Hybrid Model for Building Performance Diagnosis and Optimal Control

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ABSTRACT

Modern buildings require continuous performance monitoring, automatic diagnostics and optimal supervisory control. For these applications, simplified dynamic building models are needed to predict the cooling and heating requirement viewing the building as a whole system. This paper proposes a new hybrid model. Half of the model is represented by detailed physical parameters and another half is described by identified parameters. 3R2C thermal network model, which consists of three resistances and two capacitances, is used to simulate building envelope whose parameters are determined in frequency domain using the theoretical frequency characteristics of the envelope. Internal mass is represented by a 2R2C thermal network model, which consists of three resistances and two capacitances. The resistances and capacitances of the 2R2C model are assumed to be constant. A GA (genetic algorithm)-based method is developed for model parameter identification by searching the optimal parameters of 3R2C models of envelopes in frequency domain and that of the 2R2C model of the building internal mass in time domain. As the model is based on the physical characteristics, the hybrid model can be used to predict the cooling and heating energy consumption of buildings accurately in wide range of operation conditions.

1. INTRODUCTION

Modern buildings are being designed with increasingly sophisticated energy management and control systems (EMCS) that have the capabilities for monitoring and controlling the conditions in buildings. Nonetheless, building system or HVAC system often fails to satisfy the performance expectations or fails with performance degradations, such as poor indoor air quality and more energy consumption, after a period of operation with correct commissioning (House and Kelly 1999). To detect and locate the causes of fails or to improve the performance of building, House and Kelly (1999) and Claridge et al. (1999) applied systematic method with top-down and bottom-up approaches for building diagnosis, viewing the building as a whole system. The two approaches are represented with the hierarchical structure of HVAC systems and subsystems in buildings commonly used for diagnostic reasoning (IEA Annex 25, 1996). The top-down approach uses performance measurements from higher levels to reason about possible lower-level causes of degradations to those higher level measures. At the top level, whole building energy use or cooling/heating load can provide useful information about the performance of a building.

For energy conservation, building thermal mass can be controlled as an alternative of thermal storage especially for large building with large inner areas. During hot season, if outdoor night temperatures are lower than indoor temperatures, it's possible to cool the building by night ventilation. Air ventilation enhances convective heat losses from mass elements and dissipates the released heat to the lower temperature outdoor heat sink (Baer 1983). When the climatic conditions do not permit the use of outdoor air, one can still pre-cool the building during off peak hours, using an air conditioning system if the electricity rate system is favorable. This in fact results in considerable savings to the user and to the electric utility (Braun 1990; Snyder and Newell 1990).

Whether for the diagnosis purpose of a whole building, or the thermal mass control strategies, even or energy saving of system retrofitting, a reference model of the building is essential. 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.

Physical modeling, also called forward modeling, begins with a description of the building system or component of interest and defines the building being modeled according to its physical description. Mostly simulation model is based on first principles, either a detailed first principles model, such as EnergyPlus (Crawley and Drury 2000), DOE-2 (Ed Kidd et al. 2001), or a simplified first principles model, such as AIRMODEL (Giebler et al. 1998) which was used by

Claridge et al. (1999) to diagnosis the building malfunction. However, a large number of parameters are needed as inputs for the simulation model. The process of collecting a physical description is time consuming and probably does not cost effective, or is impossible for some case (the thermal properties of furniture, inner thermal mass properties, etc.). In the modeling process, such indefinitive variables are usually assumed as constants. Unsuitable assumptions can make the model deviate, thus decrease the confidence of the model.

Data driven models are based on the empirical behavior of the building as they relate to one or more driving forces or the behavior of similar buildings. They consist of benchmarking models, steady state inverse models and dynamic state inverse models

Benchmarking is one type of data driven model. The performance of the building of concern is compared to that of similar buildings using a database of the actual performance of a statistically selected sample of comparable buildings. The comparison is usually made in terms of whole building electricity and fuel consumption. This benchmarking process can only provide an approximate assessment of relative performance from the very modest input data, typically building type, floor area and geographical location. An example of the available comparison data set is the EUI (energy use intensity) for a 100,000 sqft large office building from a Northern California simulation prototype developed from energy analysis of 74 similar buildings (Akbari et al. 1993). One limitation of the method is that comprehensive comparison data sets have to be established. The other is that the reliability of assessment according to the comparison result is reduced greatly if the prerequisites such as building type, floor area and geographical location are different.

Inverse models, including steady state and dynamic, are typical data driven models. Many researchers have developed steady state inverse models, such as univariate multiple parameters models by performing a regression analysis on monthly utility consumption data against average billing period temperature (Fels 1986; Ruch and Claridge 1991; Thamilseran and Haberl 1995) and multiple regression modeling (Ruch and Chen et al. 1993; Reddy and Claridge 1994). Dynamic inverse models are capable of capturing dynamics such as mass dynamics to some extend and better suited to handle inter-correlated forcing functions or independent parameters. Examples of dynamic inverse models include ARMA (autoregressive moving average) models (Subbarao et al. 1990), Fourier series models (Dhar et al. 1999) and artificial neural networks (Kalogirou et al. 1997; Minoru et al. 1995). Appling regression techniques above can lead to models that do not respect the proper physics. It is generally necessary to acquire data over a long period of time with widely varying conditions in order to train black box models that can provide accurate predictions, or even trends, under all conditions. Furthermore, it is not known how well the models would perform in predicting building energy use if there were a major change in the control strategies employed, such as there would occur in going from a night setup control to pre-cooling control strategy, because those parameters do not respect the proper physics or the parameters cannot represent the physical properties.

Therefore, a kind of simplified models, which can represent the physical properties of building system is preferred for diagnosis, optimal control etc. Braun and Chaturvedi (2002) developed an inverse gray-box thermal network model for transient building load prediction. In the approach, second order transfer function was established from an assumed 3R2C thermal network model, which consists of three resistances and two capacitances, to predict building load. The parameters of the 3R2C models, whose values are assumed in certain ranges, were identified by a nonlinear regression algorithm in time domain to minimize errors between predictions of the transfer function and the measured operation data.

However, some information of building system, such as building envelopes and occupant activities, is easily available. We can establish detailed physical models. Other information of building system, such as internal structures and furniture etc., is difficult to obtain. Nevertheless, we can view all the materials inside the building as a whole called internal mass, and assume the form which can describe the physical thermal meanings. Consequently, a new hybrid model is proposed. Half of the hybrid model is represented by detailed physical parameters and another half is described by identified parameters using operation data. 3R2C models are utilized to simulate building envelopes. From the view of system theory, the frequency characteristics of the simplified 3R2C model should approach the theoretical frequency characteristics of the building envelope as closely as possible. The parameters of 3R2C model, which are constrained to the total thermal resistance and capacitance, are determined using the theoretical frequency characteristics of the envelope. Internal mass is represented by a 2R2C model whose resistances and capacitances are assumed to be constant. The node placement of internal mass is identified with the 3R2C model of building envelope and the operation data.

Searching the best values of the model parameters is a nonlinear optimization process. House and Smith (1991) employed a sequential quadratic programming to compute the optimal values. Nizet et al. (1984) used a conjugate gradient method to develop an

optimal control method. Both optimization methods as well as other conventional optimization methods have to start from initial guesses of optimal variables and their convergence speed is affected by their initial guesses in most cases. The genetic algorithm (GA) is a better optimization method especially when an optimal problem is not perfectly smooth and unimodal (Mitchell 1997). The genetic algorithm can quickly find a sufficiently good solution (i.e. near optimal solution) and can be applied when a task does not require an "absolute" optimum. The algorithm has been used to search for global optimal solutions in air conditioning fields (Wang and Jin 2000; Wang and Wang 2002). In the study presented in this paper, GA is also utilized to search for optimal parameters of the hybrid model to minimize the errors between measured values and prediction of the hybrid model.

2. DEVELOPMENT OF HYBRID MODEL

For retrofitting analysis, performance monitoring and diagnostics, control strategy development, and on-line control applications of building system, a virtual concept is developed. A schematic of a virtual system for a typical building is shown in Figure 1. The major components of the system are the building envelopes, internal mass, cooling/heating sources, and a virtual air handling unit (AHU). Such a virtual AHU can accomplish the functions of maintaining air temperature and humidity within the building, and satisfying the indoor air quality with optimized energy consumption at work hours instead of all the installed AHUs in the building. The proposal of the virtual concept facilitates the understanding of the building to be viewed as a whole. In order to predict overall energy requirements, a hybrid model is developed to represent the whole building including occupant activities, lighting, and something else related to cooling/heating loads.

Hybrid is not a new concept in academic field. It is often employed to describe a model which consists of different approaches (Bahai and Esat 1994; Padhy 2001; Wu and Thompson 2002). Petermeier et al. (2002) developed a hybrid model for the fouling process in tubular heat exchangers, which incorporate qualitative knowledge and quantitative data. In the study, hybrid modeling is the compounding of both physical modeling and data-driven modeling. It begins with physical descriptions of some components if their detailed physical characteristics are available and assumption of the physical structures of some components if their detailed physical characteristics cannot be available. The parameters of the assumed physical models are identified with the known physical descriptions and operation recorded data to provide the most accurate representation for the assumed model forms and the data sets. Such model not only describes the behavior or performance of the system, but also can explain the system physically. Therefore, such model can predict reliably the performance of the building system.

The cooling requirement for a building (Q_b) can be separated into latent and sensible contributions. Latent heat gains, which become cooling load (Q_{bl}) directly, are associated with the addition of water vapor into the air, which must ultimately be removed by air handling system. In a building, latent gains primarily consist of occupant respiration, infiltration of moisture, induced fresh air, and aesthetic sources such as plants and fountains. Among these, the latent gains from occupants and induced fresh air are easy to estimate and measure respectively.

Sensible load (Q_{se}) of the buildings is due to the heat

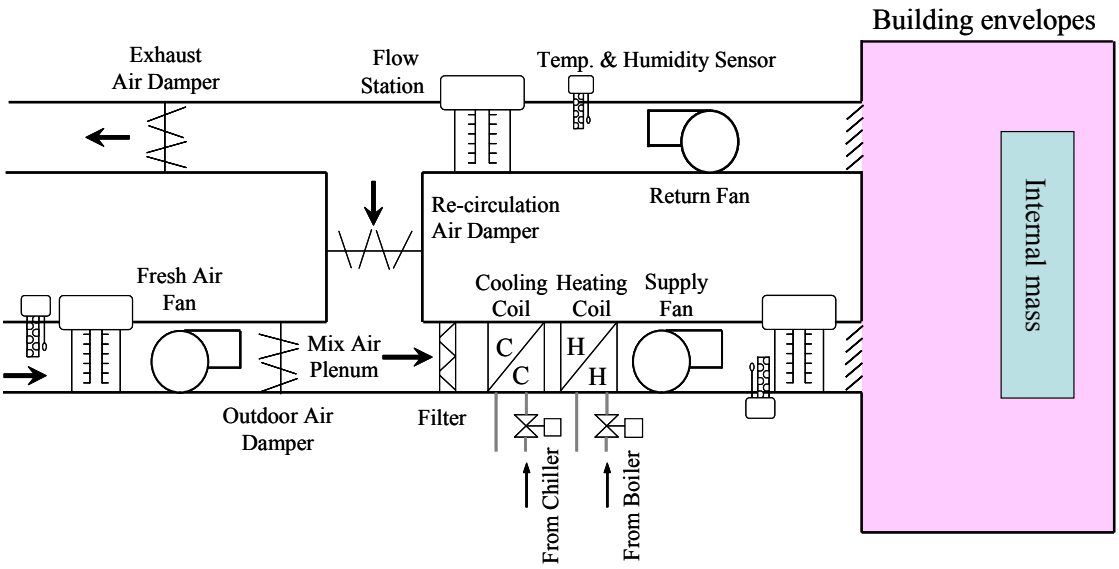


Figure. 1 schematic of a virtual system for a typical building

transfer from "warm" surfaces within the buildings. The sources of sensible heat gains can be categorized as internal and external to the building. Typical internal sources are occupants, lights, equipments (computers, copy machines, etc.), internal structures and furniture, etc. External sources for heat gains consist of solar radiation transmitted through windows and absorbed on external walls and energy conduction through external walls and windows due to the difference between the ambient and space temperatures.

Figure 2 depicts a schematic representation of an electrical analog for the hybrid model. Four big categories are considered: (1) external walls, (2) ceiling/roof, (3) windows, and (4) internal mass. External walls should be considered respectively according to the orientations because the dynamic models of the external walls at different orientations have different forcing functions due to the changing position of the sun. External walls and ceiling/roof are considered as 3R2C models. The windows have negligible energy storage and represented with pure resistances. Internal mass includes floors, internal walls, and furniture etc. It absorbs radiant heat through the windows and that from occupants, lighting, and machine etc., and then releases the heat gradually to the air space. Internal mass is viewed as 2R2C model as shown in Figure 2. All resistances and capacitances are assumed to be time invariant. The effect of varying wind velocity on exterior wall convection coefficients is not considered. The whole building energy balance can be represented with the following differential equations.

$$C_{rf,2}\frac{dT_{rf,2}(t)}{dt}=\frac{T_e(t)-T_{rf,2}(t)}{R_{rf,1}}-\frac{T_{rf,2}(t)-T_{rf,4}(t)}{R_{rf,3}} \quad (1)$$

$$C_{rf,4}\frac{dT_{rf,4}(t)}{dt}=\frac{T_{rf,2}(t)-T_{rf,4}(t)}{R_{rf,3}}-\frac{T_{rf,4}(t)-T_{in}(t)}{R_{rf,5}} \quad (2)$$

$$C_{ei,2}\frac{dT_{ei,2}(t)}{dt}=\frac{T_e(t)-T_{ei,2}(t)}{R_{ei,1}}-\frac{T_{ei,2}(t)-T_{ei,4}(t)}{R_{ei,3}} \quad (3)$$

$$C_{ei,4}\frac{dT_{ei,4}(t)}{dt}=\frac{T_{ei,2}(t)-T_{ei,4}(t)}{R_{ri,3}}-\frac{T_{ei,4}(t)-T_{in}(t)}{R_{ei,5}} \quad (4)$$

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

$$C_{im,2}\frac{dT_{im,2}(t)}{dt}=Q_{r,2}+\frac{T_{im,1}(t)-T_{im,2}(t)}{R_{im,1}}-\frac{T_{im,2}(t)-T_{in}(t)}{R_{im,2}} \quad (6)$$

$$C_{in}\frac{dT_{in}(t)}{dt}=\sum_{i=1}^{n}\left(\frac{T_{ei,4}(t)-T_{in}(t)}{R_{ei,5}}\right)+\frac{T_{rf,4}(t)-T_{in}(t)}{R_{rf,5}}+\frac{T_{im,2}(t)-T_{in}(t)}{R_{im,2}} \quad (7)$$
$$+(Q_{cond,w}+Q_{fr}+Q_{conv,l}+Q_{conv,p}+Q_{conv,e}+Q_{la})-Q_{act}$$

Traditional CTF method recommended by ASHRAE is suited to building energy prediction with fixed time step (conventionally an hour) (Park et al. 1986; Klein et al. 1994). However, short time step may be required for detailed dynamic simulation and evaluation of building system and control strategies. The developed hybrid model can be used easily for variable time steps.

The model parameters of the building envelope (i.e. external walls and roofs) are identified using the detail property data and a GA-based method in frequency domain as illustrated in Session 3. The model parameters of the building internal mass (i.e. internal structure, furniture, etc.) are identified using the operation data and a GA-based method in time-

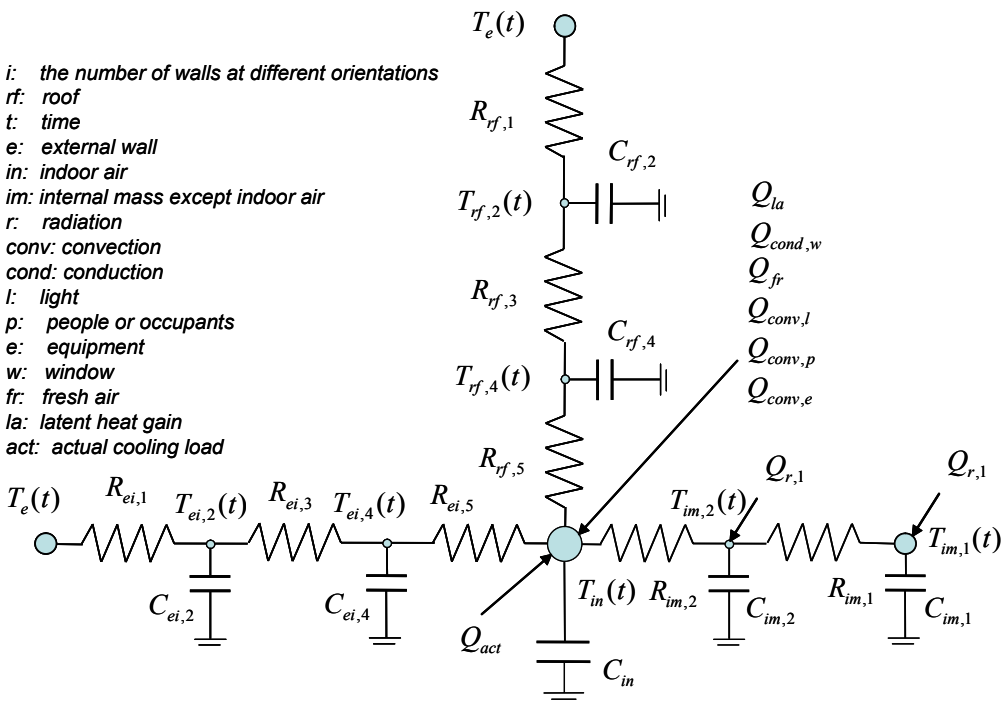


Figure 2 Schematic of thermal network for the hybrid model of building system

domain as illustrated in Session 4, while the model of building envelope is obtained in advance.

3. OPTIMAL NODAL PLACEMENT OF 3R2C MODEL OF BUILDING ENVELOPE

Here presents an innovative nodal placement methodology of 3R2C model (Figure 3) in frequency domain. With reference to system theory, if only the dynamic models of a system are completely equivalent to the real system, they should behave with the completely identical response characteristics. Phase lag and amplitude are two important indices of frequency characteristics. Therefore, we developed the methodology in frequency domain to identify the values of individual resistances and capacitances to make the simplified 3R2C model to fit the real system as described as follows. First, the frequency characteristics of the theoretical transmission matrix are calculated within the frequency range concerned. Second, the frequency characteristics of the simplified 3R2C model are calculated with random values of resistances and capacitances which constrain to the total thermal resistance and capacitance. Then, calculate the errors between the theoretical model and the simplified model. Finally, adjust the values of individual resistances and capacitances to minimize the total errors using GA (GA will delivered in later session).

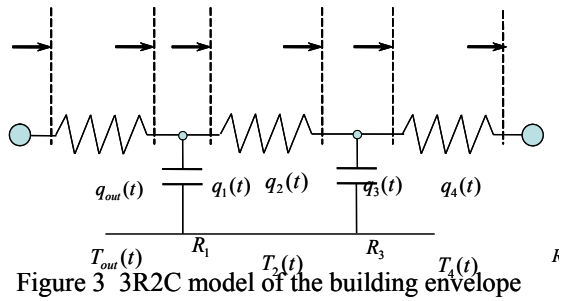
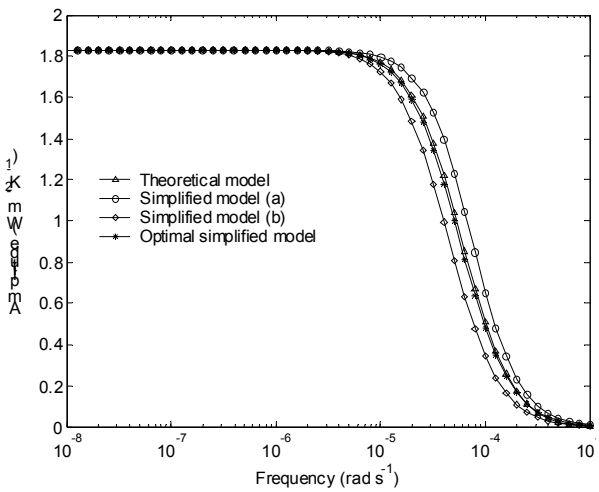
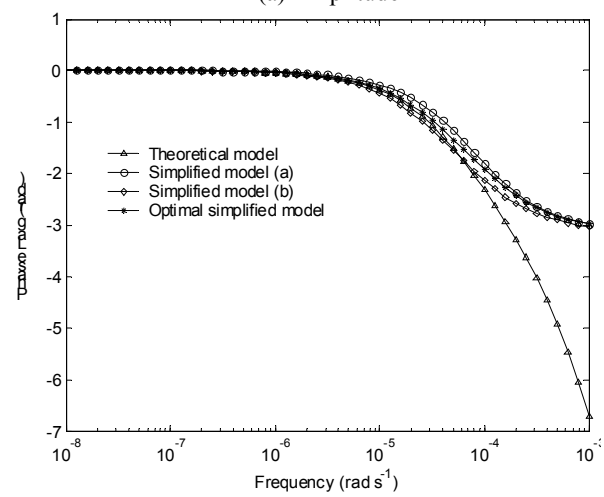


Figure 3 3R2C model of the building envelope

The developed optimal 3R2C model of a brick/cavity wall was validated in frequency response by comparing with the other three models. One is the theoretical model. The other are simplified model (a) and model (b). For model (a) (Seem and Klein et al. 1989), three resistances are outside conductive

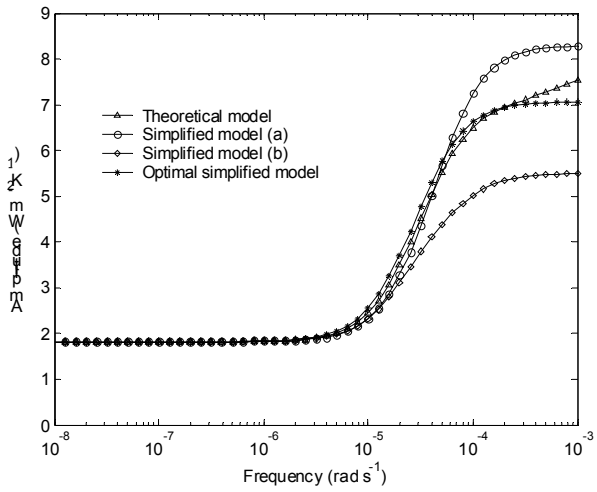


(a) Amplitude

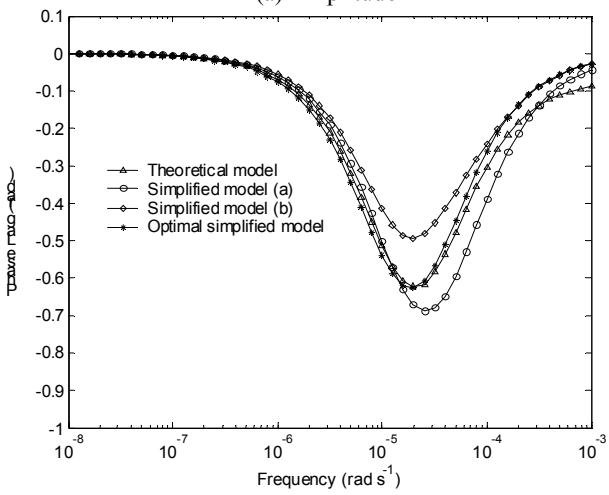


(b) Phase Lag

Figure 4 Frequency responses of cross heat conduction for the brick/cavity wall



(a) Amplitude



(b) Phase Lag

Figure 5 Frequency responses of internal heat conduction for the brick/cavity wall

resistance, wall conduction resistance and inside conductive resistance respectively, the value of individual capacitance is half of the total capacitance. For model (b) (Braun and Chaturvedi 2002), three resistances and two capacitances are distributed evenly. The frequency responses of cross and internal heat conductions have been compared numerically among the theoretical model and three simplified thermal network models within the frequency range of concern (10^{-10} to 10^{-3} $rad\ s^{-1}$). The cross and internal heat conductions are related to the indoor transient thermal load.

For the frequency response characteristics of the cross heat conduction, Figure 4(b) indicates that the three simplified models have similar phase lag deviating from the theoretical phase lag in high frequency region. The amplitude of the optimal simplified model fit close to that of the theoretical model, while the amplitude of simplified model (a) is greater than that of the theoretical model and the amplitude of the simplified model (b) less than that of the theoretical model in high frequency region (Figure 4(a)). For the frequency response characteristics of internal heat conduction, Figure 5(a) and (b) indicate that the amplitude and phase lag of the optimal simplified model fit closer to those of the theoretical model than those of simplified model (a) and (b). The amplitudes of simplified model (a) and (b) deviate greatly from that of the theoretical model at high frequency region.

As shown in the Figure 4 and 5, we can find that the optimal simplified model approximates much more closely to the theoretical model compared with two simplified models (a, b). However, there exists the deviation of phase lags of all the three simplified models, which is inherently caused by the simplified process.

4. PARAMETER ESTIMATION OF 2R2C MODEL OF INTERNAL MASS

The model (3R2C) of building envelope is available now. The model parameters of the building internal mass (i.e. internal structure, furniture etc.) are identified further using the operation data. The GA-based method in time-domain is described as follows.

4.1 The Objective Function of Optimization

The simulated prediction of the hybrid model with the differential equations (1-7) is used to compare with the operation data. The optimized parameters of the hybrid model are the resistances and capacitances of 2R2C model of internal mass which give the best fitting with the operation data. The objective function (J) of such optimization employs the integrated root-mean-square error defined in equation (8).

$$J(C_{im,1}, R_{im,1}, C_{im,2}, R_{im,2}) = \sqrt{\frac{\sum_{k=1}^{N}(Q_{m,k} - Q_{e,k})^2}{N-1}} \qquad (8)$$

where, Q is the cooling/ heating load, N is the number of the data points, the subscripts m and e denote the predictions and the operation data, $C_{im,1}$, $R_{im,1}$, $C_{im,2}$, $R_{im,2}$ are the parameters of 2R2C model. This is a typical nonlinear optimization problem. GA (genetic algorithm) is employed to search for the optimal values as illustrated below.

4.2 Genetic algorithm

GA is an advanced search and optimization technique. It has been developed to imitate the evolutionary principle of natural genetics. GA was invented by Holland (1992) and further developed in 1960s and the 1970s. Goldberg (1989), Davis (1991) and Mitchell (1997) provided comprehensive overviews and introductions to GA. Deb (1996) compared the GA search method with traditional methods (the direct exhaustive search method and the gradient-directed search method) for function optimization. One of the main advantages of GA is that it is generally robust in finding global optimal solutions, particularly in multimodal and multi-objective optimization problems (Deb 1996). Extensive research on the theoretical fundamentals and applications of GA is still going on, aimed at better computation efficiency, improved robustness, and so on (Salomon 1998).

Generally, GA uses three operators (selection, crossover and mutation) to imitate the natural evolution processes. The working procedures of a simple GA using binary coding are summarized as follows.

1) *Initialization*: to create an initial population of bit-strings (chromosomes), randomly, which represent a population of trial solution candidates.

2) *Evaluation*: to calculate the fitness corresponding to each bit-string (each trial solution candidate) in the population. The fitness function is designed such that the better the value of the optimization objective function, the larger the fitness.

3) *GA operations*: to repeat the following operations until a new population of bit strings is formed.

Selection (or *reproduction*): to select a pair of good bit-strings in the current population (parent population). The probability of a string in the parent population being selected (to mate with other string) is an increasing function of its fitness. Thus, a trial solution candidate that produces better values is more likely to be selected than those that produce inferior values of the objective function.

Crossover: to exchange (crossover) randomly chosen portion(s) of the two strings, with certain probability (crossover probability or crossover rate), to form two offspring. Crossover is the dominating operation in GA.

Mutation: to mutate the offspring bit-strings at each locus with a certain probability (the mutation probability or mutation rate). Mutation rate is usually small.
4) *Replacement*: to replace the parent population with the obtained offspring bit-strings.
5) *Evaluation*: the same as step 2.
6) *Termination*: to stop after a pre-specified number of *generations* (one loop from step 3 to step 5 is called a *generation*) or when a criteria that determines the convergence is satisfied. Otherwise, go to step 3.

The procedures described above form a *run*. They are the basis for most applications of GA. There are a number of details to fill in, such as the size of the population and the probabilities of crossover and mutation.

4.3 GA estimator

Figure 6 shows schematically the flowchart of the GA estimator developed for the parameter identification of the 2R2C model of building internal mass. It starts with the initial estimates of the individual capacitors and resistors within assumed ranges. The component with grey background represents the procedures of a GA *run*. Multiple *runs*

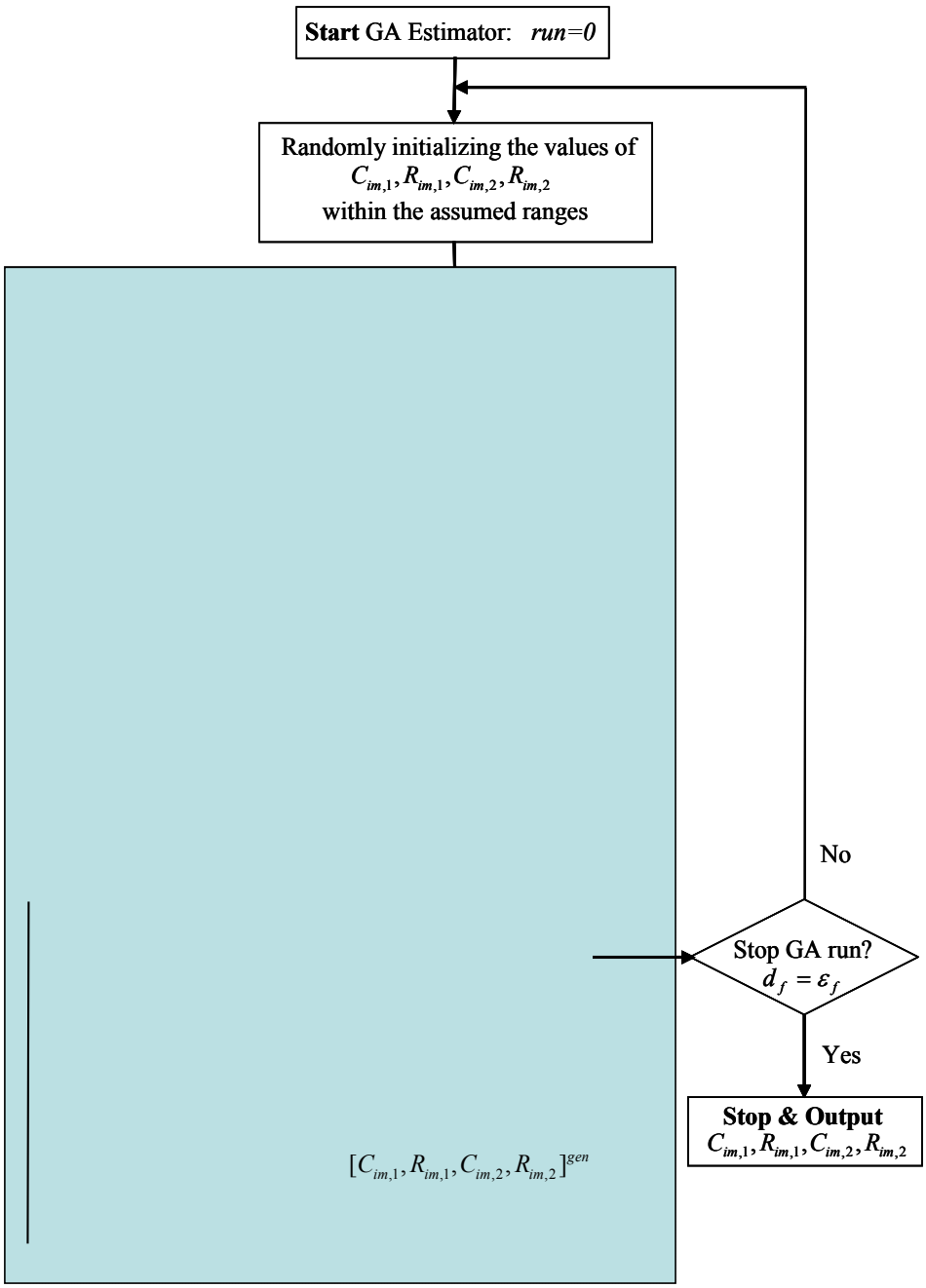


Figure 6 Flow chart of GA estimation of hybrid model

are allowed. Equation (9) represents the fitness function (*f*), which is the reciprocal of the objective function (Equation 8).

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

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 produce the initial population to start a GA *run*.

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 processes 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 (d_f) is less that a threshold value (ε_f, e.g., equals to 0.0001), then, the GA Estimator is stopped. A GA driver developed by Carroll [2001] is revised for use.

5. APPLICATION OF HYBRID MODEL

In Hong Kong, Time of Use (TOU) Rate has been implemented since 2001 to encourage people to reduce their electricity consumption during the peak-load period and/or to shift their load off-peak either by a change in consumption behavior or by an adoption of load shifting technologies. The identified hybrid model can be used to determine the best control strategy (such as optimal ventilation strategy at night and pre-cooling the building at off-peak period) and estimate the amount of energy savings.

The developed hybrid model can also be used to predict the load demand to monitor the building performance for diagnosis purposes. A baselining methodology is crucial to verify savings from energy conservation program, and to determine progress toward preset energy-efficiency goal. The methodology is also necessary for implementing performance-based shared energy savings contracts. The hybrid model can further be used to develop the baselining methodology to gauge the extend to which energy use over the years has been saved with respect to baselining model either as a result of retrofits or due to energy efficiency, operation and maintenance (O&M) practices.

6. SUMMARY AND DISCUSSION

A simplified and accurate model, viewing the building as a whole, is necessary for building performance monitoring, optimal control strategies and estimation of energy savings of retrofits etc. The simplified RC (3R2C and 2R2C) models can accomplish the need of these applications. The use of the hybrid model allows the parameters of the RC models to be identified partially using building property data and operation data. As the properties of the external envelope are relatively easy to obtain, the use of them in identifying the parameters of the hybrid model significantly reduces the number of the parameters to be identified using operation data. It avoids the need of data from very long period operation. Furthermore, it allows the parameters of model are physically meaningful. Therefore, the parameters allow the model to be more reliable and robust even if the data of short operation period are used for the parameter identification of the building simplified RC models.

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