MEESG - A TOTAL ENERGY DEMAND PREDICTION AND OPTIMIZATION PROGRAM FOR ARCHITECTURAL SCHEME DESIGN STAGE

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ABSTRACT

In this research, a new energy-saving design method and a design-aided program MEESG (Most-Energy-Efficient-Scheme-Generator) are developed. The program aims to aid energy-saving design by means of optimization algorithms at a very early design stage, when the building shape is not even determined by the architects. In this program, a simplified prediction model BEFPM (Building Energy Demand Fast Prediction Model) is established to simulate the building total energy demand very quickly. Meanwhile, by introducing Genetic Algorithm into BEFPM, from shape and envelope parameters to HVAC system forms, the computer can automatically generate the design parameters of the most energy efficient scheme(s).

INTRODUCTION

In the past 5 years, the issue of building energy-saving has been a major concern of the Chinese government. Not only a seires of new national standards and green building labelling system have been proposed, but the building designers also have been well encouraged to use building simulation to aid their design. Anyways, in the author's opinion, it still remains two key problems which may restrict the development of building simulation for energy saving.

(1) HVAC load and building envelope are over-emphasized in simulation process due to their high research maturity and manoeuvrability. Hence, the influence to building energy demand of HVAC/lighting equipment and building passive energy-saving strategies is often ignored.

(2) To control energy consumption level should be considered in throughout the whole building design process from the scheme stage to the construction drawing stage. However, the scheme stage, which probably takes the most important role in building energy-saving design, is often neglected owing to the lack of input information for building modelling.

In view of the above, a new building energy-saving design method and its related program (MEESG - Most Energy Efficient Scheme Generator) are developed. This method focuses on total building energy demand including HVAC and lighting systems, and can be utilized in a very early design stage when the building shape is not even determined. The structure of this method is:

(1) A fast prediction model (BEFPM) for building total energy demand, in which the sub-models are validated by some well-accepted simulation softwares such as DeST (Jiang 1997), Radiance (Ward et al. 1996) and Daysim (Reinhart 2001), or established by mass practical testing data.

(2) A Genetic Algorithm (GA) model with BEFPM as its fitness evaluation function to pick the most energy efficient schemes by computer automatically.

The structure of this research is shown in Figure 1.

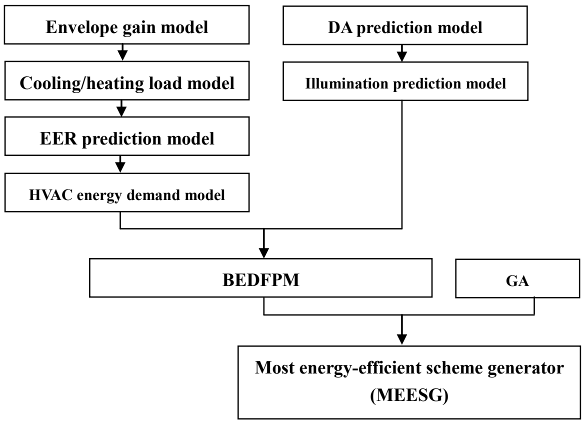


Figure 1 The structure of this research

BEFPM – BUILDING ENERGY DEMAND FAST PREDICTION MODEL

As mentioned above, before a building scheme is designed, there are too few known parameters to build up a specific building model. And it is also infeasible to build up models of all possible schemes by detailed simulation software to carry out comparison or analysis work. Hence, a fast energy demand prediction model should be established to realize scheme optimization at such early stage. This model may not be numerically accurate but should correctly reflect the comparative advantages among different schemes. And it should integrate all the energy-related factors, such as building envelope gain, natural lighting & ventilation, HVAC/lighting equipment and control strategies.

The Building Energy Fast Prediction Model (BEFPM) proposed in the paper generally meet the features mentioned above. This model is composed of five sub-models:

Building envelope gain prediction model

Accumulated building envelope gain can be evaluated by a transient equation (Zeng 2006, Xia 2008) as:

$$Q_E = \beta^* \frac{\sum_{i=1} \left\{\left[(1-\omega_i)K'_{wall,i} + \omega_i K'_{win,i}\right] \cdot A_i \Delta\overline{T}^*\right\}}{1000\, F_{bldg}} \tau \quad (1)$$

Where,

$$K'_{wall,i} = K_{wall,i} + \frac{K_{wall,i} e_i}{\alpha^*_{out,i}} \cdot \frac{\overline{q}^*_{solar,wall,i}}{\Delta\overline{T}^*} \quad (2)$$

$$K'_{win,i} = K_{win,i} + SHGC_i \cdot \frac{\overline{q}_{solar,win,i}}{\Delta\overline{T}^*} \quad (3)$$

Four corrections (denoted by the terms with superscript *) have been made in this research to this equation:

Correction 1: apply "envelope integrated heat transfer temperature difference considering nighttime thermal process" $\Delta\overline{T}^*$ instead of $\Delta\overline{T}$. $\Delta\overline{T}^*$ comprehensively takes three processes of daytime heat transfer, nighttime heat transfer/thermal mass effect, and nighttime ventilation into account. It can be divided into $\Delta\overline{T}^*_{ex}$ and $\Delta\overline{T}^*_{in}$, representing $\Delta\overline{T}^*$ for building's exterior and interior zone respectively.

Correction 2: apply $\overline{q}^*_{solar,wall,i}$ and $\overline{q}^*_{solar,win,i}$ instead of $\overline{q}_{solar,i}$ · $\overline{q}^*_{solar,wall,i}$ and $\overline{q}^*_{solar,win,i}$, which are derived from the blackbody radiation theorem based on some certain hypothesis and simplifications, not only consider solar radiation in the daytime, but also long-wave radiation in the nighttime.

Correction 3: Correct roof convective heat transfer coefficient $\alpha_{out,roof}$ to $\alpha^*_{out,roof}$ (Shao et al. 2008), which is calculated as:

$$\alpha^*_{out,roof} = 7.64\overline{v} + 2.05 \quad (4)$$

Where, $\overline{v}$ is hourly average wind speed (m/s) within cooling/heating season.

Correction 4: "Weekend Shutdown Coefficient" β is introduced to Equation (1), in order to consider the dynamic effect of weekend shutdown of cooling sources (Xia 2008). In this paper, β is redefined as:

$$\beta^* = 1 + \left(\alpha_T \overline{K} \cdot STVR + \alpha_S \cdot STVR\right) \quad (5)$$

Here, $\alpha_T \overline{K} \cdot STVR$ denotes the influence ratio to next week's cooling load of envelope heat transfer at the weekend. Obviously, the larger $\overline{K}$ and *STVR* are, the more siginificant this influence is. Meanwhile, $\alpha_S \cdot STVR$ similarly denotes the above influence ratio of solar radiation at the weekend. Since the window-to-wall ratio of different building is generally not very different, this influence can be considered mainly related to *STVR*. Through regression analysis, α_T and α_S for different building sites and functions can be calculated by the dynamic building thermal simulation software DeST. It is demonstrated that the standard deviations of the regression analysis are smaller than 5% in most cases.

Besides the above four major corrections, several other algorithm corrections and functional expansions have been introduced into Equation (1) (e.g. correction for heating season predication, calculation methods for courtyard, atrium, podium, etc.).

Building cooling/heating load prediction model

Considering a simple building divided by four exterior zones and one interior zone (Figure 2), prediction equations of the cooling load in cooling season can be simplified to Equation (6)-(7).

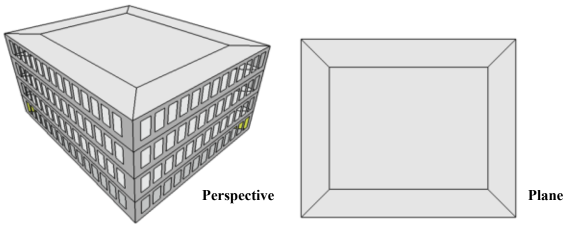


Figure 2 A simple rectangular building

$$Q_{cc,ex} = \quad (6)$$

$$\hat{N}\left\{Q_{E,ex} + A_{ex}\frac{\tau_c}{1000}\left[o \cdot pd + q^*_{lt} + q_{eq} + 0.28\rho\Delta i_c\left(o \cdot fa + r \cdot \inf\right)\right]\right\}$$

$$Q_{cc,in} = \quad (7)$$

$$\hat{N}\left\{Q_{E,in} + (1 - A_{ex})\frac{\tau_c}{1000}\left[o \cdot pd + q_{lt} + q_{eq} + 0.28\rho\Delta i_c o \cdot fa\right]\right\}$$

Where, $\hat{N}$ is non-negative operator, because all the building zones are in cooling or non-air-conditioned state in the cooling season. However, either heating or cooling load may exist in either exterior or interior zones, in the heating season, therefore, the load predication equations (not given in the paper) for heating season are more complicated due to the judgement of the load type for each zone.

Cooling/heating *EER* prediction model

According to large numbers of testing data of practical commercial buildings in Beijing provided by Building Energy Research Center of Tsinghua University, cooling/heating *EER* prediction model is established in the form of providing *EER* check tables shown as Table 1, for example.

In Table 1, EER_{cc} is the *EER* of cooling in the cooling season, also, EER_{hc} and EER_{hh} (check tables are not given) are *EER* of cooling in the heating season, and of heating in the heating season, respectively. *EER* value of each cooling/heating source is converted to that of electricity.

Row number A-F in Table 1 refers to the different terminal form of HVAC system (Table 2), and column number 1-12 refers to the different cooling/heating source combination (Table 3).

Table 1
EER_{cc} check table

EER_{cc}	A	B	C	D	E	F
1	1.17	1.67	1.17-1.19	1.67-1.99	1.99	-
2	1.17	1.67	1.17-1.19	1.67-1.99	1.99	-
3	1.17	1.67	1.17-1.19	1.67-1.99	1.99	-
4	1.01	1.36	1.01-1.56	1.36-1.56	1.56	-
5	1.01	1.36	1.01-1.56	1.36-1.56	1.56	-
6	1.14	1.60	1.14-1.89	1.60-1.89	1.89	-
7	0.88	1.14	0.88-1.28	1.14-1.28	1.28	-
8	0.88	1.14	0.88-1.28	1.14-1.28	1.28	-
9	1.11	1.55	1.11-1.82	1.55-1.82	1.82	-
10	-	-	-	-		1.80
11						1.80
12						1.80

Table 2
Terminal forms of HVAC system

NO.	CORRESPONDING TERMINAL FORM
A	CAV system
B	VAV system
C	CAV with FCU+OA system
D	VAV with FCU+OA system
E	FCU+OA system
F	split air conditioning or VRV system

Table 3
Cooling/heating source combinations

NO.	CC	HH	HC
1	water-cooled chiller	gas boiler	fresh air or cooling tower
2	water-cooled chiller	coal-firing boiler	fresh air or cooling tower
3	water-cooled chiller	gas boiler	water-cooled chiller
4	wind-cooled heat pump	wind-cooled heat pump	fresh air or cooling tower
5	wind-cooled heat pump	wind-cooled heat pump	wind-cooled heat pump
6	ground source heat pump	ground source heat pump	ground source heat pump
7	direct-fired air conditioner	direct- fired air conditioner	fresh air or cooling tower
8	direct-fired air conditioner	direct- fired air conditioner	direct- fired air conditioner
9	absorption chiller	gas boiler	fresh air or cooling tower
10	split A/C or VRV	split A/C or VRV	fresh air or cooling tower
11	split A/C or VRV	coal-firing boiler	fresh air or cooling tower
12	split A/C or VRV	split A/C or VRV	split A/C or VRV

Daylighting and lighting energy demand prediction model

Besides HVAC system, lighting equipment also takes a large proportion of about 40% of building energy consumption, and has a large energy-saving potential as well, if proper natural daylighting strategies and control strategies are introduced. Generally, the index for illumination energy-saving potential is Daylight Autonomy (DA), which is defined as the fraction of the occupied times per year, when the required minimum illuminance level at a point can be maintained by daylight alone. In contrast to the more commonly used daylight factor (DF), DA considers all sky conditions throughout the year.

DA can be classified into DA_{con} and DA_{max}, which are used for photosensor-controlled dimmed lighting control and photosensor-controlled on/off lighting control, respectively. Thus, the illumination energy density of a building zone that is controled by photo-sensor can be determined as the function of DA at the sensor point:

$$q^*_{lt,con} = (1 - DA_{con})q_{lt,b} \tag{8}$$

$$q^*_{lt,\max} = (1 - DA_{\max})q_{lt,b} \tag{9}$$

Through the detailed building daylighting and lighting performance simulation software Daysim, we established the relation of DA_{con}/DA_{max} with building orientation (θ_s), window-to-wall ratio (ω), window comprehensive transperancy (tr) and the ratio of storey height to room depth (λ), by means of polynomial curve fitting. Thus, building annual illumination energy demand can be written as:

$$E_{lt} = \frac{q^*_{lt} \cdot \tau^*_{lt}}{1000} + \frac{q_{lt} \cdot (\tau_{lt} - \tau^*_{lt})}{1000} \tag{10}$$

Where, if $\theta_s \geq 0$ ($\theta \in [-45^\circ, 45^\circ]$), namely the building's south facade orients south or southwest:

$$q^*_{lt} = q_{lt} - \frac{nq_{lt}}{100F_{bldg}} \cdot \begin{pmatrix} A_S & A_W & A_N & A_E \end{pmatrix} \times \left[\frac{90 - \theta_S}{90} \cdot B_S \times \begin{pmatrix} 1 \\ \lambda_S \\ tr_S \\ \lambda_S^2 \\ tr_S^2 \end{pmatrix} + \frac{\theta_S}{90} \cdot B_W \times \begin{pmatrix} 1 \\ \lambda_W \\ tr_W \\ \lambda_W^2 \\ tr_W^2 \end{pmatrix} \right] \tag{11}$$

While, if θ<0, namely the building's south facade orients southeast:

$$q^*_{lt} = q_{lt} - \frac{nq_{lt}}{100F_{bldg}} \cdot \begin{pmatrix} A_S & A_W & A_N & A_E \end{pmatrix} \times \left[\frac{90 + \theta_S}{90} \cdot B_S \times \begin{pmatrix} 1 \\ \lambda_S \\ tr_S \\ \lambda_S^2 \\ tr_S^2 \end{pmatrix} - \frac{\theta_S}{90} \cdot B_E \times \begin{pmatrix} 1 \\ \lambda_E \\ tr_E \\ \lambda_E^2 \\ tr_E^2 \end{pmatrix} \right] \tag{12}$$

Where, B is the fitting coefficient matrix of DA for different city, win-to-wall ratio and control method, of which the subscript ($S/W/N/E$) denotes that B goes with the row of the corresponding orientation's curve-fitting coefficient sequence as its first row. For example, as for a building located in Beijing with full glass curtain wall and photosensor-controled on/off control strategy, B_E can be written as:

$$B_E = \begin{pmatrix} -64.5 & 41.2 & 134.6 & 0 & 0 \\ -80.3 & 59.0 & 162.0 & 0 & 0 \\ -74.0 & 50.7 & 134.0 & 0 & 0 \\ -56.8 & 35.0 & 101.2 & 0 & 0 \end{pmatrix} \begin{pmatrix} \text{row of east} \\ \text{row of south} \\ \text{row of west} \\ \text{row of north} \end{pmatrix} \quad (13)$$

If the database of matrix B is established, through Equation (10)-(12), different building's illumniation energy demand can be predicted quickly.

Building total energy demand prediction model

With the sub-models described above, the annual total energy demand of a building is calculated as:

$$E_{bldg} = \frac{Q_{cc}}{EER_{cc}} + \frac{Q_{hh}}{EER_{hh}} + \frac{Q_{hc}}{EER_{hc}} + E_{lt} \quad (14)$$

MEESG-MOST ENERGY EFFICIENT SCHEME GENERATOR

Introduction of MEESG and its basic principle

Genetic Algorithm (GA) is an optimization algorithm developed from Darwin's natural selection theory (Holland 1975), which is often utilized to solve complicated mathematical models. In GA programs, the optimum solution candidate, which is termed as an "individual", is considered to be a living entity. Each "individual" is described by a vector of characteristic values called a "chromosome", which can be evaluated by its "fitness value" (just like creature's fitness to the nature) calculated by an/some evaluation function(s) of all the characteristic values in the chromosome. After an initial population of individuals are determined, generation by generation, GA performs genetic operations such as selection, crossover, and mutation to the chromosomes, to find an optimal individual that has the smallest fitness value. The standard operation flow of GA is shown in Figure 3.

Since BEFPM simulates one case only in much less than one second by computer, it becomes possible that we establish a GA model to find the building scheme of the lowest energy demand level, by taking the unit building as the "individual", BEFPM model as the fitness evaluation function, and the energy demand result as the "fitness value".

The model utilizing this method in this paper is called "Most Energy Efficient Scheme Generator" (MEESG). Its basic mathematical model is:

$$\begin{cases} \min \quad E_{bldg} = f(A, X) \\ s.t. \qquad A = U \\ \qquad\qquad X \in R \end{cases} \quad (15)$$

Where, $A = [a_1, a_2, \cdots a_n]^T$ are the user-defined constants such as building area, ground floor area, floor height, etc., which are generally determined beforehand in the project assignment paper and considered not able to be changed in the design process. $X = [x_1, x_2, \cdots x_n]^T$ are the variables to be optimized, such as the building orientation, number of the standard floors, U-value of walls and windows, etc., which are the designing parameters that the designers care about.

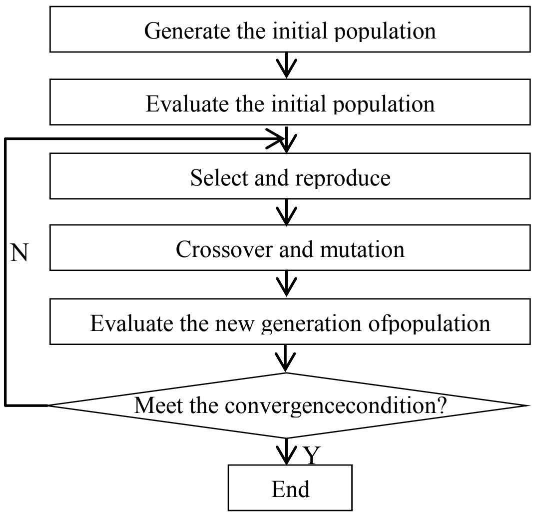


Figure 3 The standard operation flow of GA

Figure 4 shows the structure of MEESG, in which all the user-defined constants and variables to be optimized are listed. In addition, any variables to be optimized can be converted to user-defined constants.

Improvement of the standard GA model

1. A more efficient GA called "Multi-island Genetic Algorithm (MIGA)" (R.Tanese 1984) is introduced to enhance the globality of the optimal searching process. The feature of this method is that the population in one generation is initially divided into several sub-populations called "Islands". And the GA process is performed on each "island" independently. In this way, MIGA is easier to find the global, rather than the partial optimum solution(s). In other words, MIGA aims to find the highest mountain in a mountain chain, whereas standard GA may only find the peak of a single mountain.

2. According to our investigation, architects generally hope aided-design tools to provide various proposed schemes with large differences among one another, rather than tell them only one answer. Because, with the various schemes proposed, architects are able to look for their preferred ones, integrate their subjective views, and find balances between energy saving and aesthetics. Therefore, a method aiming to find various optimum solutions is developed. In this method, GA process repeats for several turns. In each new turn, the individuals that are too close to the optimum solutions calculated in the former turns are easier to be eliminated.

Define the "scheme characteristic distance" as:

$$L_{k\to j} = \sqrt{\sum_{i=1}^{n} \rho_i \left(\frac{P_{i,k} - P_{i,j}^{opt}}{\Delta P_i} \right)^2} \tag{16}$$

Where, ρ_i is the weight for each variable to be optimized, which is determined by the user; $P_{i,k}$ is the value of the i^{th} variable to be optimized in a certain individual in the k^{th} turn; $P_{i,j}^{opt}$ is the value of the i^{th} variable to be optimized in the optimum solution in the j^{th} turn; ΔP_i is the difference between the upper and lower thresholds of P_i. If $L_{k\to j} \le L_o$ (L_o is determined by the user), namely the individual in the k^{th} turn is too close to the optimum solution of the j^{th} turn, a "fitness punishment term" (determined beforehand) will be added to the fitness value of the individual, giving it a "bad" fitness, thus the known optimum solutions are no more optimum and new optimum solutions are obtained.

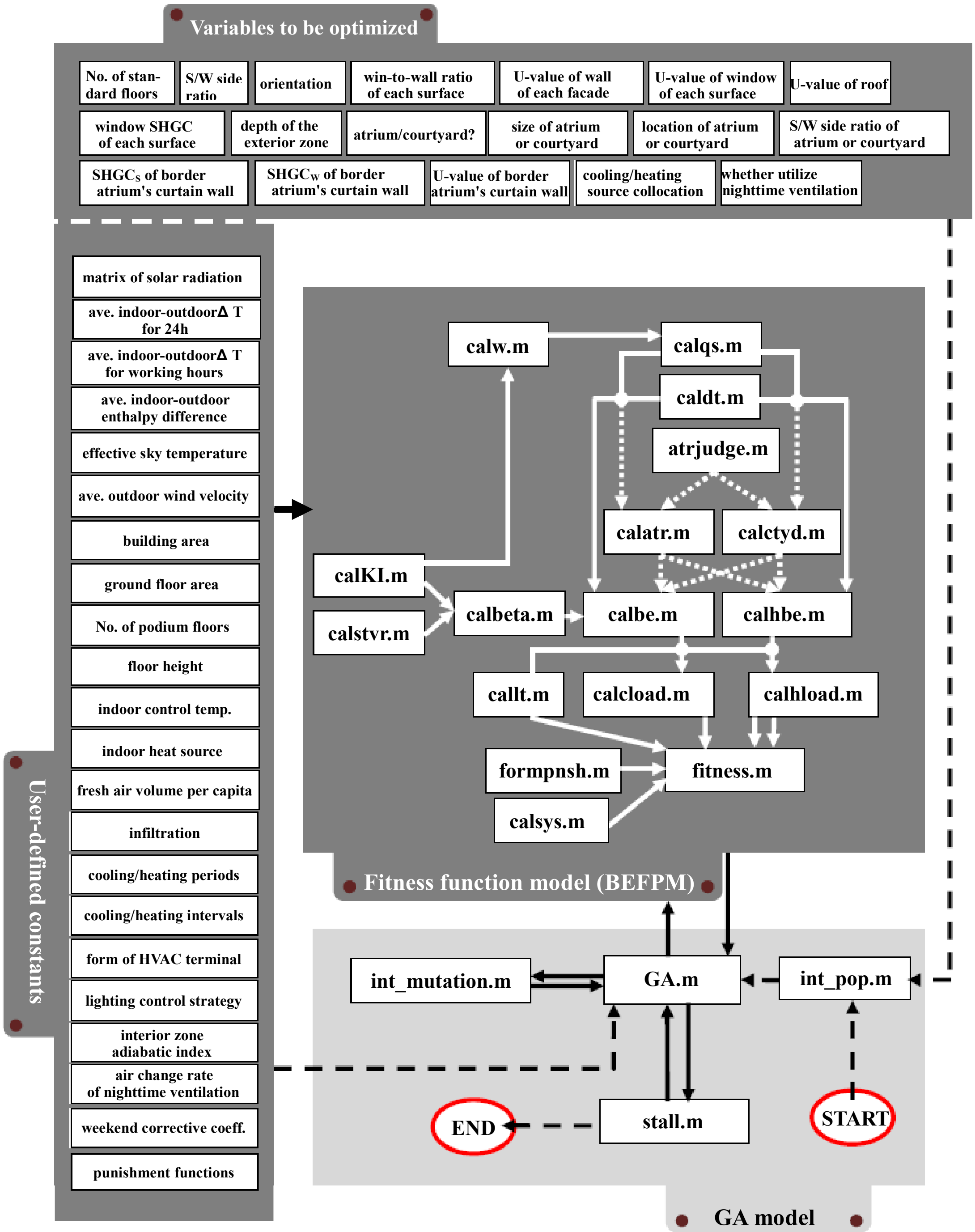


Figure 4 The structure of MEESG

MODEL VALIDATION

Validation of BEFPM

The building cooling load predicted by BEFPM of the following five schemes (Figure 5) is compared with that simulated by DeST. The scale and envelope information of the five schemes is listed in Table 4.

Figure 6 shows the comparison results of the annual accumulative cooling load. The average relative errors between BEFPM and DeST are smaller than 6% for the five schemes located in Harbin, Beijing, Shanghai and Guangzhou (ranked by the latitude from north to south), respectively. It means that BEFPM has a high accuracy, in the addition, the accuracy is higher when the city's latitude is lower (i.e., the cooling load level is higher).

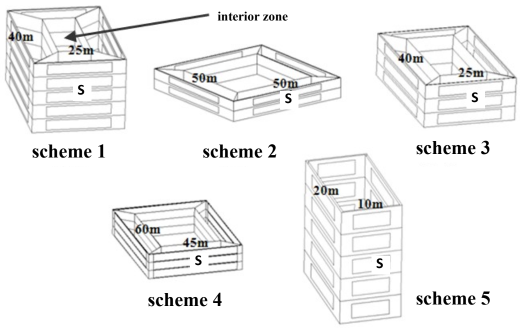


Figure 5 Schemes for BEFPM validation

Table 4
Information of the building schemes for validation

SCH	K_{wall} (W/m^{2}K)	K_{roof} (W/m^{2}K)	K_{win} (W/m^{2}K)	SHGC	ω	F_{bldg}
sch 1	0.6	0.5	1.4	0.6	0.5	5000
sch 2	1.2	0.8	2.4	0.7	0.4	5000
sch 3	0.6	0.3	3.0	0.7	0.5	3000
sch 4	1.2	1.0	2.0	0.4	0.8	8000
sch 5	0.4	0.3	1.2	0.3	0.4	1000

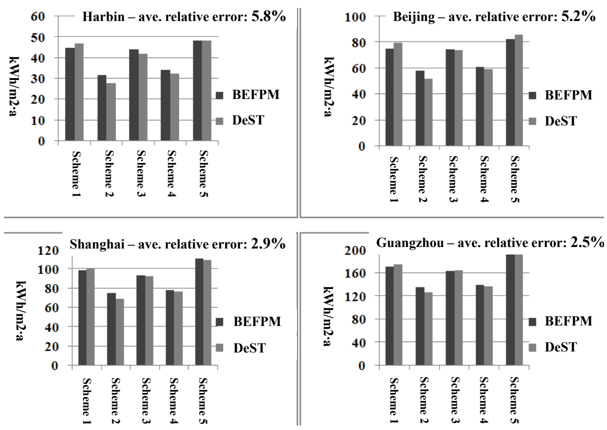


Figure 6 Accumulative cooling load prediction comparison between BEFPM and DeST

Validation of MEESG

As mentioned above, the objective of MEESG is to identify the scheme with a lowest energy demand level. Hence, it is especially important that whether MEESG can reflect the comparative advantages among different schemes. The steps to verify it is:

(1) Determine the "user-defined constants" and the thresholds of the "variables to be optimized". Each parameter is assigned with its common value.

(2) Find the most energy efficient scheme, using MEESG (The sub-model of lighting energy demand is not considered).

(3) Make different small change to the gene sequence of the most energy efficient scheme for N times, creating N new schemes.

(4) Calculate the annual accumulative HVAC energy demand of these N+1 schemes (including the optimal one) using DeST and BEFPM, respectively.

(5) Rank the N+1 schemes by their energy demand predication results calculated by BEFPM and DeST, simultaneously, and see if the rankings provided by the two tools are consistent.

Figure 7 shows the ranking results for four Chinese cities. It is demonstrated that BEFPM's rankings are basically consistent with DeST's, especially for the cooling-load-dominated regions such as Guangzhou and Shanghai. However, the rankings provided by the two tools are not very consistent for the northern cities such as Beijing and Harbin.

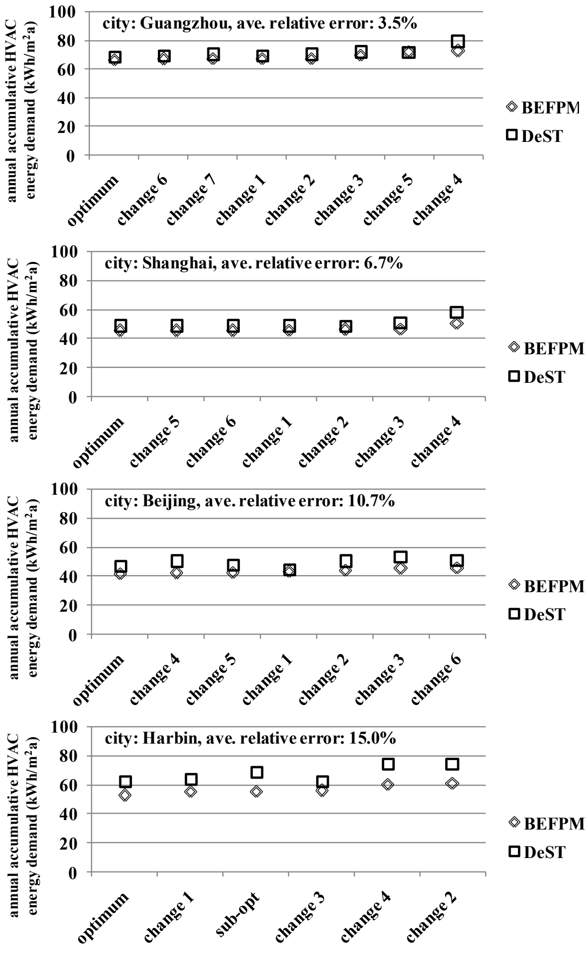


Figure 7 Validation of MEESG

CASE STUDY

Four cases upon MEESG application are studied. The major user-defined information is listed in Table 5.

The shapes of the optimal schemes of the four cases calculated by MEESG are shown in Figure 8. And the optimal scheme's other features are listed in Table 6. The conclusions drawn from this case study are basically the same as what we concluded from the studies of dynamic simulation softwares. For instance, BEFPM and DeST simultaneously shows that, in hot-summer-and-warm-winter regions (such as Guangzhou), the worse the insulation capacity of building envelope is, the smaller the annual accumulative cooling load becomes on the contrary, because, in these regions, the demand of building envelope heat dissipation throughout a year is even greater than that of envelope heat insulation.

Table 5
Major known information of the four cases studied

	CASE1	CASE2	CASE3	CASE4
City	Harbin	Beijing	Shanghai	Guangzhou
F_{bldg}	50,000m^2	80,000m^2	107,500m^2	50,000m^2
Fun.	government	office	office	government
Podium	×	×	√	×
LT ctrl	×	×	on/off	×

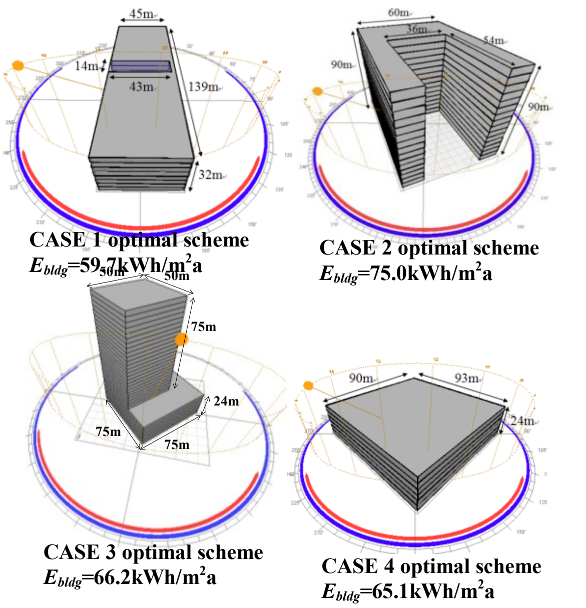


Figure 8 Shapes of the optimal schemes

Table 6
Features of the optimal schemes

FEATURE	CASE1	CASE2	CASE3	CASE4
Orient.	S	SSE	SW	SE/SW
Depth	○	□	○	Δ
ω	Δ	Δ	Δ	Δ
K_{wall}	Δ	Δ	Δ	Δ
K_{win}	Δ	Δ	○	□
K_{roof}	Δ	Δ	Δ	Δ
$SHGC_{win}$	N>E>W>S	Δ	Δ	Δ
HVAC Sys	6	6	2	2

In Table 6, "Δ", "○" and "□" denote the minimum, medium, and maximum value, respectively. The item of "HVAC system" can be checked in Table3.

SOFTWARE DEVELOPMENT

The software of MEESG is currently being developing. Its main components (Figure 10) are:

(1) Input interface: users can decide which parameters are variables to be optimized, and which are pre-defined by users. Users input the climate data, user-defined constants, thresholds of the variables to be optimized, and punishment terms step by step, by means of the "setting wizard panel".

(2) Kernel program: basically the same as BEFPM /MEESG models described above. Users can not only use MEESG to find optimal schemes, but also calculate building energy demand of known schemes.

(3) Output interface: output the optimization proposal and report generated by the computer automatically, the 3-D diplay of the optimal schemes, and the sensitivity analysis curves based on the optimal schemes of each varible to be optimized (Figure 9).

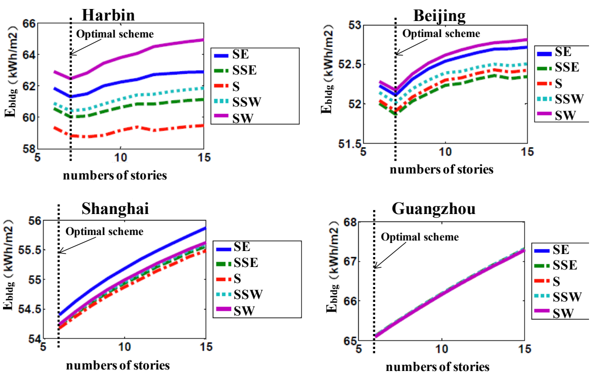
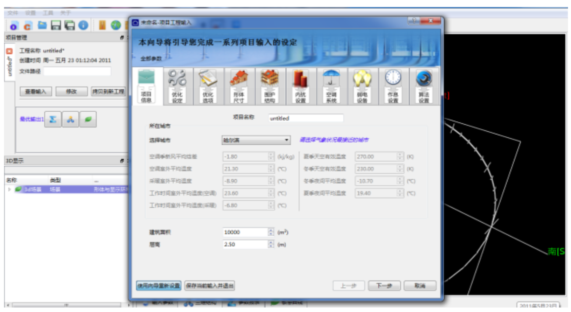
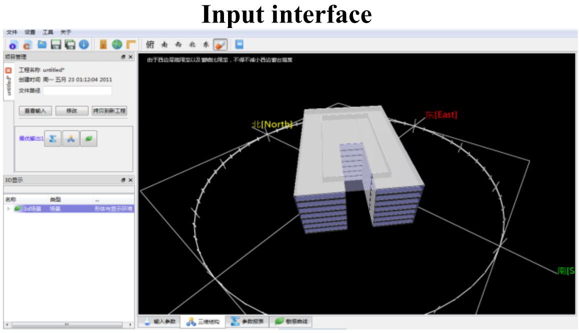


Figure 9 An example of the sensitivity analysis (upon the number of stories) based on the optimal scheme



Input interface



Output interface

Figure 10 Input and output interfaces of MEESG

DISCUSSION

It remains four important issues to be studied further in the future work:

(1) How to introduce natural ventilation and a more effective building system model into the method?
(2) The "Total energy demand" may not be the only judgement of a building's energy performance. How to employ other optimization objectives such as peak load or daily performance?
(3) How to simulate a complex-shaped building with polygon or curved surface?
(4) How to make software users believe the results drawn from the method? Is an interface to other detailed softwares for result validation and follow-up simulation necessary?

ACKNOWLEDGEMENT

The research was supported by National Key Technology R&D Program in the 11th Five Year Plan of China.

NOMENCLATURE

Q_E building accumulated envelope gain (W/m^2)
β weekend shutdown coefficient
ω win-to-wall ratio
K U-value (W/m^{2}K)
A surface area (m^2)
$\Delta\overline{T}$ average temperature difference (℃)
τ accumulated hours (h)
F_{bldg} building area (m^2)
e surface absorptivity
α_{out} outer surface convective heat transfer coeff.
$\overline{q}_{solar}$ average solar radiation power density (W/m^2)
$\overline{K}$ building envelope average U-value (W/m^{2}K)
$STVR$ building surface to volume ratio (m^{-1})
o occupancy in the working hours (p/m^2)
pd occupant heat gain (W/p)
q power density (W/m^2)
ρ air density (kg/m^3)
Δi enthalpy difference between indoor and outdoor
fa fresh air volume per occupant (m^3/(h·p))
r storey height (m)
inf infiltration air change rate (h^{-1})
τ_{lt} accumulated lighting hours (h)
τ_{lt}^* daylight-utilized lighting hours (h)
E energy demand (kWh/m^2)
EER energy efficient ratio
n numbers of floors
λ the ratio of storey height to room depth
tr window comprehensive transparency
θ orientation of building south facade

SUBSCRIPT & SUPERSCRIPT

wall, win, roof wall, window and the roof
i the ith surface
lt lighting
eq indoor equipment
c cooling
h heating
in interior zone
ex exterior zone
S, W, N, E south, west, north and east
* correction introduced

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