STUDY ON DISTRICT ENERGY CONSUMPTION PREDICTION MODEL OF OFFICE BLOCKS IN COLD REGION, CHINA WITH SIMULATION AND REGRESSION ANALYSIS

Sun Cheng [1], Zhang Ran[1]
[1]School of Architecture, Harbin Institute of Technology, Harbin, CHINA

ABSTRACT

Prediction of district energy consumption plays an important part in building energy conservation. In this study, the simulation method is adopted to predict the energy consumption of standard building, and the statistical data combined with Bayesian model for optimized forecasting district energy consumption is also used. A sample survey is first conducted in Harbin. And, standard buildings sets are developed according to classification employing orthogonal experiment. Moreover, simulation is performed based on typical morphological data set derived from the sample survey. The Bayesian model is adopted to optimize method of area superposition with energy consumption value of standard buildings and statistical data. And finally, the prediction model for district energy consumption and a simplified energy consumption formula for office district are obtained by the integrated method. Compared with other prediction methods, the optimized approach has a significant influence on accuracy in terms of error analysis. The method proposed in this study can accurately predict the district energy consumption of office building blocks in the planning stage where detailed building information is lacked, to guide the energy planning, project design, product development etc.

INTRODUCTION

With the development of economic growth and urbanization in China, the demand for energy is on the rise in all fields. Building energy planning is the basis of energy efficiency. In addition, there is a growing trend for science, technology, and research institutions in the form of building complexes like office blocks. Therefore, the study on energy prediction of building blocks in the early stage of planning has become one of the most important concerns for building energy efficiency.

Prediction method of district building energy consumption is relatively at their infancy stage. Current prediction methods of district buildings include the area index method (AIM) (Jin et al, 2008), the trend extrapolation method based on historical data, including regression analysis and artificial intelligence, scenario analysis method (Yuan & Long, 2008) and simulation analysis method (Stevanovic et al, 2009). However, the existing perdition methods and models have limitations. Some methods fail to predict the energy consumption of building group directly in the phase of regional planning and some existing models still have some problems. The integrated prediction model will be a method predicting the regional energy in the future.

This paper expects to go more deeply into a study of an optimized method to predict office block energy consumption in cold regions of China, combining with simulation and regression analysis, as well as developing a more stable, efficient and accurate prediction model. The approach has been applied to office blocks for more than one city.

LITERATURE REVEW

Although there are more and more researchers studying prediction methods of district energy consumption, it turns out that most of their study results have limitation and poor applicability. Seldom do they emphasize the energy prediction of office blocks combining with the advantages of different kinds of prediction models, and some even do not highlight it at all.

In order to predict the energy consumption of the large districts, the researchers mostly use two basic analytical methods: Top-down and Bottom-up.

Top-down can infer the amount of energy applied on the basis of the impact on the energy of construction industry development during a long time. This method is simple, and the data is also easy to collect. However, the specific situation of the single building energy is not able to known by using this methodology and it is not true for the changes of society, environment and economy.

Bottom-up is a method of analyzing the situation of the single building, and then integrating it into the whole. There are 4 main ways: AIM, simulation, artificial intelligence (AI) and regression analysis.

AIM is the most effective and widely used method for predicting the district energy consumption. This method is usually used to calculate energy consumption of one building via the formula of Eq. (1), and then add together energy consumption of each building.

$$Q = qF \tag{1}$$

Where Q is total energy consumption of buildings; q is building energy consumption index of unit area which comes from related statistics data; F is total building area.

The simulation is achieved by developing the building model with detailed design information. It is an efficient and economical method for predicting monomer building. Huang et al. (Huang et al, 1991) built a number of typical commercial building models to evaluate the cogeneration potential of 13 major cities in United States by DOE-2. The emphases of simulation is to build typical models for accurate results when using simulation software to predict energy consumption of district building. Then, characteristic curve of energy consumption per unit area is obtained by simulation in order to expand to the overall energy consumption in the district.

Artificial intelligence method includes artificial neural network (ANN), Support Vector Machine (SVM) and Grey Theory. Kreider and Wang (Kreider & Wang, 1991) first introduced the neural network method into the prediction of building air conditioning equipment energy consumption. ANN was inspired by the biological structure of the human brain, in analogy to the function of the neuron. They learn the relationship between the input and output variables by studying previously recorded data. ANN is designed as an information processing systems, which is non-algorithmic, non-digital, and intensely parallel.

Regression analysis is a method often used for data analysis in various fields of study. Recently, this approach has begun to be adopted for the prediction of district energy consumption. Dotzauer et al. (Dotzauer & Stang, 2002) proposed two models of thermal load via factors of temperature outdoor and human behaviour to predict district thermal load in Stockholm. Pedersen et al. (Pedersen et al. 2008) used 2 regression models to predict the building thermoelectric load on the basis of measured regional thermoelectric values. These studies have confirmed that the application of regression analysis can be adopted as an effective method assessing the district energy consumption.

However, AIM is not accurate enough and it may overestimate district building energy consumption. AI and Regression analysis need a large number of historical data for calculation, especially for prediction of district energy consumption. At present, it is difficult to provide a large amount of accurate energy consumption data in China. Besides, using AI or simulation, parameter input and detail operation will take a lot of time. In summary, all the prediction methods above have limitations and in inapplicability.

DETAILED METHOD

The research consists of four steps. Typical geometric parameters ranges of buildings in office district are derived from the sample survey. Based on orthogonal experiment and energy consumption influence factors, the buildings in the office blocks are classified and established into all kinds of standard models. This enables detailed building energy consumption simulation on standard building prediction. In the last section, the method of optimizing AIM by adopting Bayesian theory is discussed, in order to better predict the district energy consumption. The prediction framework of this study is summarized in Fig.1.

Sample survey

A survey of 100 office-buildings is conducted in Harbin, a representative of northeast city in cold regions of China. The samples accounted for 43.5% of the total of office building built from 2003 to 2013. In addition, the basic characteristics of 32 subsidiary buildings have been investigated. The data derived from the sample survey provides basic information for standard models and morphological data sets.

The sample survey is fulfilled by measurement, questionnaire and interview. And the investigation is accomplished via building design features including shape parameters, function organization and other general building information, which have a significant impact on the energy consumption of a building. Design factors affecting energy consumption in cold regions of China are put forward according to analysis of the calculation method of energy consumption. Eq. (2) shows calculation formula of energy consumption of buildings in cold regions.

$$q_H = q_{H\cdot\mathrm{T}} + q_{INF} - q_{I\cdot H} - q_s \tag{2}$$

Eq. (3) illustrates heat transfer per unit area of building envelope.

$$q_{H\cdot\mathrm{T}} = {\sum K_i F_i (t_i - t_e)}/{A} \tag{3}$$

Eqs. (4) (5) can be used to calculate air infiltration heat consumption per unit area (q_{INF}) and heat inside the building ($q_{I\cdot H}$). Radiant heat of the building (q_S) is related to solar radiation of vertical surface hourly and window area (Davide, 2011), which can be evaluated by energy simulation software.

$$q_{INF} = {NVFc_\rho \rho (t_i - t_e)}/{A} \tag{4}$$

$$q_{I\cdot H} = q_{personnel} + q_{lightening} + q_{\mathrm{devices}} \tag{5}$$

In the previous study, design factors affecting energy demand is summarized as building shape coefficient (S), surface-area coefficient, building orientation, the size of width and depth and ratio of window to wall (WWR) (Liu et al, 2009) (Houcem et al, 2010).

Considering the formulas and analysis above, these factors are classified into 2 ranks: morphological parameters and non-morphological parameters (Tab.1), which offers essential information for investigation and parameters settings of simulation. These summarized morphological parameters are the direct design factors, which are easy for architects to use and control. The ranges of the design factors and typical morphological data set according to the survey are shown in Tab.2.

The establishment of standard building models

The principle of office buildings classification complies with the following conditions:

- A similar level of energy consumption
- Similar characteristics of energy consumption
- A similar unit area index

The processes of grouping buildings can be divided into two steps: first, the architectural function; secondly, the office building scale (Huang et al, 1991) (Chow et al, 2004). In this study, office buildings and the affiliated business buildings are classified into two groups (Tab.3). According to the previous study (Zhang et al, 2013) (Wang, 2010) and analysis above, the large buildings cover an area of_over 2000 m^2 while the small buildings cover less than 2000 m^2.

Design factors affecting energy consumption in cold regions of China are illustrated in Tab.1, from which it can be inferred that the impact factors related to the building models are the morphological parameters. It is pointed out that the maximum influence factors of building energy consumption are S and WWR from the literature. In this study, it takes the geometric parameters to determine the model sample size, employing orthogonal experiment. The standard buildings discussed in this paper are the office buildings with rectangle shape and best building orientation. Office buildings have 4 factors with 3 levels, while the subsidiary commercial buildings have 3 factors with 3 levels (Tab.4), according to the factors and levels, and orthogonal table defined as $L_9(3^4)$(Tab.5). The sample capacity and geometric parameters of standard buildings are shown in Tab.6.

Simulation

After developing the typical morphological data set from sample survey, the models are built in Open Studio and simulation experiments are produced in Energy plus 7.2.0 regarding detailed weather file of Harbin. Energy plus 7.2.0 is a powerful building energy and thermal simulation software, considering the thermal exchange by the envelope and the influence of internal gains on air conditioning system performance in an hourly heat balance calculation. The simulation is performed in one typical city, since the main purpose of the research is to undertake a study into an optimized approach of district energy consumption prediction rather than to extend the conclusions to the locations under different climate conditions.

The building geometric parameters of the models for simulation refer to the typical morphological data set derived from the sample survey. Non-morphological parameters input for the simulation programs are on the basis of the < Design standard for energy efficiency of public buildings GB50189-2005> (tab.7).

The objects in this research are the buildings with no concrete information and the simulation model is simplified, which lead to a higher simulation result compared with the actual value. To modify the simulation value, governing error of 20% is adopted according to previous study (Chow et al, 2004).

A total of 18 models are simulated. Data derived from the experiments are used as the prior information in the Bayesian model for developing prediction model below.

Bayesian theory

To optimize the prediction of district energy consumption, a new method combining simulation, AIM and Bayesian theory are applied. Although the calculation results of standard building energy consumption employing simulation have certain representativeness, they fail to evaluate the energy consumption accurately by using area superposition method or characteristic curve. The statistical regression method relies on the regional energy consumption statistics. It is difficult to achieve, since the required data is too big. However, the accuracy will be improved if combing advantages of these methods as well as overcoming the shortcomings of these methods.

Bayesian theory is a statistical inference based on overall information, sample information and priori information. Overall information is the information offered by general distribution; and sample information is provided by the overall sample; while priori information is mainly from experience and historical data.

Two basic concepts of Bayesian theory are the priori distribution and posterior distribution. The priori distribution ($\pi(\theta)$) refers to a certain understanding before sampling, while the posterior distribution ($\pi(\theta/x)$) reflects the understanding after sampling, where the difference between them is the adjustment of θ after sample information appearance. The Bayesian model is represented as Eq. (6).

$$\pi(\theta/x) = \frac{p(x/\theta)\pi(\theta)}{\int p(x/\theta)\pi(\theta)d\theta} \tag{6}$$

Where x is the sample information of θ; $\pi(\theta)$ is the priori density; $\pi(\theta/x)$ is the posterior density; $p(x/\theta)$ is likelihood function. The posterior information ($\pi(\theta/x)$) is more effective and reasonable for the statistical inference of θ. Fig.2 illustrates the relation clearly.

The energy demand can be calculated according to Eq. (7) by putting the area together, after improving area superposition method based on the building classification research above.

$$Q = \sum_j^p q_j S_j \tag{7}$$

Where Q is energy consumption of buildings in office district, q_j is energy consumption per unit area of j kinds of buildings and can be called energy consumption forecasting factor; S_j is the total area of building district of the j buildings; p is the total number of the building types.

The problems of incomplete matching between the standard buildings and buidlings in the district as well as the issues of statistical randomness can be solved by using Eq.(8). And the formula of energy consumption prediction of office buidling district can be adjusted according to:

$$Q = \sum_j^p \left(q_j S_j + \varepsilon_j S_j\right) \quad (8)$$

Where ε_j is residual error of the energy consumption in a certain building district ($\varepsilon_j \sim N(0, {\sigma_{et}}^2)$).

The following regional energy consumption is related to the occurrence rate of the previously known standard building energy consumption. The previous understanding information (energy consumption of standard buildings) can be controlled and modified with the data of energy consumption, which was acquired from others office building district in the same climate zone.

From the analysis above, it is proved that Bayesian theory can be used to predict the regional office building energy consumption. The Bayesian modle caculates via method of Markov Chain Monte Carlo (MCMC), and the results is tested by validation method of relative error.

RESULTS

Prediction model of office district energy consumption

Based on Bayesian theory, posterior distribution $p(q/Q)$ of the event of existing district energy consumption is proportional to priori distribution $p(q)$ and density function $p(Q/q,S)$. It has built a bridge for the calculation of district energy building based on monomer building. Energy consumption of standard buildings is considered to obey the normal distribution. Conditional density of Q is represented as below:

$$p(Q/q,S) = (2\pi{\sigma_{et}}^2)^{-\frac{n}{2}} ept\left[-\frac{1}{2{\sigma_{et}}^2}(Q - Sq)^T(Q - Sq)\right] \quad (9)$$

The prediction model of energy consumption of office building district is summarized as Eq. (10).

$$Q = \sum_j^p q_j{}' S_j \quad (10)$$

Where $q_j{}'$ is energy consumption per unit area of j kinds of buildings. It is the posterior information and can be regarded as adjusted energy consumption forecasting factor. The procedure of building developing the prediction model is shown in Fig.3.

The model of simple area superposition method (Eq. (7)) is modified to a novel formula of energy consumption prediction model of office district (Eq. (10)). The posteriori information is finally obtained as prediction factor of district energy consumption, using the observation data and design value in the same climate as sample information to modify the priori information of standard buildings. And energy consumption prediction factor of standard buildings is optimized and updated.

Simplified formula for office district energy consumption

The sample of geometric parameters of each standard model is presented in Tab. 6.The sample contains different geometric parameters of each building type which basically reflects all kinds of buildings in the office block. S is under 0.3 meeting the regulations of energy conservation.

The simulation standard buildings in the sample set are conducted according to the typical parameter set determined in the survey. From the modified simulation results, q_j is obtained, which the average of the priori distribution. The detailed value of the priori information is shown in Tab. 8.

Six office districts are selected as the sample area randomly from the existing energy consumption statistics database. And the posterior information $q_j{}'$is caculated by the method of MCMC employing the programme MATLAB 8.3 (Tab.9). The formula for office district energy consumption is presented as below:

$$Q = 58.9S_{Os} + 69.5S_{Ol} + 119.9S_{cs} + 128.4S_{cl} \quad (11)$$

Where Q is the energy consumption of buildings in office blocks, S_{Os} is the area of middle and small offcie buiding, $S_{Ol}$is the area of large office buidling, $S_{cs}$is the area of smalle commercial building, $S_{cl}$is the area of large commercial buidling.

This formula is teseted by the data from office district A of the sample information. And the construction area is shown in Tab.10. The data caculation by area superposition method is value 1 and the data by the Bayesian model is value 2. The results of value 1, value 2 and measured value are compared with each other (Fig.4). The relative error of the area superposition method is over 30% and the new formula is less than 20%, which shows the superiority of the optimized method based on simulation and Bayesian theory.

CONCLUSION

This paper undertakes a study into an integrated prediction approach of district energy consumption of office buildings, which has the potential to overcome some difficulties remaining in the existing prediction method of district energy consumption.

- An overall comparison and analysis between exist prediction methods is conducted. The discussion points out that the necessity and advantages of combining simulation and regression.
- The study summarizes the influence factors of building energy consumption(Tab.1) A

set of typical morphological data for building types in office district derived from the sample survey are proposed (Tab.2).

- Buildings in office district are divided into 2 categories and 4 small classes according to the buidling classification theory (Tab.3). Orthogonal experiment method is adopted to determine the sample size of different types of buildings due to sample survey and the existing research, the detailed data is shown in Tab.6. Delicate simulation models of standard buildings are developed to acquire the priori information.
- The prediction model (Eq.(10)) based on Bayesian theory modifies the priori information from the simulation results into posterior information, by the sample information coming from the statistical data, so as to enable the optimization of area superposition model.
- The prediction formula (Eq.(11)) allows designers to calculate energy consumption during the schematic design phrase of district office buildings. The scope of application is for the office districts in Harbin. When the construction scale of an office district planning is determined, the architects can obtain the value of district energy consumption by inputting the construction scale of different building types.

An important challenge of this study is that the classification of buildings needs to be further refined, so that the standard builidng can represent the actual building more accuratly. The sample information of this study does not have enough statistical data. More timely detection energy consumption data is necessary for ensuring the accuracy of the prediction model. This appoach can extend into other cities in various climatic regions, while a large amount of sample surveys and simulation experience are needed to improve the model.

NOMENCLATURE

AIM, the area index method;
AI, artificial intelligence;
ANN, artificial neural network;
Q, total energy consumption of buildings;
q, building energy consumption index of unit area;
F, total building area;
SVM, Support Vector Machine;
q_H, energy consumption of per unit building area;
$q_{H\cdot T}$, heat transfer per unit area envelope;
K_i, heat transfer coefficient of building envelope;
F_i, area of building envelope;
t_i, indoor temperature;
t_e, outdoor temperature;
A, construction area;
q_{INF}, air infiltration heat consumption per unit area;
N, rate of ventilation;
V, volume of ventilation;
C_ρ, specific heat capacity of air;
ρ, density of air;
$q_{I\cdot H}$, internal heat of unit building area;
$q_{personnel}$, heat of personnel;
$q_{lightening}$, heat of lighting;
q_{devices}, heat of devices;
S, building shape coefficient;
WWR, ratio of window to wall;
MSE, lowest mean square error;
$\pi(\theta)$, the priori density;
$\pi(\theta/x)$, the posterior density;
Q, energy consumption of buildings in office district;
q_j, energy consumption forecasting factor;
S_j, the total area of building district of the j building;
p, total number of the building types;
ε_j, residual error of the energy consumption in a certain building district;
$q_j{}'$, adjusted energy consumption forecasting factor;
$MCMC$, Markov Chain Monte Carlo;
$SWWR$, ratio of window to wall on south facade;
$NWWR$, ratio of window to wall on north facade;
$EWWR$, ratio of window to wall on east facade;
$WWWR$, ratio of window to wall on west facade.

ACKNOWLEDGEMENT

The authors would like to acknowledge that this paper is financially supported by The National Science Foundation of China (Grant No. 51278149).

REFERENCES

Jin Hongguang, Zheng Danxing, Xu Jianzhong. 2008. Device and application of distributed combined cooling heating and power system, China Electric Power Press.

Yuan Xiang, Long Weiding. 2008. Prediction of cooling load of regional buildings with scenario analysis, HVAC.

Stevanovic V D, Zivkovic B, Prica S, et al. 2009. Prediction of thermal transients in district heating systems, Energy Conversion and Management.

Huang Y J, Akbari H, Rainer L, et al. 1991. 481 Prototypical commercial buildings for 20 urban market areas, Lawrence Berkeley Laboratory Applied Science Division Berkeley.

Chow T T, Chan A L S, Song C L. 2008. Energy modelling of district cooling system for new urban development, Applied Energy.

Kreider J F, Wang X A. 1991. Artificial neural networks demonstration for automated generation of energy use prediction for commercial buildings, ASHRAE Trans.

Dotzauer E, Stang J. 2002. Simple model for prediction of loads in district-heating systems, Applied Energy.

Pedersen L, Stang J, Ulseth R. 2008. Load prediction method for heat and electricity demand in buildings for the purpose of planning for mixed energy distribution systems, Energy and Buildings.

Liu Jiaping, Tan Liangbin, He Quan. 2009. Energy saving design of architectural, China Architecture & Building Press.

Houcem Eddine Mechri, Alfonso Capozzao li, Vincenzo Corrado. 2010. Use of the ANOVA approach for sensitive building energy design, Applied Energy.

Zhang Xiaotong, Liu Jinxiang, Chen Xiaochun et al. 2013. Sensitivity analysis and Forecast Method Research on the influence factors of district cold (hot) load, Building Science.

Wang Zhengjiang. 2010. Study on predicting method of building cooling load in urban energy planning, Dalian University of Technology.

Figures and Tables

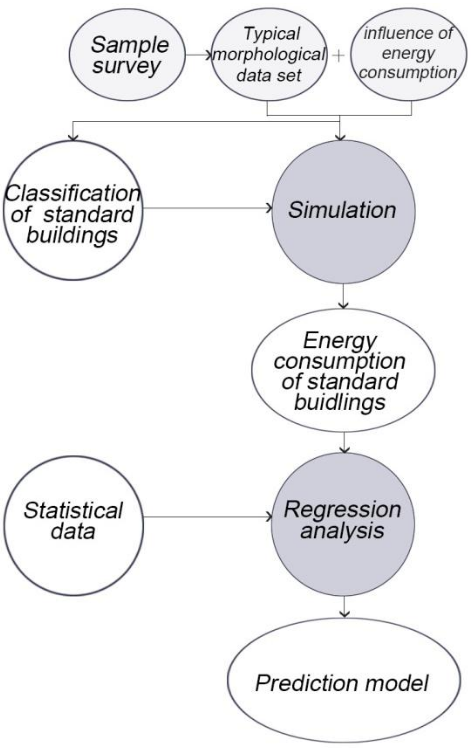

Figure 1 The framework of the study

Table 1 Classification of building energy consumption influencing factors

COMPONENT OF BUILDING ENERGY CONSUMPTION	MORPHOLOGICAL ELEMENTS	NON-MORPHOLOGICAL ELEMENTS
building envelope heat transfer& energy consumption	area of each building component	heat transfer coefficient
		indoor and outdoor air temperature
		heat transfer correction of building envelope
heat of air infiltration per building area	building envelope bounder area	air density
		specific heat capacity
		air change rate
		ventilation volume
heat inside	plane area	heat emission of human activities
		heat emission of lighting
		heat emission of devices
building radiant heat	opening area of window	hourly solar radiation on vertical surface

Table 2 Typical morphological data set

GEOMETRIC PARAMETERS	RANGE OF PARAMETERS	
	OFFICE BUIDLING	AFFILIATED COMMERCIAL BUILDING
building plane form	rectangle	square
building orientation	-60°	-60°
width	40m~100m	40m~80m
depth	20m~40m	40m~80m
height of one layer	3.6m~4.2m	4.5m~4.8m
building storey	5~10	3~6
window width on south facade	1800mm~2400 mm	1500mm~2400 mm
window height on south facade	1500mm~2400 mm	1500mm~2700 mm
window width on north facade	1800mm~2100 mm	1500mm~2400 mm
window height on north facade	1500mm~2400 mm	1500mm~2700 mm
window width on east facade	900mm~1500mm	900mm~2100mm
window height on east facade	1500mm~2400 mm	1500mm~2700 mm
window width on west facade	900mm~1500mm	900mm~2100mm
window height on west facade	1500mm~2400 mm	1500mm~2700 mm
SWWR	0.15~0.18	0.15~0.18
NWWR	0.13~0.15	0.12~0.15
EWWR	0.13~0.15	0.13~0.15
WWWR	0.13~0.15	0.12~0.15

Table 3 Classification of various types of standard buildings

BUILDING TYPES	LEVEL	FACTORS
office district	office building	middle and small office building
		large office building
	commercial building	small commercial building
		large commercial building

Table 4 Factors and Levels of buildings

BUILDING TYPES	LEVEL	FACTORS			
		length	width	Lay-ers	WWR
office building	1	60m	30m	6	0.15
	2	100m	40m	10	0.16
	3	40m	20m	15	0.18
subsidiary commercial building	1	40m	40m	6	0.15
	2	60m	60m	6	0.16
	3	80m	80m	6	0.18

Table 5 Orthogonal table of $L_9(3^4)$

EXPERIMENT NUMBER	COLUMN			
	1	2	3	4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Table 8 The priori information (W/m^2)

BUILDING TYPES	ENERGY PER TOTAL BUIDLIGN AREA
middle and small office buildings	64.8
large office buildings	77.6
small commercial building	115.1
large commercial building	125.8

Table 7 Non-morphological parameters

PARAMETERS	RANGE OF PARAMETERS
latitude and longitude	E126°， N45°
landform environment	City
air Specific Heat	0.28Wh/(kg · K)
climate region	I(A)
air density under T_e	1.332Kg/m^2
heat transfer coefficient of roof	0.35W/(m^2 · K)
heat transfer coefficient of outer wall	0.45W/(m^2 · K)
heat transfer coefficient of south window	2.8W/(m^2 · K)
heat transfer coefficient of north window	2.8W/(m^2 · K)
heat transfer coefficient of east window	3.0W/(m^2 · K)
heat transfer coefficient of west window	3.0W/(m^2 · K)
working days per week	Monday to Friday
office electrical appliances	20W/m^2
heat insulation coefficient of lamp shade	0.8
daily working hours	8am-9pm, 10hr
ventilation frequency	2(1/h)

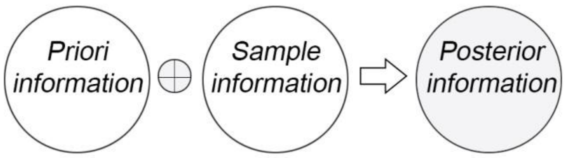

Figure 2 Relationship of information

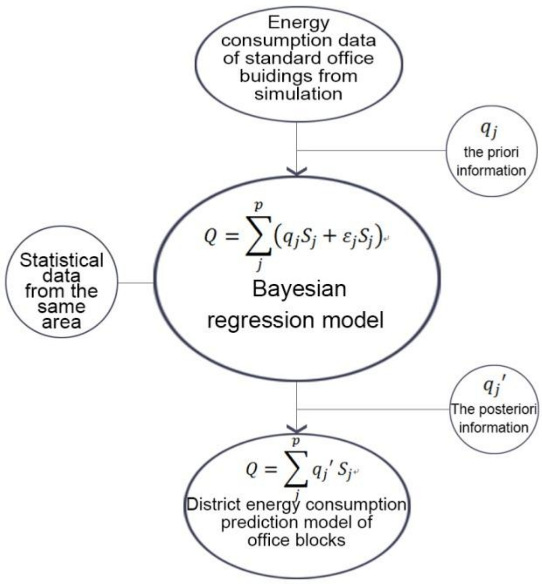

Figure 3 Framework of building the district energy consumption prediction model of office building

Table 9 The posterior information (W/m^2)

BUILDING TYPES	ENERGY PER TOTAL BUIDLIGN AREA
middle and small office buildings	58.9
large office buildings	69.5
small commercial building	119.9
large commercial building	128.4

Table 10 Constriction area of various types of buildings in district A (W/m^2)

BUILDING TYPES	AREA	STOREY	REM-ARKS
middle and small office buildings	86400m^2	6/12	6
large office buildings	57660 m^2	16	2
small commercial building	12800 m^2	4	2
large commercial building	38400 m^2	6	1

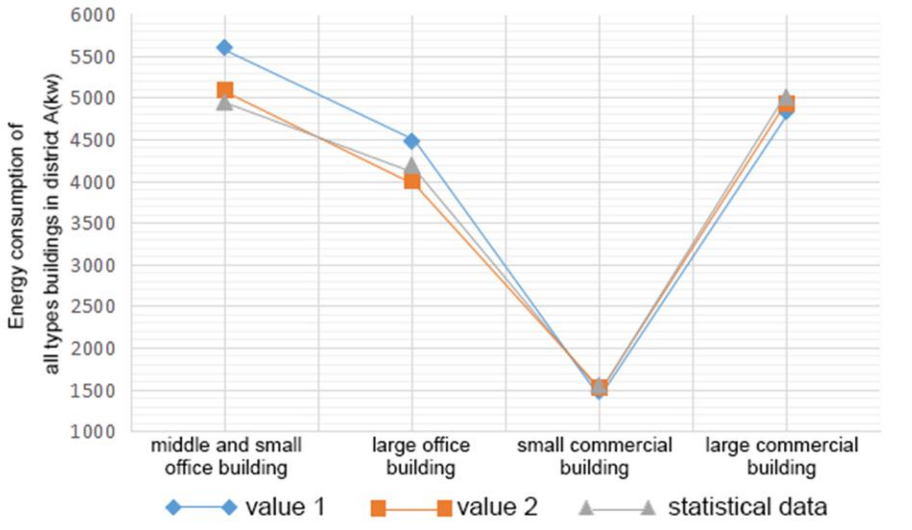

Figure 4 Comparison of the results of value 1, value 2 and measured value

Table 6 Sample capacity and geometric parameters of standard buildings

BUILDING TYPE	EXPERIMENT NUMBER	LENGTH	WIDTH	HEIGHT	WWR	BUIDING AREA	*S*(1/M)
middle and small office buildings	1	40m	20m	4m×6	0.15.	4800m^2	0.20
	2	40m	30m	4m×10	0.16	12000m^2	0.15
	3	60m	20m	4m×10	0.18	12000m^2	0.16
	4	60m	40m	4m×6	0.16	14400m^2	0.13
	5	100m	30m	4m×6	0.18	18000m^2	0.13
large office building	1	40m	40m	4m×15	0.18	24000m^2	0.12
	2	60m	30m	4m×15	0.15	27000m^2	0.12
	3	100m	20m	4m×15	0.16	30000m^2	0.14
	4	100m	40m	4m×10	0.15	40000m^2	0.10
small commercial building	1	40m	20m	4.5m×6	0.15	4800m^2	0.14
	2	40m	30m	4.5m×6	0.16	18000m^2	0.12
	3	60m	20m	4.5m×6	0.18	18000m^2	0.11
	4	60m	40m	4.5m×6	0.18	14400m^2	0.12
	5	80m	30m	4.5m×6	0.16	14400m^2	0.11
Large commercial building	1	40m	40m	4.5m×6	0.15	48000m^2	0.10
	2	60m	30m	4.5m×6	0.16	54000m^2	0.10
	3	80m	20m	4.5m×6	0.18	48000m^2	0.10
	4	80m	40m	4.5m×6	0.15	48000m^2	0.09