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Towards fast energy performance evaluation: A pilot study for office buildings

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ABSTRACT

Given the growing concern about building energy efficiency and the difficulty in applying complex simulation tools during retrofit practices, the need for easily and quickly estimating the building energy performance becomes pressing. As a pilot test, this study proposes a systematic method to develop a model, which can immediately assess the annual electricity consumption for office buildings with fan coil system in Shanghai. First, a base-case building model is established by EnergyPlus to create a pool of candidate inputs using orthogonal experiment design. Then, analysis of variance is used to identify a total of 10 key building design parameters, which are selected as the input variables in the support vector regression (SVR) model based on a well-structured database. The performance of SVR is optimized using genetic algorithm (GA) based on radial basis function kernel. Finally, two real office buildings in Shanghai with reliable measured data serve to evaluate the developed hybrid model. The resulting differences between the predicted and measured values are generally within 10%. It is expected that the developed database and model can be used to assess the likely energy savings/penalty related with certain parameter changes to some extent during the retrofit process for office buildings.

1. Introduction

For building professions throughout the world, energy is one of the key issues in the overall efforts to realize sustainable development [1]. According to International Energy Agency (IEA), buildings represent about 32% of total final energy use [2]. In terms of primary energy consumption, buildings account for around 40% in most IEA countries [2]. These figures could be higher in major cities (e.g. Shanghai), due partly to the significant economic growth and the shift of local economy from manufacturing-oriented to service-based. In the meantime, office building is one of the fastest growing parts in the building sector, particularly in some major cities of China [3]. Energy efficiency is thus of great importance to sustainable building design, especially for office buildings.

During the past decades, researchers have made great efforts in the improvement of building energy efficiency. In particular, building energy prediction has drawn increasing attention [4,5], since it is valuable to develop various retrofit concepts and strategies for enhancing building energy performance. Examples of the computer simulation introduced into architectural and engineering retrofit practices are DOE-2 [6], EnergyPlus [7], TRNSYS [8], etc. However, discussions with architects and engineers have revealed that full hourly physics-based building energy simulations are usually complicated, costly and time-consuming. Instead, most building owners and stakeholders, who lack unique expertise and resources, tend to depend on rule-of-thumb assessments. These approaches, though initially inexpensive, may result in design strategies for isolated measures without considering interactive effects between the measures. Such case will remain a challenge for maximizing the energy savings or economic benefits. Thus, there is a need for simple estimation models, especially during the decision making process when various energy retrofit concepts and schemes need to be quickly considered and compared.

Many previous studies have developed some simple energy prediction models for commercial and office buildings by using regression analysis [9–15]. But few models have been updated on recent performances of parameters in the building system, as well as have been validated or evaluated through real cases. In addition, many existing studies mainly adopted simple methods to select input variables and develop linear models, indicating the possibility that some useful information may be underestimated in a non-linear building system. Therefore, more advanced techniques and more sound energy audits of real buildings are needed to develop and evaluate related models for improving the accu-

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Nomenclature

c	Regularization constant
Err_i	Relative error between predicted and measured values for building i (%)
F	F-test value
f	Degree of freedom of the error
f	Degree of freedom of factor j
g	Inverse width of Gaussian radial basis function
n	Number of measurements
R^2	Coefficient of determination
SS_A	Sum of squared deviations
V_A	Variance
$\bar{Y}$	Mean of measured and predicted values
Y	Measured value for building i
$\hat{Y}_i$	Predicted value for building i

Abbreviation

AEC	Annual electricity consumption (kWh/m^2 a)
ANN	Artificial neural network
ANOVA	Analysis of variance
COP	Coefficient of performance
CSWD	Chinese standard weather data
COMBAT	Commercial building analysis tool
DEEP	Database for energy efficiency performance
DOE	Department of energy
EQ	Equipment load density (W/m^2)
FCU	Fan coil unit
FE	Fan efficiency
FEMP	Federal energy management program
GA	Genetic algorithm
HPC	High performance computing
HVAC	Heating, ventilation, and air-conditioning
IEA	International energy agency
LBNL	Lawrence Berkeley national laboratory
LL	Lighting load density (W/m^2)
MSE	Mean square error
OED	Orthogonal experiment design
OP	Occupant density (m^2/person)
PAT	Parametric analysis tool
PE	Pump efficiency
RBF	Radial basis function
SC	Shading coefficient of window
Sig	Significance
SST	Summer set point temperature (°C)
SVR	Support vector regression
WU	Window U-value (W/m^2 K)
WWR	Window-to-wall ratio

racy and stability of building energy predictions. These practical reasons motivate the authors to make an exploration of the non-linear performance for estimating building energy consumption by using hybrid statistical techniques.

To provide an easy and reliable solution for fast energy retrofit estimation, a large set of simulations performed by experts seems to be necessary. Although the pre-simulated method has some limitations, such as the geometrical mismatch between the prototype and actual buildings, it still can give us an immediate and authentic energy estimation. Some massive pre-simulated databases developed in the past five years include the LBNL's COMBAT (Commercial Building Analysis Tool) [16] and DEEP (Database for Energy Efficiency Performance) [17], Energy Impact Illinois' EnCompass [18], and US DOE's 179D easy calculator [19]. With recent advancement in computing environment, executions of large scale simulations

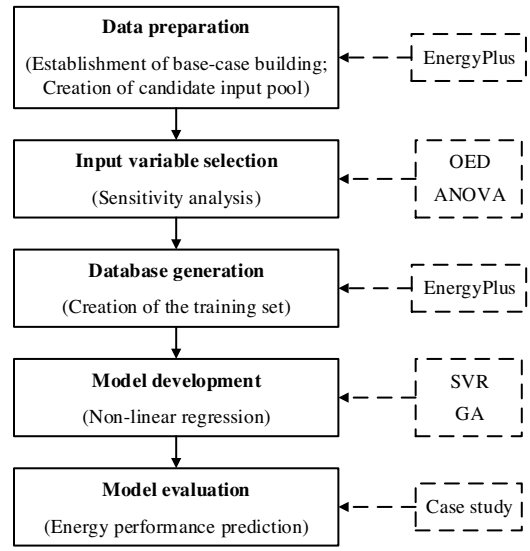

Fig. 1. Schematic outline of the research.

for building energy database development can offer users more new resources to conduct reliable energy estimations quickly. However, the work is usually challenging and expensive, which makes the building energy modeling sometimes unfeasible to small projects. In order to promote the use of these resources, there is an increasing need for a systematic establishment of the energy performance database.

As a pilot test, this study intends to develop an energy prediction model, which can easily estimate the annual electricity use of office buildings with FCU system in Shanghai. Fig. 1 shows the schematic outline of the present research, which includes five main aspects:

(i) Establishment of a base-case model for the office building to generate simulation data for the study.
(ii) Identification of key design variables for the office building using sensitivity analysis technique.
(iii) Generation of an energy use database via a series of simulations using orthogonal experiment design.
(iv) Development of a prediction model based on the pre-simulated database using support vector regression.
(v) Evaluation of the developed model against the measured data from two office buildings in Shanghai.

The resulting database and model are expected to provide a simple direct decision making process for helping estimate the energy-saving potential of some energy conservation measures to retrofit existing office buildings quickly.

2. Base-case building design

EnergyPlus [7] is employed as the simulation tool in the present study because it can provide the capability to simulate a wide range of building design features and energy conservation measures. Although EnergyPlus can perform energy modeling with a good accuracy, it is quite complex and error-prone to conduct such a large number of simulations due to the huge amount of data to be analyzed. To ensure model robustness and consistency, great care should be taken to first establish the model building in a simplified form, and then to refine the building system with more details.

A base-case office building is created to serve as a baseline reference, which is of great importance since all the subsequent calculations and analyses are performed based on it. The established base-case model is a 12-storey office building (40 m × 40 m)

Table 1
Summary of parameter inputs of the base-case building.

Input parameter	Value
Building load	
Orientation	N-S
Roof U-value	0.6 W/(m^2 K)
Wall U-value	1 W/(m^2 K)
Window U-value	3 W/(m^2 K)
Window-to-wall ratio	0.4
Shading coefficient of window	0.5
Equipment load density	13 W/m^2
Lighting load density	11 W/m^2
Occupant density	6 m^2/person
Infiltration rate	0.1 ACH
HVAC system	
Heating/cooling	Gas-fired boiler/centrifugal chiller
Outdoor fresh air	30 m^3/(h person)
Summer set point temperature	24 °C
Winter set point temperature	22 °C
Fan efficiency	0.7
HVAC plant	
Chiller COP	5.5
Chilled water temperature	7/12 °C
Cooling water temperature	32/37 °C
Pump efficiency	0.7

with the curtain-wall design and a centralized HVAC system. The floor-to-floor height is 4m, and the gross floor area is 19,200 m^2. The air-conditioning design is set as fan coil system with five air-conditioned zones – four at the perimeter and one interior (20m × 20 m). The building and HVAC systems operate on a 10 h day (08:00–18:00) and a 5-day week basis. The descriptions of the base-case model are based on careful selections of typical design and construction with corresponding data taken from local building design/energy codes [20] and prevailing engineering practices. A summary of key input parameters is shown in Table 1. Apart from the building descriptions, the external weather data is another vital factor in the simulations. In this study, Chinese standard weather data (CSWD), including hourly records of prevailing weather conditions in Shanghai, is selected for the simulations.

The annual electricity use per unit gross floor area of the base-case building is predicted to be 101.94 kWh/m^2. Besides, the predicted electricity consumption patterns show distinct seasonal variations with peak electrical demands occurring in the summer months. These simulated results of the base-case model are highly consistent with the monitored results of over 600 local office buildings in Shanghai [21]. Thus, we can confidently expect that the base-case model can represent a typical office building in Shanghai, and can be applied in the following sensitivity analysis and prediction model development.

3. Parametric simulation and sensitivity analysis

Before developing the prediction model, it is important to determine what input variables are to be studied. Selecting and defining the key input variables is often an arduous task which requires a sensible engineering judgment and a good understanding of the building system.

Sensitivity analysis is the study of whether and how the output of a system is influenced by different inputs [22]. It offers to researchers the insight as to what is important and what is not in a specific system. Theoretically speaking, sensitivity analysis has two separate and distinct steps: (1) experiment design and (2) statistical analysis. In practice, the energy performances of many building systems have been examined and optimized through a series of one-factor-at-a-time experiment designs [11–13,23,24], in which most factors in the system are set constant while one factor is focused on and varied to evaluate its effect. This experiment design, though acceptable, has the disadvantage that it may yield grossly biased estimates of factor effects. On the other hand, few studies have explored the application of orthogonal experiment design, which has good properties for parametric simulations, to optimize the building design for energy consumption. Thus, the objective of this section is to create a pool of candidate inputs, to apply the orthogonal experiment design for collecting the data, and to identify the key system components using analysis of variance.

Table 2
Factors and levels of the orthogonal experiment design for sensitivity analysis.

Factor	Parameter	Unit	Level		
			1	2	3
A	Building orientation	deg	0	15	30
B	Window-to-wall ratio	–	0.35	0.45	0.7
C	Wall U-value	W/(m^2 K)	1.5	1	0.5
D	Window U-value	W/(m^2 K)	3.5	3	2.5
E	Shading coefficient of window	–	0.55	0.5	0.45
F	Summer set point temperature	°C	24	26	28
G	Winter set point temperature	°C	22	20	18
H	Occupant density	m^2/person	4	6	8
I	Lighting load density	W/m^2	11	15	18
J	Equipment load density	W/m^2	20	17	13
K	Fan efficiency	–	0.6	0.7	0.8
L	Chiller COP	–	4.5	5.5	6.5
M	Pump efficiency	–	0.6	0.7	0.8

Note: The building orientation is defined as the degree to which the building axis deviates from the north axis.

3.1. Selection of candidate input parameters

A list of input variables, which represents a variety of different factors encountered in the building design, should be prepared to enhance the value of the pre-simulated database. These are the options that architects and engineers will consider during different stages of the design or retrofit process. About 36 input parameters in total can be deduced and categorized into three main groups [13]: building load, HVAC system, and HVAC plant. According to Lam and Hui [23], each main group can be further divided into different sub-groups:

- Building load: building envelope, building configuration, space condition, and building thermal mass.
- HVAC system: system operation, fans and air handling, and system control.
- HVAC plant: refrigeration and heat rejection, chilled water pump and boiler, and chilled water circuit.

The effectiveness of energy conservation measures depends on the building characteristics, such as location, size, building envelope, HVAC system properties, etc. Based on previous studies [9–15,23,24] and local engineering practices, a total of 13 design parameters are selected in the parametric simulations for the present study. These parameters are the common retrofit techniques used for office buildings in Shanghai. Perturbations are introduced by assigning a range of different numerical levels to each input parameter for the subsequent experiment design. Table 2 illustrates a summary of the 13 parameters and the corresponding levels used in the parametric simulations. These values are taken based on local building design codes [20], detailed surveys of real buildings and prevailing engineering practices in order to include most possible scenarios, even though some values may exceed the range of thermal comfort. For the remaining unselected variables, the corresponding values are taken from the data shown in Table 1. It is envisaged that this candidate input pool is created with reasonable considerations for the following experiment design and statistical analysis.

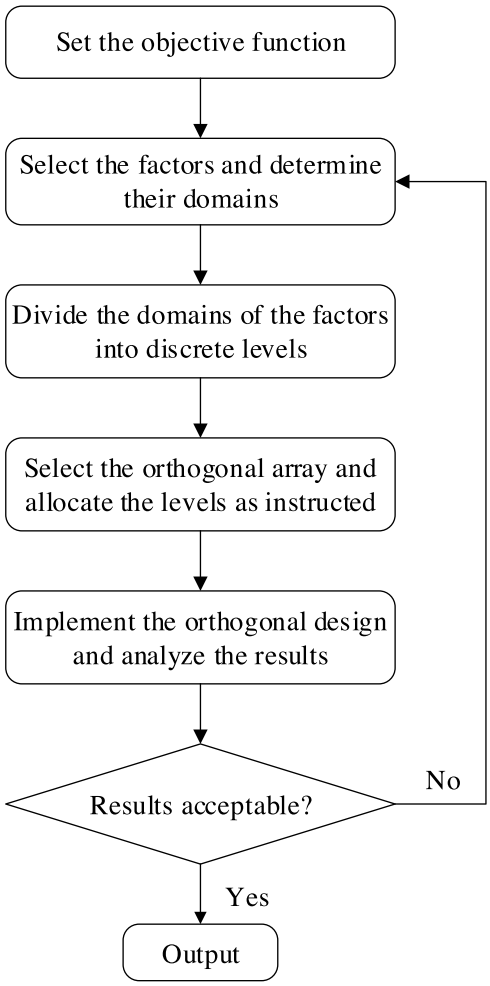

Fig. 2. Orthogonal experiment design procedure.

3.2. Orthogonal experiment design

Orthogonal experiment design (OED) is a commonly used experiment design method for sensitivity analysis [25,26]. It selects representative data points from full factorial design in a way that these points are distributed evenly within the test range. Thus the primary virtue of OED is that it uses only a fraction of the runs needed for full factorial design, while still yields good effect estimates (small bias and high precision). OED is usually developed based on the orthogonal array [26], which makes the design fast, efficient and economical. Fig. 2 depicts the orthogonal experiment design procedure in detail. Considering the superiority of OED to obtain excellent sensitivity analysis conclusions, we select OED as the method for the experiment design.

Factors and levels are shown in Table 2. The 13 parameters are selected as the control factors labeled as A–M. Each factor has three levels represented by digits 1–3. The orthogonal array $L_{27}(3^{13})$ [26] is used for the design, as shown in Table 3. The 27 indicates 27 trials. The 3 indicates the number of levels. The 13 indicates the maximum number of factors. The 13 control factors are assigned to the columns, and the 27 trials are allocated to the rows. Each level is repeated the same number of times (9) in each column. For each trial, the annual building electricity consumption in kWh/m^2 is calculated using EnergyPlus, as shown in Table 3. Effects due to the coupling between various factors will be investigated in the future.

Table 3
The $L_{27}(3^{13})$ orthogonal array and the experiment results for sensitivity analysis.

No.	A	B	C	D	E	F	G	H	I	J	K	L	M	AEC
1	1	1	1	1	1	1	1	1	1	1	1	1	1	136.07
2	1	1	1	1	2	2	2	2	2	2	2	2	2	115.88
3	1	1	1	1	3	3	3	3	3	3	3	3	3	101.80
4	1	2	2	2	1	1	1	2	2	2	3	3	3	119.71
5	1	2	2	2	2	2	2	3	3	3	1	1	1	119.34
6	1	2	2	2	3	3	3	1	1	1	2	2	2	108.89
7	1	3	3	3	1	1	1	3	3	3	2	2	2	124.57
8	1	3	3	3	2	2	2	1	1	1	3	3	3	113.47
9	1	3	3	3	3	3	3	2	2	2	1	1	1	117.17
10	2	1	2	3	1	2	3	1	2	3	1	2	3	108.76
11	2	1	2	3	2	3	1	2	3	1	2	3	1	127.30
12	2	1	2	3	3	1	2	3	1	2	3	1	2	112.88
13	2	2	3	1	1	2	3	2	3	1	3	1	2	138.26
14	2	2	3	1	2	3	1	3	1	2	1	2	3	97.28
15	2	2	3	1	3	1	2	1	2	3	2	3	1	115.90
16	2	3	1	2	1	2	3	3	1	2	2	3	1	105.78
17	2	3	1	2	2	3	1	1	2	3	3	1	2	104.71
18	2	3	1	2	3	1	2	2	3	1	1	2	3	144.01
19	3	1	3	2	1	3	2	1	3	2	1	3	2	120.31
20	3	1	3	2	2	1	3	2	1	3	2	1	3	103.32
21	3	1	3	2	3	2	1	3	2	1	3	2	1	124.00
22	3	2	1	3	1	3	2	2	1	3	3	2	1	90.05
23	3	2	1	3	2	1	3	3	2	1	1	3	2	129.83
24	3	2	1	3	3	2	1	1	3	2	2	1	3	131.42
25	3	3	2	1	1	3	2	3	2	1	2	1	3	121.10
26	3	3	2	1	2	1	3	1	3	2	3	2	1	141.48
27	3	3	2	1	3	2	1	2	1	3	1	3	2	93.47

Table 4
The analysis of variance for annual electricity consumption.

Factor	SS_A	f	V_A	F_j	Sig
A	0.29	2	0.15	1.0	○
B	17.23	2	8.61	59.0	⋆
C	2.72	2	1.36	9.3	○
D	6.94	2	3.47	23.8	⋆
E	14.09	2	7.05	48.3	⋆
F	1080.67	2	540.33	3704.1	⋆⋆
G	1.76	2	0.88	6.0	○
H	116.46	2	58.23	399.2	⋆⋆
I	1949.10	2	974.55	6680.7	⋆⋆
J	1826.75	2	913.38	6261.3	⋆⋆
K	22.29	2	11.15	76.4	⋆
L	178.54	2	89.27	612.0	⋆⋆
M	80.53	2	40.26	276.0	⋆⋆
Error	0.29	2	0.15		
Total	5297.36	26	2648.83		

Note: (a) The critical F value for different significance levels are: $F_{0.01}(2,2) = 99$ and $F_{0.05}(2,2) = 19$; (b) ⋆⋆ represents a highly significant ⋆ relatively significant, and ○ statistically insignificant.

3.3. Variance analysis for annual electricity consumption

Analysis of variance (ANOVA), which can largely reduce the number of required experiments and can achieve good results, is one of the most versatile statistical methods. In this study, the variance analysis and F-test [25] are performed to distinguish the effect of the factor from the fluctuation errors and to assess the statistical significance of each factor. The influencing factor with a larger variance value is indicated to have a greater impact on the system performance. Also, the significance of the influencing factor can be judged by comparing the F-test value and critical F value. Meanwhile, the contribution rate of each influencing factor is introduced to evaluate the relative importance. It is defined as the percentage ratio between the variance of each influencing factor and the sum of all the influencing factor variance.

The results are shown in Table 4 and Fig. 3. For the degrees of freedom ($f_j = 2$ and $f_e = 2$), the critical F values for different levels are: $F_{0.01}(2,2) = 99$ and $F_{0.05}(2,2) = 19$. The subscripts 0.01 and 0.05

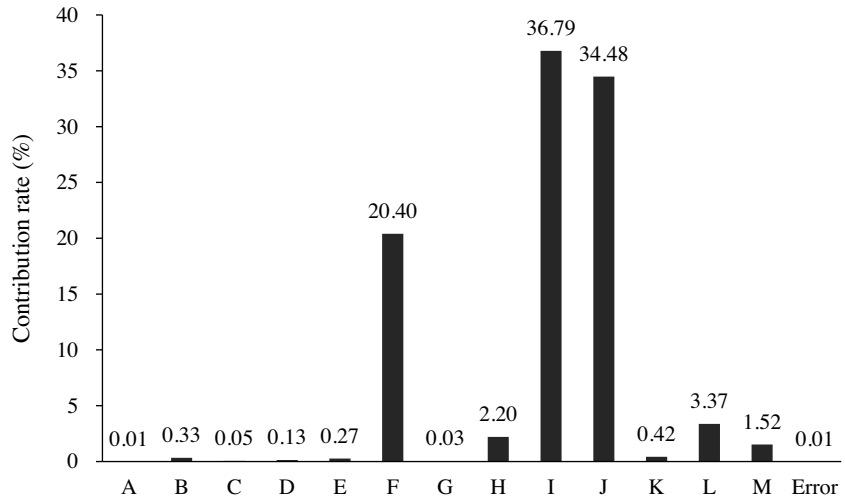

Fig. 3. Effect of experiment factors on annual building electricity consumption.

indicate a confidence level of 99% and 95% respectively. A larger *F*-test value compared to the critical *F* value means that the impact of the corresponding factor on the annual building electricity consumption is more significant than that of the error. In this study, the significance of each factor is divided into three levels based on the following rules:

(i) If $F_j > F_{0.01}(f_j, f_e)$, factor j is highly significant (marked as ★★).
(ii) If $F_{0.05}(f_j, f_e) < F_j < F_{0.01}(f_j, f_e)$, factor *j* is relatively significant (marked as ★).
(iii) If $F_j < F_{0.05}(f_j, f_e)$, factor *j* is statistically insignificant (marked as ○).

The *F*-test values of the summer set point temperature (F), occupant density (H), lighting load density (I), equipment load density (J), chiller COP (L) and pump efficiency (M) are greater than $F_{0.01}(2,2)$. This indicates that these six factors are highly significant to the annual building electricity consumption. Besides, the window-to-wall ratio (B), window U-value (D), shading coefficient of window (E) and fan efficiency (K) are found to be relatively significant. In contrast, the building orientation (A), wall U-value (C) and winter set point temperature (G) tend to exert nearly no impact on the annual building electricity use.

It is worth noting that the lighting load density (I) and equipment load density (J) have significantly high *F*-test values, indicating their crucial importance in the energy performance of office buildings. This can be attributed to their dual effects on the system behavior. On one hand, the lighting/equipment load density can affect the lighting/equipment electricity use directly. On the other hand, the lighting/equipment system would gradually deliver heat into the indoor air, which could further affect the operation of air-conditioning system indirectly. In addition, the summer set point temperature (F) is also observed to have an extremely high *F*-test value. Because the HVAC system has to remove all the heat gains from the conditioned space for maintaining the predetermined thermal environment, these three factors should be considered with priorities during the design or retrofit process of the office buildings with FCU system. In comparison, the building envelope generally has a small, even slight, impact on the electricity consumption. This suggests that less care need to be taken to select the envelope design, given the strict requirements on the thermal parameters in current local building design codes [20].

The corresponding result is deduced in the context of the specific humid subtropical climate in Shanghai. Thus, the sensitivity analysis would be quite particular under these limitations. Different climates will affect the identification of significant design parameters, especially for the factors regarding the building load.

In general, a total of 10 key design parameters are identified: window-to-wall ratio, window U-value, shading coefficient of window, summer set point temperature, occupant density, lighting load density, equipment load density, fan efficiency, chiller COP, and pump efficiency. These 10 parameters are thus selected as the input variables of the pre-simulated database and prediction model.

4. Model establishment and evaluation

The basic objective of this section is to build a database and a regression model relating a dependent output variable to independent input variables. The support vector regression (SVR) algorithm is used to develop prediction models. By varying the selected input variables for the base-case building, a well-planned series of simulations is run to generate a database for deriving a regression model relating the annual building electricity consumption to specific design parameters.

To evaluate the predictive power of the developed model, some test cases should be used. Previous related studies [9–15] have also examined the performances of developed models through some independent sets of simulation results. Unfortunately, to the authors' knowledge, nearly none of them have been validated against real cases. In this section, two office buildings in Shanghai with detailed information are selected to evaluate the developed SVR model.

4.1. Database generation

It is believed that the number of simulations required for generating the database depends on the number and the properties of the parameters involved. Generally, the more the simulations are run, the more representative the regression model will be. The database used for regression analysis should ideally consist of simulated values covering all possible combinations of the input variables. However, when the number of input parameters is large, the sum of simulations for all these combinations may be unacceptably huge [17]. To overcome this problem, many studies [11–13] have used random experiment approaches, or Monte Carlo methods [27], to create the database and to estimate the main characteristics "on the average". But the primary disadvantage of these pseudo-random

Table 5
Input parameters and levels of the orthogonal experiment design for prediction model establishment.

Input parameter	Abbr.	Unit	Level				
			1	2	3	4	5
Window-to-wall ratio	WWR	–	0.3	0.4	0.5	0.6	0.7
Window U-value	WU	W/(m^2 K)	2	2.5	3	3.5	4
Shading coefficient of window	SC	–	0.3	0.35	0.4	0.45	0.5
Summer set point temperature	SST	°C	24	25	26	27	28
Occupant density	OP	m^2/person	4	5	6	7	8
Lighting load density	LL	W/m^2	9	11	13	15	17
Equipment load density	EQ	W/m^2	20	17	15	13	11
Fan efficiency	FE	–	0.5	0.6	0.7	0.8	0.9
Chiller COP	COP	–	3.5	4.5	5.5	6.5	7.5
Pump efficiency	PE	–	0.5	0.6	0.7	0.8	0.9

generators is that the required sample size for desired precision usually exceeds an affordable sample size as well. In the present study, OED is used to obtain a set of "normally distributed" simulation results for generating the database.

The input parameters and levels are displayed in Table 5. The 10 key design variables with detailed abbreviations and units are identified through sensitivity analysis in Section 3. Each parameter is set with five numerical levels represented by digits 1–5. The level range of each parameter has been determined and examined through design experience. Some values may exceed the range of thermal comfort, since we want the pre-simulated database to include most possible scenarios.

The orthogonal array $L_{50}(5^{11})$ [26] is used in the design of database generation. The 50 implies 50 trials. The 5 implies the number of levels. The 11 implies the maximum number of parameters (only 10 are used here). The 10 parameters with corresponding values are assigned to the columns, and the 50 trials are allocated to the rows. Each level is repeated the same number of times (10) in each column. For each trial, the annual building electricity consumption in kWh/m^2 is calculated using EnergyPlus, as shown in Table 6. It is important to note that the Chinese standard weather data is replaced by the measured weather data during the year 2013, including the dry-bulb temperature and relative humidity, in this series of simulations. This is because the subsequent developed prediction model will be validated and evaluated against the electricity consumption data of two office buildings monitored in 2013. Thus the influence of weather conditions could be ruled out to some extent through this replacement. In general, simulations have been conducted based on a well-structured experiment design using EnergyPlus to form a reliable database, which serves to establish the prediction model.

4.2. Case study

The two office buildings with representative local architectural and engineering design are located in the urban district of Shanghai. Besides, these two buildings are selected based on their logistics of performing energy audits and site surveys to ensure the availability of electricity consumption data for at least one complete year. In order to retain the individual anonymity, they are referred to as Building 1 and Building 2. Information about the building design and the building service installation was acquired from the original design and the contract document wherever. Additional information was extracted through on-site visits and discussions with the corresponding architects, engineers and building management personnel. A set of simple rules was deduced based on the engineering experience to identify abnormal raw data and to remove these outliers. The final results are the mean values of the pre-processed data for showing the statistical significance.

Table 6
Experiment results based on the $L_{50}(5^{11})$ orthogonal array.

No.	WWR	WU	SC	SST	OP	LL	EQ	FE	COP	PE	AEC
1	0.3	2	0.3	24	4	9	20	0.5	3.5	0.5	146.20
2	0.3	2.5	0.35	25	5	11	17	0.6	4.5	0.6	119.34
3	0.3	3	0.4	26	6	13	15	0.7	5.5	0.7	106.27
4	0.3	3.5	0.45	27	7	15	13	0.8	6.5	0.8	98.31
5	0.3	4	0.5	28	8	17	11	0.9	7.5	0.9	93.19
6	0.4	2	0.35	26	7	17	20	0.6	5.5	0.8	131.36
7	0.4	2.5	0.4	27	8	9	17	0.7	6.5	0.9	91.35
8	0.4	3	0.45	28	4	11	15	0.8	7.5	0.5	99.05
9	0.4	3.5	0.5	24	5	13	13	0.9	3.5	0.6	126.29
10	0.4	4	0.3	25	6	15	11	0.5	4.5	0.7	111.53
11	0.5	2	0.4	28	5	15	13	0.5	5.5	0.9	102.53
12	0.5	2.5	0.45	24	6	17	11	0.6	6.5	0.5	119.66
13	0.5	3	0.5	25	7	9	20	0.7	7.5	0.6	110.45
14	0.5	3.5	0.3	26	8	11	17	0.8	3.5	0.7	112.10
15	0.5	4	0.35	27	4	13	15	0.9	4.5	0.8	107.91
16	0.6	2	0.45	25	8	13	11	0.7	3.5	0.8	108.59
17	0.6	2.5	0.5	26	4	15	20	0.8	4.5	0.9	135.24
18	0.6	3	0.3	27	5	17	17	0.9	5.5	0.5	125.70
19	0.6	3.5	0.35	28	6	9	15	0.5	6.5	0.6	92.21
20	0.6	4	0.4	24	7	11	13	0.6	7.5	0.7	99.22
21	0.7	2	0.5	27	6	11	13	0.7	4.5	0.5	104.83
22	0.7	2.5	0.3	28	7	13	11	0.8	5.5	0.6	90.73
23	0.7	3	0.35	24	8	15	20	0.9	6.5	0.7	142.46
24	0.7	3.5	0.4	25	4	17	17	0.5	7.5	0.8	137.72
25	0.7	4	0.45	26	5	9	15	0.6	3.5	0.9	108.90
26	0.3	2	0.3	27	8	15	15	0.6	7.5	0.6	106.28
27	0.3	2.5	0.35	28	4	17	13	0.7	3.5	0.7	117.08
28	0.3	3	0.4	24	5	9	11	0.8	4.5	0.8	94.75
29	0.3	3.5	0.45	25	6	11	20	0.9	5.5	0.9	114.24
30	0.3	4	0.5	26	7	13	17	0.5	6.5	0.5	116.98
31	0.4	2	0.35	24	6	13	17	0.8	7.5	0.9	110.00
32	0.4	2.5	0.4	25	7	15	15	0.9	3.5	0.5	129.92
33	0.4	3	0.45	26	8	17	13	0.5	4.5	0.6	119.99
34	0.4	3.5	0.5	27	4	9	11	0.6	5.5	0.7	86.29
35	0.4	4	0.3	28	5	11	20	0.7	6.5	0.8	105.91
36	0.5	2	0.4	26	4	11	11	0.9	6.5	0.6	92.45
37	0.5	2.5	0.45	27	5	13	20	0.5	7.5	0.7	118.15
38	0.5	3	0.5	28	6	15	17	0.6	3.5	0.8	121.39
39	0.5	3.5	0.3	24	7	17	15	0.7	4.5	0.9	126.58
40	0.5	4	0.35	25	8	9	13	0.8	5.5	0.5	95.29
41	0.6	2	0.45	28	7	9	17	0.9	4.5	0.7	97.58
42	0.6	2.5	0.5	24	8	11	15	0.5	5.5	0.8	112.00
43	0.6	3	0.3	25	4	13	13	0.6	6.5	0.9	104.33
44	0.6	3.5	0.35	26	5	15	11	0.7	7.5	0.5	103.74
45	0.6	4	0.4	27	6	17	20	0.8	3.5	0.6	141.70
46	0.7	2	0.5	25	5	17	15	0.8	6.5	0.7	123.77
47	0.7	2.5	0.3	26	6	9	13	0.9	7.5	0.8	82.87
48	0.7	3	0.35	27	7	11	11	0.5	3.5	0.9	93.46
49	0.7	3.5	0.4	28	8	13	20	0.6	4.5	0.5	123.24
50	0.7	4	0.45	24	4	15	17	0.7	5.5	0.6	137.46

Table 7 illustrates a summary of the key design information. These figures are real inputs (not design assumptions) in the subsequent model evaluation. The two buildings were completed in the late 1990s when the curtain-wall design was prevalent. Both buildings has one major air-conditioning system commonly used for office buildings in Shanghai – fan coil unit (FCU). Both the air-side and water-side chiller plants are set with a COP of 4.5 in Building 1 and 6 in Building 2. The normal operating schedule is a 10 h day (08:00–18:00) and a 5-day week basis with an indoor set point temperature of 26 °C in summer and 21 °C in winter.

The monthly electricity use data metered during the year 2013 was collected from each building. Considering the difference in building size, the annual electricity use data of each building is divided by the corresponding gross floor area to provide a normalized performance indicator. It is calculated that the metered energy use per unit gross floor area is 108.50 kWh/m^2 for Building 1 and 94.43 kWh/m^2 for Building 2. All the processed data is believed to have a good reliability and can be used in the following evaluation of the developed model.

Table 7
Descriptions of the two office buildings.

Building characteristics	Building 1	Building 2
General information		
Number of storeys	26	36
Gross floor area (m^2)	49,650	87,765
Summer indoor condition (°C)	26	26
Winter indoor condition (°C)	21	21
Operation hours	08:00–18:00 (weekday)	08:00–18:00 (weekday)
Building envelope		
Roof U-value (W/m^2 K)	0.5	0.45
Wall U-value (W/m^2 K)	1.6	1.9
Window U-value (W/m^2 K)	4.43	5.22
Window-to-wall ratio	0.25	0.67
Shading coefficient of window	0.45	0.36
Floor-to-floor height (m)	3.3	2.8
Building load		
Occupant density (m^2/person)	8	6
Lighting load (W/m^2)	18	9
Equipment load (W/m^2)	13	17
HVAC system		
Air-side system	FCU	FCU
Type of chiller compressor	Screw	Centrifugal
COP	4.5	6
Number of chillers	4	4
Fan efficiency	0.7	0.8
Pump efficiency	0.78	0.77

4.3. Support vector regression analysis

Support vector regression (SVR) was developed by Vapnik in 1995 to handle regression problems [28]. SVR, based on the structural risk minimization inductive principle, usually achieves a higher generalization performance than the traditional neural networks in solving many machine learning problems. A more comprehensive introduction of SVR is presented in Ref. [29]. The use of SVR in the forecasting of building energy performance is quite recent [30–33], but the results prove to be very encouraging. In this study, SVR is applied to predict the annual electricity consumption (AEC) for office buildings in Shanghai. It is important to note that all the inputs are standardized in the regression analysis.

SVR uses kernel functions to solve non-linear problems. In this study, the Gaussian radial basis function (RBF) is selected as the kernel function, since it is very effective in handling non-linear problems [30–33]. Two parameters, i.e., the regularization constant (c) and the inverse width of Gaussian RBF (g), need to be optimized for SVR in order to precisely reflect the performance on regressing unknown data and to prevent over-fitting problems. Traditionally, the efficiency of 'grid-search' is low because such method computes the performance with all the (c, g) to obtain the performance surface. So in this study, the optimization of model parameters is performed using the genetic algorithm, which has been investigated by many researchers [34–36]. Such hybrid applications have also been conducted in the development of artificial neural network (ANN), with genetic algorithm [37], bees colony [38], and particle swarm optimization [39].

Genetic algorithm (GA), developed by Holland in 1975 [40], is a stochastic optimization algorithm deduced from an analogy with the evolution theory of Darwin. It deals with a powerful optimization method able to resolve every problem provided the convexity of the describing function [41]. It is worth mentioning that the GA can give several final solutions to a complicated problem with a large number of inputs. So the difficulty in generating the optimal solution through GA is the adjustment of the algorithm. To obtain the mature optimization results from GA, the population size, number of generation, crossover probability, mutation chance and proportion of elitism are set to be 20, 100, 0.7, 0.01 and 0.1, respectively.

Table 8
Evaluation results of the developed SVR model.

Annual electricity consumption	Building 1	Building 2
Measured value Y (kWh/m^2 a)	108.50	94.43
Predicted value $\hat{Y}$ (kWh/m^2 a)	117.63	101.31
Err (%)	8.42	7.29

Two sets of performance indices are used in the regression analysis. The first set adopts mean square error (MSE) and coefficient of determination (R^2) for SVR parameter optimization using GA. MSE is a scale-dependent metric. R^2 can reflect the goodness-of-fit of the model. The definitions of these two metrics are given in Eqs. (1) and (2).

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{n} \tag{1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2} \tag{2}$$

The second set of indices uses the percentage error (Err) to assess the prediction accuracies. To evaluate certain degree of accuracy, the measured results are compared with those predicted by the developed SVR model using the same input design parameters. There have been a great number of works on assessing or calibrating prediction models for building energy performance [42]. The common practice is to follow the criteria set by established international or professional standards/guidelines. The present study mainly adopts the FEMP guideline [43], which stipulates that the difference between the measured and predicted yearly energy consumption should be smaller than 10% for an acceptable prediction model. In this study, such difference is simply defined as follows:

$$Err_i = \frac{\hat{Y}_i - Y_i}{Y_i} \times 100\% \tag{3}$$

To improve the regression fit and the model stability, further investigations of data transformation and optimization algorithm (e.g. principle component analysis) may be considered in the future.

5. Result and discussion

One optimization process of SVR model parameters using GA is shown in Fig. 4. The optimal c value is 31.4322, and the optimal g value is 0.025368. After the best (c, g) is found, the training set is trained again to generate the final SVR model. The resulting R^2 value is 0.987, indicating that about 98.7% of the variation in the annual electricity consumption resulting from the changes in these 10 design parameters can be explained by the developed SVR model.

It can be seen in Table 8 that the predicted annual building electricity consumption using the developed SVR model is 117.63 kWh/m^2 for Building 1 and 101.31 kWh/m^2 for Building 2, showing a relative error of 8.42% and 7.29% respectively compared with the measured values. In addition, both the errors are positive, indicating that the developed SVR model tends to overestimate the annual electricity use. Generally, the deviations are acceptable (within 10%). The predicted values can follow quite closely those from the measurements. Therefore, we can confidently believe that the developed database and regression model can be used to assess the likely energy savings/penalty related with certain parameter changes to some extent during the retrofit process for office buildings in Shanghai.

The present pilot research focuses mainly on the factors that are essential to assessing the retrofit potential of office buildings with FCU system in Shanghai. The corresponding analysis is per-

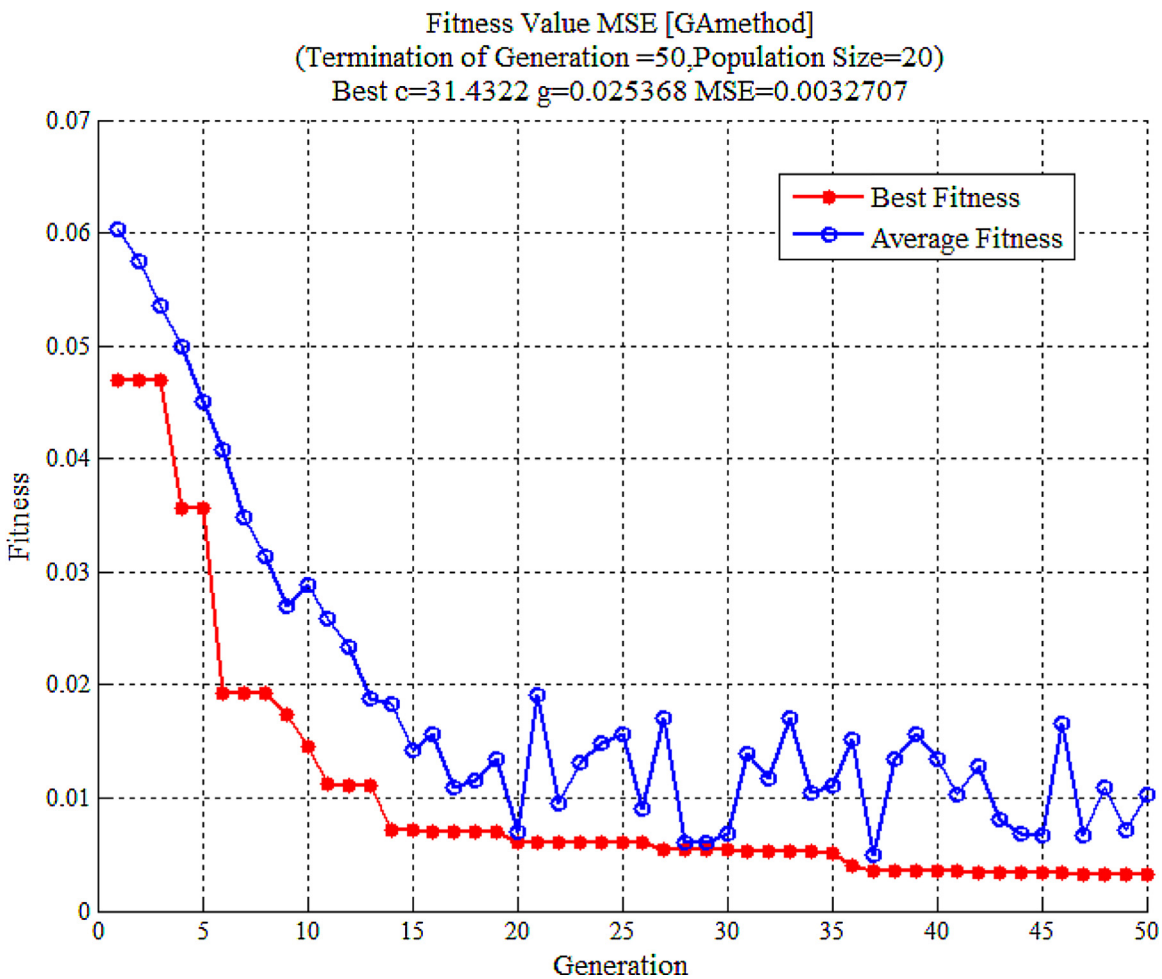

Fig. 4. Optimization process of the SVR parameters *c* and *g* using GA.

formed in the context of the specific climate in Shanghai. Thus, the results and interpretations would be quite particular under these limitations. Nevertheless, we believe that the application of this flexible methodology can be extended to other building types at other locations with other simulation tools. General characteristics regarding the concerned issues can then be extracted and established through comparisons and evaluations among various models. The most important thing is to fully understand the basic principles and to reasonably quantify the relative importance of the selected input parameters to the output results.

It is worth discussing why the developed SVR model with an extremely high R^2 value (0.987) still yields a relative error of around 8% compared with real cases. In addition to the measurement inaccuracy, there are two main causes of such error. One reason is the fact that the established pre-simulated database uses the base-case building which often cannot exactly match the geometry of a specific building. Even though the reference energy models have been widely used to estimate energy performance, the related analysis is often limited to a particular building stock description. Another cause of such error may lie in the modeling uncertainty [44]. Usually, the built environment presents a formidable challenge in terms of energy modeling and prediction. A building is typically characterized by a multiplicity of dynamic (fabric property and HVAC system), stochastic (occupant) and probabilistic (weather) elements, which would commonly lead to inaccuracy and uncertainty in simplified building models [45,46]. Modeling errors are mainly caused by difficulties in capturing how exactly a building system is operated, due to software limitations and inaccurate descriptions of input parameters and weather data. In addition, simplifications of many other complex factors, such as the building material properties [47], the boundary conditions [48] and the occupant behaviors [49], act as increasingly prominent sources of uncertainty in model predictions. Due to the particular lack of detailed input descriptions in the present-day building simulation tools (e.g. EnergyPlus), it still remains a mystery to what extent will these factors influence the energy characteristics for a specific case. Therefore, it is essential to consider and minimize the possible errors at every stage of the energy simulation for improving the prediction accuracy.

The inputs and outputs involved in the sensitivity analysis are generally isolated, but they might also be a time series, namely a chronological sequence of observations on a specific variable. If a time series is considered, the sensitivity estimation will be more complicated with the use of statistical methods in time series analysis. Thus, more advanced sensitivity analysis techniques should be applied to more design parameters for developing more reliable pre-simulated databases. Besides, more non-linear methods (e.g. artificial neural network, bees colony, particle swarm optimization, etc.) should be considered to further refine the regression model. Considering the availability of substantial building electricity use data due to the widespread deployment of reliable energy-related sub-metering devices and longitudinal data collection technologies, more real cases with reliable detailed measurements are expected to further validate and evaluate the prediction models. In addition, some new approaches of passive design (e.g. natural ventilation) or renewable energy use (e.g. solar energy) are not

included in the present database. Careful considerations of these issues will be explored in our future studies.

The pre-simulated database and prediction model are developed manually in this pilot test. However, some existing tools allow for automated parametric runs to explore design options, which can bring new opportunities to accelerate the energy estimation for office buildings. For example, The OpenStudio PAT (Parametric Analysis Tool) [50] and jEPlus [51] can provide a shell to define parameter values for different design concepts and call EnergyPlus to run multiple and automated simulations. Besides, the use of the cloud-based HPC (high performance computing) can reduce the computation time for parametric simulations, contributing to a potentially higher accuracy of building energy estimation [52]. It is possible that the proposed methodology, including the theory of orthogonal experiment design, can be coupled with these tools to realize automated development of energy use databases and prediction models. Further research is needed to test how useful these tools are in providing fast retrofit estimations automatically.

6. Conclusion

The growing concern about building energy efficiency and the difficult application of current simulation tools in the energy retrofit process have motivated the authors to propose a systematic method, which can provide the possibility of developing reliable databases and prediction models to quickly estimate the building energy performance. Using sensitivity analysis and support vector regression (SVR) technique, this pilot study carefully developed a model to predict the annual electricity consumption for office buildings with FCU system in Shanghai.

First, a base-case building model is established by EnergyPlus to create a pool of candidate inputs using orthogonal experiment design. Then, analysis of variance is used to identify a total of 10 key building design parameters, which are selected as the input variables in the SVR model based on a well-structured database. The performance of SVR with respect to two parameters, c and g, is optimized using genetic algorithm (GA) based on radial basis function kernel. Finally, two real office buildings in Shanghai with reliable measured data serve to validate and evaluate the developed hybrid GA-SVR model. The resulting coefficient of determination R^2 is 0.987, indicating that about 98.7% of the variations in the annual building electricity use can be explained by changes in these 10 selected parameters. The differences between the predicted and measured values are generally within 10%. Therefore, it is expected that the developed database and model can be used to assess the likely energy savings/penalty related with certain parameter changes to some extent during the retrofit process for office buildings with FCU system in Shanghai.

Although the present pilot work is conducted under certain limitations, we believe that the application of this flexible methodology can be extended to other building types at other locations with other simulation tools. More detailed investigations of physics-based modeling, sensitivity analysis, data quality, non-linear regression, and optimization algorithm should be considered in the future. To make the best use of the proposed method, researchers should try to get a better understanding of the sensitivity theory, the simulation result, and the computing tool.

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