevent the model from becoming too complex to reduce overfitting.

Consider the case of interaction effects: Further formulas, including the interaction effect, are developed while considering the potential interaction effects among diverse design parameters.

To confirm the precision of the regression equation: By regression using 180 simulation results, the leftover 20 samples are employed to corroborate the precision of the regression equation. This ensures the accuracy and generalization ability of the regression model for predicting and revealing the relationships of diverse design parameters. affecting energy consumption as well as the interaction relationships. Through regression analysis, we can have an insight into the influence of design parameters on building energy use and offer specific recommendations for optimizing the design process.

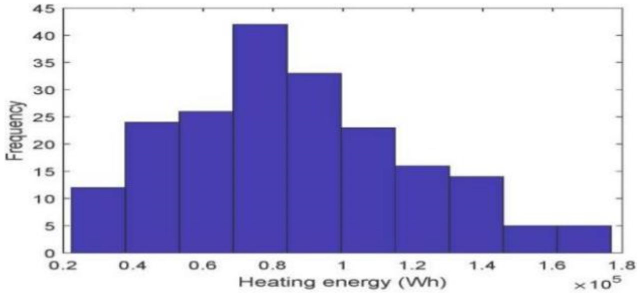
3 RESULTS AND DISCUSSION

3.1 Sensitivity

By performing 180 simulations, we obtain the distributions of total energy consumption E_t, cooling energy E_c, and heating energy E_h, shown in the following figure. A relatively small calorie consumption is observed, ranging between 2,000-18,000 Wh, whereas the cooling energy usage is roughly 3-4 times the heating consumption, in the range of 20,000 – 50,000 Wh. This indicates that building refrigeration energy should be given priority in the choice of energy saving measures in office buildings. The energy distribution results are shown in Figure 3.

Differences exist: Viewed through the lens of the primary effect and aggregate effect, disparities in box plot representations exist between the two indices of each principal parameter, suggesting an interactive influence among the variables.

Interactive coupling impact: Although present, the boxplot discrepancies are not substantial. Additional regression techniques are essential to assess the magnitude of the interaction and its potential influence on the design evaluation.



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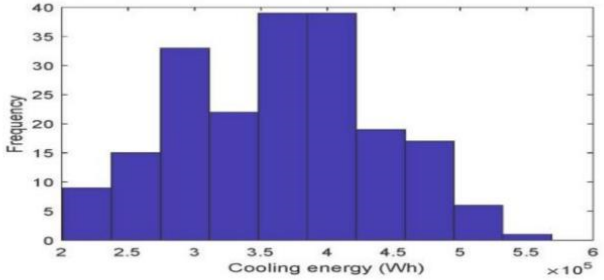

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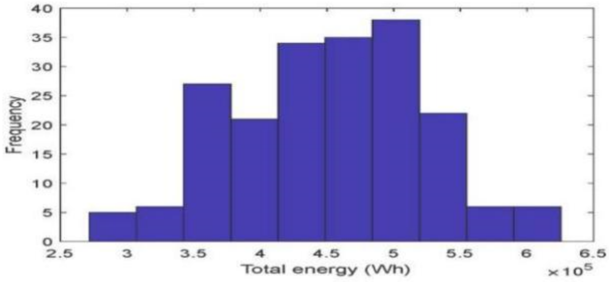

(c) Et

Fig. 3. Energy consumption distribution.

3.2 Regression Model Analysis

In Figure 4, We illustrate the correlation matrix of energy use (heating, cooling, overall energy consumption) in relation to each design parameter. By observation, we can draw the following conclusions:

1. Correlation significance: Every category of energy consumption exhibits a substantial correlation with roughly 3-5 design parameters, whereas the association with other design elements is minimal.

2.The effect of insulation measures is negligible: the influence of wall and roof insulation on energy use is trivial.

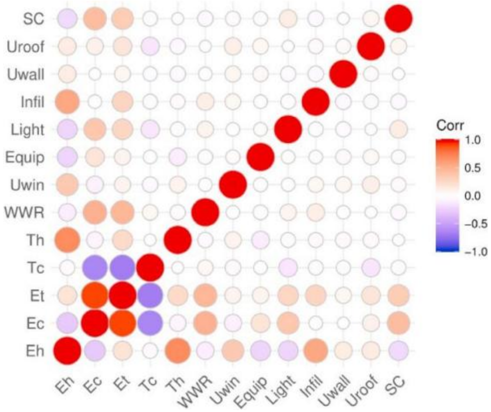

Fig. 4. Correlation matrix depicting the relationship between energy use (heating, cooling, and overall consumption) and individual design parameters.

Based on these observations, we performed a stepwise regression analysis with the following results:

1. Total energy consumption model:

Regardless of interactions: associated with 9 of the 10 design variables.

Consider interactions: Related to these 10 variables, and there are interactive coupling effects between 7 variables.

2. Cooling energy consumption model:

Regardless of interactions: related to the seven design variables.

Consider interaction: associated with 8 variables, there is an interactive coupling effect. The results as shown in table 2.

Table 2. Gross energy expenditure.

variable	Estimates	se	tStat	pValue
thorium	17642	740.35	23.8	4.52E-5
equip	2744.6	300.15	9.144	1.80E-16
lamp	2252.9	310.97	7.2446	1.44 e-11
sc	1.07 e+05	3919.7	27.265	5.79E-64

3.3 Analysis of the Interactive Coupling Effects

In the study, we focused on interactions between multiple design variables to gain a deeper understanding of their complex effects on energy consumption. The following is our analysis of the three important interactive coupling effects:

Through the comparison in figure 5, we found that the cooling energy consumption decreases with increasing cooling set point temperature in the model regardless of the interaction. However, considering the interaction of air penetration, there is an interaction point, below that temperature, low air penetration leads to lower energy consumption, while higher than that temperature, low air penetration instead leads to higher energy consumption. This implies that air infiltration could result in contrasting energy-saving impacts at varying cooling set temperatures.

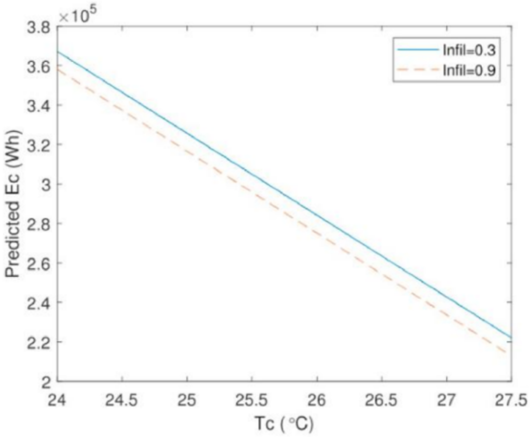

Fig. 5. The interactive effect of cooling temperature settings and air permeability on cooling energy usage.

4 CONCLUSION

By thoroughly examining diverse design parameters and their interplay in exemplary office structures., this study reveals the influence of potential coupling effects among design parameters on energy use. By adopting an amalgamation of tree Gaussian process regression linear regression, we obtain a more comprehensive and accurate energy consumption model, which is more practical than the traditional linear regression model that solely accounts for the primary effects.

The research results emphasize that building energy conservation should pay more attention to summer heat insulation measures in hot summer and cold winter areas in China. Cooling energy occupies a large proportion in the total energy consumption, so it is suggested that designers should prioritize the summer overheating issue mitigation, take shading measures, control the ratio of windows to walls, and reduce the internal thermal gain.

In addition, the influence of human behavior on The influence of building performance exceeds that of the insulation effect of the envelope. Hence, energy efficiency can be improved more effectively by a reasonable regulation of human behavior, such as setting a reasonable heating / cooling set value temperature.

There are coupling relationships between design variables, especially the interaction the relationship between the window heat transfer coefficient, the relationship between the window heat transfer coefficient, the area, and air infil. When the window wall is relatively large, it is suggested to consider more heat insulation and heat dissipation measures, rather than pay too much attention to thermal insulation performance.

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