Hybrid Model of Existing Buildings for Transient Thermal Performance Estimation

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Abstract: Building level energy models are important to provide accurate prediction of energy consumption for building performance diagnosis and energy efficiency assessment of retrofitting alternatives for building performance upgrading. Simplified but physically meaningful models for existing buildings are preferable for practical applications. In this study, a hybrid building model is developed to describe building system for thermal performance prediction at building level. The model includes two parts. One part is the detailed physical models, which are the CTF models of building envelopes based on the easily available coincident detailed physical properties. The other part is the simplified 2R2C model for building internal mass, whose parameters are estimated and optimized using short-term monitored operation data. A genetic algorithm estimator is developed to optimize these parameters. The parameter optimization of the simplified model and the hybrid building model are validated in a high-rise commercial office building under various weather conditions.

Key words: Hybrid building model, dynamic thermal performance, simplified model, building internal mass, parameter optimization

1. INTRODUCTION

For the diagnosis and evaluation purposes of building system, a reference building energy model is very important to accurately predict absolute performance data for performance benchmarking [1]. At the building level as a whole process, many researchers have developed different reference models, which can be categorized into physical models and data driven models and gray models.

Available simulation models such as EnergyPlus [2] and DOE-2 [3] etc., are typical detailed physical models. However, a large number of parameters are needed as inputs for simulation, and the process of collecting physical descriptions is time consuming and probably does not cost effective. One is building envelope information, which is relatively easy to obtain according to design data or site survey. The other is the description of building internal mass, which includes internal partitions, floors, furniture etc. Obviously, it is unimaginable to describe the building internal mass physically piece by piece. To simplify the description process of building internal mass, a reference RTF (room transfer function) [4][5] is often used. However, the parameter selection is based on the actual building configuration which should be similar to the specified configurations of reference building. The estimation of cooling load may deviate greatly if the actual building configuration of concern differs greatly from the specified configuration of a reference building. As a matter of fact, such situation occurs often.

Dynamic data driven models are capable of capturing dynamics such as mass dynamics to some extends and better suited to handle inter-correlated forcing functions or independent parameters [6][7]. However, it is generally necessary to acquire data over a long period of time in order to train the models for accurate prediction. Gray models assume the physical structure and their parameters have definite physical meanings. The parameters can be backed out with operation data. Braun and Chaturvedi [8], Liao and Dexter [9] developed a gray second-order physical model to simulate the dynamic behavior of existing buildings. The gray models can predict long term energy performance with short term operation data monitoring. Although gray models can represent the physical properties of building system and predict energy consumption, some easily available building information can be utilized to enhance the simplified models and reduce the number of parameters to be identified with operation data.

This paper presents a hybrid building model to represent a building system for dynamic thermal performance prediction at building level for the performance diagnosis and evaluation of existing buildings. A parameter optimization method to identify partial parameters of the hybrid model (namely hybrid building model) is developed also. The hybrid model consists of detailed physical models of building envelopes and a gray model of building internal mass. The properties of building envelopes are relatively easily available to establish the detailed physical models of building envelopes to calculate the heat transfer using the traditional CTF method. Building internal mass, such as internal structures, partitions, and furniture etc., is difficult to describe. It is represented using a gray model with the physical structure of a 2R2C model and parameters to be optimized by minimizing the difference between model prediction and measurement. Searching the best values of the 2R2C model parameters is a typical nonlinear optimization process. Genetic algorithm [10] can quickly find a sufficiently good solution (i.e. near optimal solution), and is applied to search for optimal model parameters. As a practical application, a hybrid model was established for a high rising commercial office building, and the parameters of the simplified gray 2R2C model were optimized on the basis of the operation data in short period time. The hybrid model was verified in various other operation conditions.

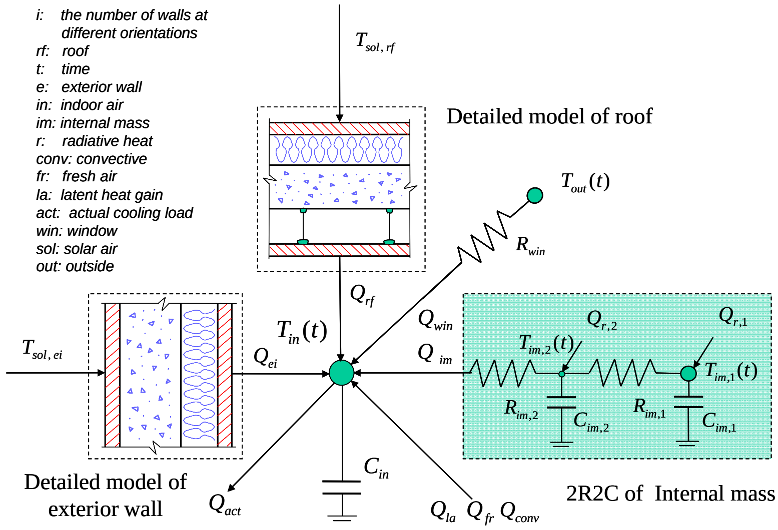

Fig. 1 Schematics of the hybrid building energy model

2. HYBRID BUILDING MODEL

Figure 1 illustrates the hybrid building model. Building envelopes are mainly exterior walls and roof(s). Exterior walls should be considered respectively according to the orientations because the dynamic models of the exterior walls at different orientations have different forcing functions due to the changing position of the sun. Exterior walls and roofs are represented as detailed physical models using traditional CTF method with detailed physical property descriptions. Building internal mass includes floors, interior partitions, furniture etc. It is represented with a 2R2C model, which consists of two resistances and two capacitances. All resistances and capacitances are assumed to be time invariant. The windows have negligible energy storage and are represented with pure resistances (R_{win}). The effect of varying wind velocity on heat transfer of building envelopes is not considered.

The heat transfer of the building system is described using the following equations. The heat transfer through exterior walls and roof can be calculated as Equation (1) and (2) using traditional CTF coefficients [11]. The window heat transfer can be represented as a pure resistance model as Equation (3) in the discrete form. The simplified building internal mass model can be represented as Equation (4) and (5) in differential form. With assumed values of the parameters of the 2R2C model, the discrete nodal temperature can be calculated using Runge-Kutta algorithm. The convective heat transfer between internal mass and indoor air can be easily calculated as Equation (6) in the discrete form. With the heat transfer from the introduced fresh air as well as convective heat from occupants, lights and equipments etc, the estimated cooling energy consumption can be read as Equation (7) in the discrete form.

$$Q_{ei}(k\Delta) = A_{ei}\left\{\sum_{j=0}^{r} b_{ei,j} T_{sol,ei}((k-j)\Delta) - \sum_{j=0}^{r} c_{ei,j} T_{in}((k-j)\Delta)\right\} - \sum_{j=1}^{m} d_{ei,j} Q_{ei}((k-j)\Delta) \quad (1)$$

$$Q_{rf}(k\Delta) = A_{rf}\left\{\sum_{j=0}^{r} b_{rf,j} T_{sol,rf}((k-j)\Delta) - \sum_{j=0}^{r} c_{rf,j} T_{in}((k-j)\Delta)\right\} - \sum_{j=1}^{m} d_{rf,j} Q_{rf}((k-j)\Delta) \quad (2)$$

$$Q_{win}(k\Delta) = A_{win}\frac{T_{out}(k\Delta) - T_{in}(k\Delta)}{R_{win}} \quad (3)$$

$$A_{im}C_{im,1}\frac{dT_{im,1}(t)}{dt} = Q_{r,1} - A_{im}\frac{T_{im,1}(t) - T_{im,2}(t)}{R_{im,1}} \quad (4)$$

$$A_{im}C_{im,2}\frac{dT_{im,2}(t)}{dt} = Q_{r,2} + A_{im}\frac{T_{im,1}(t) - T_{im,2}(t)}{R_{im,1}} - A_{im}\frac{T_{im,2}(t) - T_{in}(t)}{R_{im,2}} \quad (5)$$

$$Q_{im}(k\Delta) = A_{im}\frac{T_{im,2}(k\Delta) - T_{in}(k\Delta)}{R_{im,2}} \quad (6)$$

$$Q_{est}(k\Delta) = \sum_{i=1}^{n} Q_{ei}(k\Delta) + Q_{rf}(k\Delta) + Q_{win}(k\Delta) + Q_{im}(k\Delta) - C_{in}\frac{T_{in}(k\Delta) - T_{in}((k-1)\Delta)}{\Delta} + (Q_{conv}(k\Delta) + Q_{fr}(k\Delta) + Q_{la}(k\Delta)) \quad (7)$$

The properties of exterior walls and roof are relatively easy to obtain. They are used to calculate CTF coefficients for heat transfer calculation. The model parameters, $C_{im,1}$, $R_{im,1}$, $C_{im,2}$, $R_{im,2}$, of the building internal mass can be optimized by minimizing the difference between the measured cooling energy consumption and the model predicted cooling energy consumption using operation data, while the CTF coefficients of building envelopes are calculated in advance. The parameter optimization of the simplified 2R2C building internal mass is illustrated in the next section.

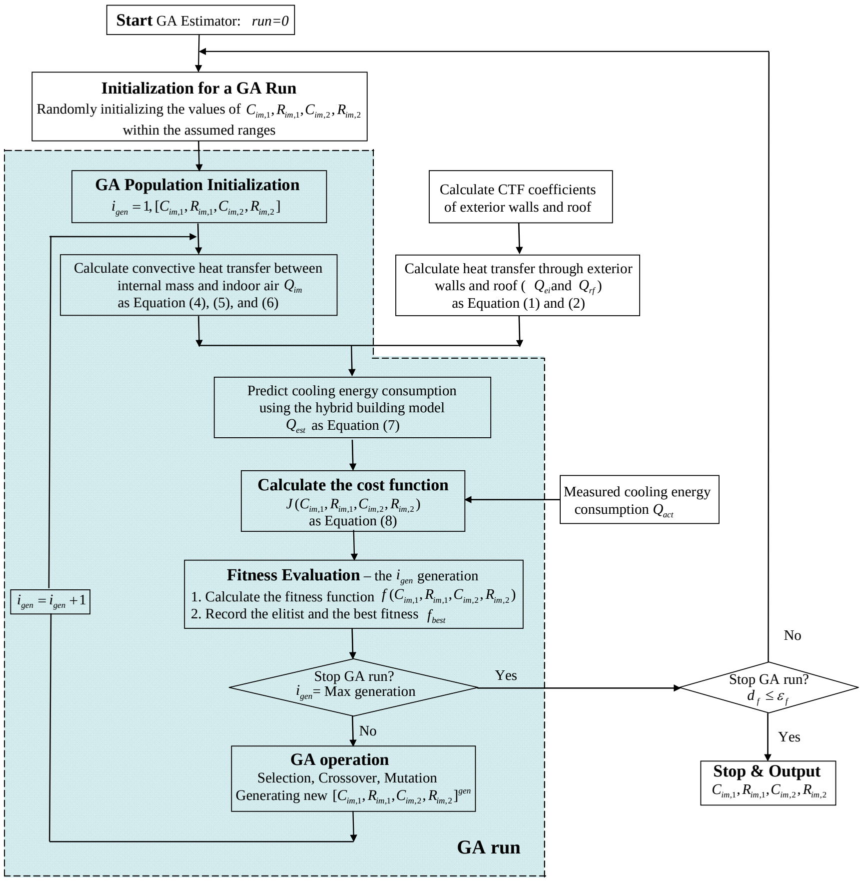

Fig.2 Flow chart of GA estimation of 2R2C model

3. PARAMETER OPTIMIZATION OF 2R2C MODEL USING GA

The essential issue of the hybrid modeling is to find the proper values of the parameters of the simplified 2R2C building internal mass model. It is a typical nonlinear optimization problem to find the optimal model parameters. Sequential quadratic programming (SQP) [12] and conjugate gradient method [13] are commonly used optimization methods. However, both methods as well as other traditional optimization methods need initially guessed values of parameters. In most cases, the initial values affect their convergence speed. Genetic algorithm (GA) is a better optimization method especially when an optimal problem is not perfectly smooth and unimodal [10]. It can quickly find a sufficiently good solution with random parameter initialization. The random initial parameter does not affect convergence speed. The algorithm was used to search for global optimal solutions in air conditioning fields, and it performed very well [14][15]. In the study, GA is utilized to search for optimal parameters of the 2R2C model of building internal mass to minimize the errors between measured values and prediction of the building model.

To find the optimal parameters of the simplified internal mass model, the cost function is constructed as Equation (8) by minimizing the difference between the measured cooling energy consumption and the predicted cooling energy consumption using the hybrid building model with Equation (1-7). The parameters to be optimized are the resistances and capacitances of the 2R2C model of building internal mass, which can give the best fitting with the operation data. The cost function (J) of such optimization employs the integrated root-mean-square error.

$$J(C_{im,1}, R_{im,1}, C_{im,2}, R_{im,2}) = \sqrt{\frac{\sum_{k=1}^{N}[Q_{act}(k\Delta) - Q_{est}(k\Delta)]^2}{N-1}} \quad (8)$$

This is a typical nonlinear optimization problem. GA is employed to search for the optimal values. The operation data needed for parameter identification and optimization are as follows. The return and supply chilled water temperatures and the chilled water flow rate are needed to calculate the measured cooling/heating energy consumption. These data can be retrieved from BMS. To predict the building cooling/heating energy consumption using the hybrid building model, indoor air temperature and humidity, outdoor air temperature and humidity, fresh air flow rate, solar radiation, occupancy and internal gains are needed. Indoor air temperature and humidity, outdoor air temperature and humidity can be retrieved from BMS.

Figure 2 shows schematically the flowchart of the GA estimator developed for the parameter optimization of the 2R2C building internal mass model. It starts with random initial estimates of the individual capacitances and resistances within assumed ranges (The ranges will be addressed in Section 4). The component with grey background represents the procedure of a GA run. Multiple runs are allowed. Equation (9) represents the fitness function (f), which is the reciprocal of the cost function as Equation (8).

$$f = f(C_{im,1}, R_{im,1}, C_{im,2}, R_{im,2}) = \frac{1}{J(C_{im,1}, R_{im,1}, C_{im,2}, R_{im,2})} \quad (9)$$

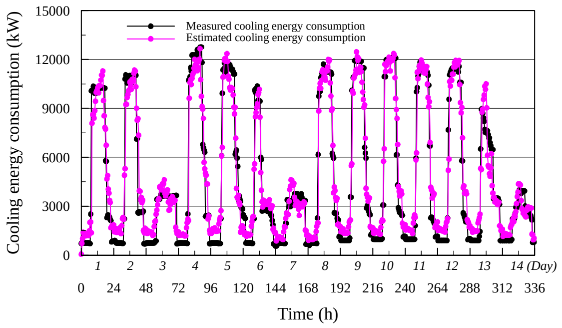

Fig. 3 Model predicted cooling energy consumption *vs* actual measured cooling energy consumption (Parameter optimization case)

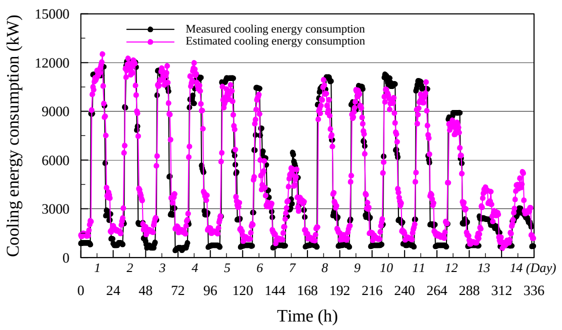

Fig. 4 Model predicted cooling energy consumption *vs* actual measured cooling energy consumption (Validation-summer case)

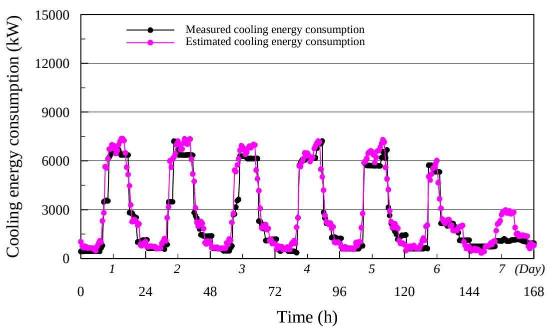

Fig. 5 Model predicted cooling energy consumption *vs* actual measured cooling energy consumption (Validation-winter case)

In the genetic algorithm, the four parameters ($C_{im,1}$, $R_{im,1}$, $C_{im,2}$, $R_{im,2}$) constitute the chromosome of an individual, the assumed ranges of these parameters are the search space for these parameters. Initializing the four parameters produces the initial population to start a GA run. With the initial values of the four parameters of the simplified building internal mass model, the convective heat transfer between the internal mass and indoor air can be calculated as Equation (4, 5, and 6). The heat transfer through exterior walls and roofs are calculated as Equation (1 and 2) using CTF method. The CTF coefficients are deduced on the basis of the detailed physical property description. With these heat transfer calculations, the total cooling energy consumption is calculated as Equation (7). By comparing the predicted cooling energy consumption and the measured cooling energy consumption, the cost function for optimization can be calculated as Equation (8). Then, the fitness functions of a generation are calculated, and the individual with the best fitness is recorded.

Termination of a GA run is decided if the number of the current generation is equal to a predefined maximum number. At least two runs of the GA process are necessary when running the GA Estimator. The criterion to stop the GA Estimator is based on the comparison of the best fitness values of two consecutive runs. If the relative difference between the two maximum fitness values is less that a threshold value (e.g., equals to 0.0001), the GA Estimator is stopped. A GA driver developed by Carroll [16] is revised and used in this study.

4. MODEL VALIDATION

The hybrid building energy model was validated in a real high rising commercial office building. The building consists of a main building of 50 floors with 180 meter high, an attached building of 7 floors with about 28 meter high. All the buildings are air-conditioned using all-air systems. The air conditioning area is about 12000 m^2. The CTF models of building envelopes were developed based on the detailed physical property description of building envelopes. Two weeks' operation data in summer season were used to optimize the parameters of the simplified 2R2C model. The optimized parameters using GA estimator are: $C_{im,1}$=648729 $J/(m^2K)$, $C_{im,2}$=73793 $J/(m^2K)$, $R_{im,1}$=0.299 m^2K/W, $R_{im,2}$=0.0282 m^2K/W.

Using the optimized parameters of the simplified 2R2C model, the cooling energy consumption was predicted with operation data such as indoor air temperature and outdoor air temperature etc. Figure 3 shows the comparison between the model predicted cooling energy consumption and the actual measured cooling energy consumption. It shows that the model predicted cooling energy consumption well followed the dynamics profile of the actual measured cooling energy consumption. The relative error was about 8% for the data points of office hours.

To validate the wide applicability of the hybrid building energy model developed, the model was used to predict the cooling energy consumption in other two operation periods. One was also in summer season lasting for two weeks, the other was in winter season lasting for one week. Figure 4 presents the model predicted cooling energy consumption profile using the building energy model compared with the actual measured cooling energy consumption profile for the summer case. Figure 5 presents the model predicted cooling energy consumption and the actual measured cooling energy consumption for the winter case. The comparison shows that the model can dynamically predict cooling energy consumption, which agreed well with the actual measured cooling energy consumption. The relative error is about 10% for data points in office hours.

The robustness of the model to predict the thermal performance owes to that the model represents the dynamic characteristics of the building system physically and the model parameters are partially determined using the building physical properties. At the same time, the accuracy of the hybrid building energy model owes partially to that part of the model parameters are identified using the actual monitored operation data by best fitting the model outputs with the operation data. The model can provide thermal performance prediction of good accuracy and robustness for practical applications.

5. SUMMARY

This paper presents a hybrid building model which consists of detailed physical models of building envelopes and the gray simplified model of building internal mass. Parameters of the detailed physical model are calculated based on detailed physical properties of building envelope. The parameters of the gray internal mass model can be identified and optimized effectively and efficiently with genetic algorithm using short-term monitored operation data.

The hybrid building model and the parameter optimization of the simplified building internal mass model were verified in a high rising commercial office building under different operation conditions. Test results demonstrate that the model predicted the cooling energy consumption with about ten percent relative error by comparing to the actual measured cooling energy consumption. The model can also well predict the average indoor air temperature. Good robustness of the hybrid building model to predict building thermal performance owes to that the model captures the dynamic characteristics of the building system correctly. The model is not only partially represented by detailed physical properties of building envelopes, but also partially physically represented by the 2R2C building internal mass model while the parameters are backed out using the actual monitored operation data by best fitting the model output with the operation data. The hybrid building model benefits practical applications by providing thermal performance prediction of good accuracy and wide applicability.

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NOMENCLATURE

A area (m^2)
b,c,d CTF coefficients
C thermal capacitance ($J/(m^2K)$ or J/K)
d_f difference between the two maximum fitness values
f fitness function
J objective function
Q energy consumption or transferred heat (kW)
R thermal resistance (m^2KW^{-1})
T air temperature (℃ or K)
t time (second or hour)

Greek symbols

ε_f threshold value (-)
Δ time interval

Subscripts

act actual
conv convective heat
ei associated with external wall at the *i*-th orientation
est estimated
fr fresh air
im associated with building internal mass
in inside, indoor air
la latent heat
out outside
r associated with radiative heat
rf associated with roof
sol associated with solar air temperature
win window

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