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A simplified dynamic model for existing buildings using CTF and thermal network models ☆

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Abstract

An alternative simplified building model is developed to describe existing building system aiming at providing performance benchmark for performance evaluation and diagnosis at building level and performance prediction for air-conditioning system optimal control. This model combines detailed physical models of building envelopes and a thermal network model of building internal mass. The detailed physical models are the CTF (Conduction Transfer Function) models of building envelopes based on the easily available detailed physical properties of exterior walls and roof. The thermal network model is the 2R2C model, and its parameters are estimated and optimized using genetic algorithm with short-term monitored operation data. The parameter optimization of the simplified building internal mass model (2R2C) and the simplified dynamic building model (i.e., $CTF + 2R2C$ model) are validated in a high-rising commercial office building under various weather conditions. This $CTF + 2R2C$ model is an alternative modeling approach for simulating the overall building dynamic thermal performance when CTF model is chosen to model the building envelope.

Keywords: Modeling; Existing building; CTF model; Thermal network model; Parameter optimization; Dynamic thermal performance

1. Introduction

Dynamic building energy model of existing buildings is very important to accurately predict absolute performance data for performance benchmarking of performance evaluation and diagnosis as well as for the building performance prediction for air-conditioning system optimal control [2,3,9,11,21]. Apart from weather condition, occupancy load, lighting load and equipment load, the physical property of a building also greatly affects its cooling energy consumption. The physical property of a building includes that of the building envelope and that of building internal mass which involves interior wall, floor, partition, carpet and furniture etc. For a building using intermittent air-conditioning, the effect of building internal mass on cooling energy consumption is significantly of importance.

The heat transfer of building envelope and building internal mass is crucial to accurately calculate the cooling energy consumption of a building. For building envelope, the physical property can be described clearly according to design data and/or site survey. Its heat transfer can be calculated using conventional "root-finding" method [20], state space methods [15,17], or frequency-domain regression (FDR) method [22,23] etc. There are also some methods to simplify the calculation of the heat transfer through building envelope based on its detailed physical description [18,26]. As for building internal mass, it is very difficult and unimaginable to describe the building internal mass physically piece by piece. The heat transfer of internal mass can be simply calculated using a reference RTF (room transfer function) [14,19]. ASHRAE research projects 359-RP [4], 472-RP [8] and 626-RP [7] identified 14 discrete screening parameters with two to five levels of characterization each by which to select RTF coefficients and modify factors appropriately for specific applications.

The coefficients of RTF method developed by the above research projects are significant to estimate the cooling load for equipment sizing or performance evaluation in design stage.

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Nomenclature

A	area	m^2
b, c, d	CTF coefficients	
C	thermal capacitance	$J/(m^2\,K)$ or J/K
CTF	conduction transfer function	
J	cost function	
f	fitness function	
Q	energy consumption or transferred heat	kW
R	thermal resistance	$m^2\,K/W$
$ReRMSE$	relative root mean square error	
$RMSE$	root mean square error	
T	air temperature	°C or K
t	time (second or hour)	

Greek symbols

Δ	time interval

Subscripts

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

The selection of coefficients is based on the actual building configuration which should be similar to the specified configurations of reference buildings including enclosing surfaces, special geometry, and related characteristics of building space. If the actual building configuration of concern differs greatly from the specified configuration of a reference building, the estimated cooling load may deviate greatly. Therefore, for energy performance evaluation of existing buildings, the developed coefficients of the RTF method may not be appropriate for practical applications in existing buildings. Available simulation models such as EnergyPlus [6] and DOE-2.2 [5] etc., are typical detailed physical models. The calibration process of simulation models is also a great challenge. 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. Experiences of some researchers show that differences of 50% or more between simulation results based on design data and measured consumption are not unusual [13]. Moreover, the calibration process of the energy model is not effective by manual parameter adjustment [16].

Recently, a simplified building energy model was developed for existing buildings to predict building thermal performance, and the parameters of building internal mass are identified automatically using genetic algorithm (GA) estimator instead of manual parameter adjustment [24,25]. In this model (i.e., *3R2C + 2R2C* model thereafter), the heat transfer process of building envelope is simplified as a 3R2C thermal network model (i.e., three resistances and two capacitances), and the heat transfer process of building internal mass is simplified as a 2R2C thermal network model (i.e., two resistances and two capacitances). The parameters of the 3R2C model can be determined with simple configurations or optimized configurations [26] using the detailed property data of the envelope. The parameters of the 2R2C model of building internal mass are identified using the actually measured cooling load based on genetic algorithm.

However, it is observed that it is also convenient or preferred to use the conduction transfer function (CTF) model to simulate the building envelope in some practical applications when these CTF coefficients are easily available [1] or can be deduced easily with existing procedures for computing CTF coefficients based on the detailed physical properties of building envelopes. In the ASHRAE handbook: fundamental [1], the CTF coefficients of 42 types of roofs and 41 types of walls are presented for practical usage. These roofs and walls are representative. Therefore, this study presents an alternative approach for modeling of existing buildings for transient thermal performance estimation by using thermal network (RC) model partially. This new simplified model (i.e., *CTF + 2R2C* model thereafter) is developed by combining the CTF models of building envelopes and 2R2C thermal network model of building internal mass, whose physical property data are hardly available. This *CTF + 2R2C* model of existing buildings is to provide an alternative for users when they would like to use CTF model of building envelope. A GA estimator is developed to identify the parameters of 2R2C model of internal mass. The main difference between the *CTF + 2R2C* model and the previously proposed *3R2C + 2R2C* model is that different methods are used to handle the heat transfer process of building envelopes. The solution processes of both models are also slightly different. This *CTF + 2R2C* model is established for real commercial office buildings using the operation data in short period time for parameter identification. This model was then verified in various operation conditions on an existing building. The predicted thermal performance of this model was also compared with the performance of the *3R2C + 2R2C* model [24] for this building. The sensitivity of the model performance of the *CTF + 2R2C* model to the changes in input variables was also studied. At the same time, this study also investigated the effects on thermal performance prediction and modeling efforts of a simplified model by considering internal mass and internal air as a whole.

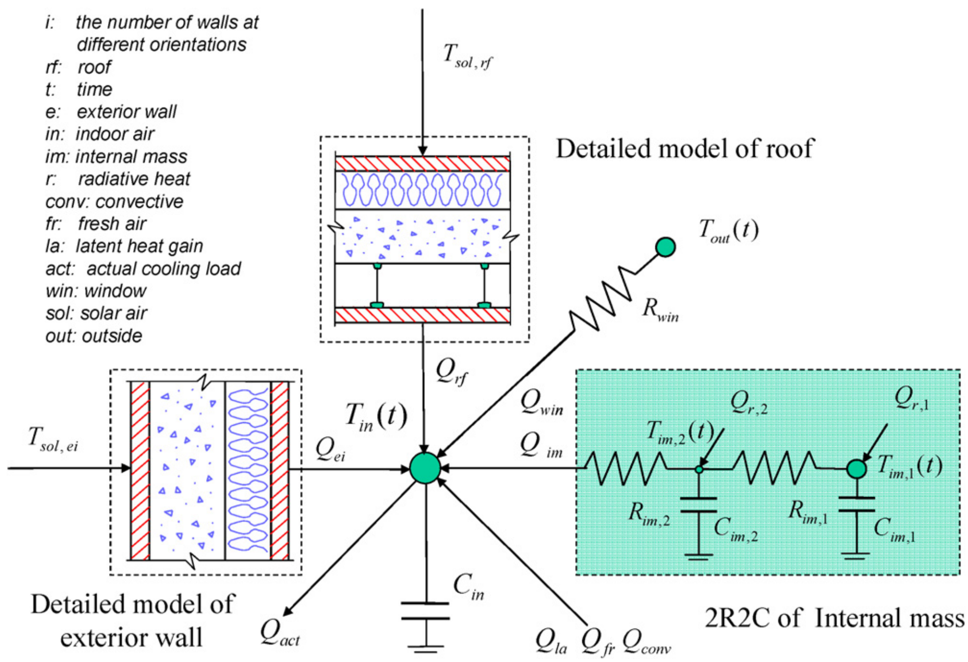

Fig. 1. Schematics of the simplified building model (*CTF* + *2R2C* model).

2. Methodology of existing building modeling

The new simplified building model (i.e., *CTF* + *2R2C* model) of existing buildings is developed mainly by modeling the heat transfer through building envelope as CTF model based on detailed physical descriptions and by modeling the building internal mass as having the physical structure of a 2R2C model. The parameters of the 2R2C model are backed out with measured operation data since it is a time-consuming description process or impossible to describe the detailed physical properties of building internal mass.

Fig. 1 illustrates the *CTF* + *2R2C* model of existing buildings. 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 conventional 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, as shown in Fig. 1. All resistances and capacitances are assumed to be time-invariant. The windows have negligible energy storage and are represented with pure resistance (R_{win}). The solar radiation through windows has great effects on cooling load. The calculation will be described in Section 3.1. 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 Eqs. (1) and (2) using conventional CTF method. The window conductive heat transfer can be represented as a pure resistance model as Eq. (3) in the discretized form. The simplified building internal mass model can be represented as Eqs. (4) and (5) in differential form. With assumed values of the parameters of the 2R2C model, the nodal temperature can be calculated using Runge–Kutta algorithm. The convective heat transfer between internal mass and indoor air can be easily calculated as Eq. (6) in the discretized form. With the heat transfer from the introduced fresh air (including mechanically introduced fresh air and infiltration) as well as convective heat from occupants, lights and equipments etc., the estimated cooling load can be read as Eq. (7) in the discretized form

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

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

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

$$A_{\text{im}} C_{\text{im},1} \frac{\mathrm{d}T_{\text{im},1}(t)}{\mathrm{d}t} = Q_{\text{r},1} - A_{\text{im}} \frac{T_{\text{im},1}(t) - T_{\text{im},2}(t)}{R_{\text{im},1}} \tag{4}$$

$$A_{\mathrm{im}} C_{\mathrm{im},2} \frac{\mathrm{d}T_{\mathrm{im},2}(t)}{\mathrm{d}t} = Q_{\mathrm{r},2} + A_{\mathrm{im}} \frac{T_{\mathrm{im},1}(t) - T_{\mathrm{im},2}(t)}{R_{\mathrm{im},1}} - A_{\mathrm{im}} \frac{T_{\mathrm{im},2}(t) - T_{\mathrm{in}}(t)}{R_{\mathrm{im},2}} \tag{5}$$

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

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

where, Q_{ei}, Q_{rf}, Q_{win}, Q_{im}, Q_{est} are the conductive heat of exterior walls and roof, conductive heat through windows, convective heat between internal mass and indoor air, estimated cooling load respectively. A is area. C and R are capacitance and resistance of per square meter (i.e., $\mathrm{J/(m^2\,K)}$, $\mathrm{m^2\,K/W}$) respectively. T is temperature. $Q_{\mathrm{r},1}$ and $Q_{\mathrm{r},2}$ absorbed by the nodes $C_{\mathrm{im},1}$ and $C_{\mathrm{im},2}$ respectively are the radiative heat which includes the radiative heat from solar radiation through windows, from occupants, lights etc. Q_{conv} is the convective part of solar radiation through windows, the convective heat from occupants, lights and equipments etc. Q_{fr} is the heat transfer because of fresh air induction as well as infiltration (exfiltration). Q_{la} is the latent heat gain from occupants etc. b, c, and d are CTF coefficients. Δ is the time interval. Subscript ei, im, rf, win, in, and sol, indicate the ith exterior wall, internal mass, roof, window, inside, and solar air respectively.

In this study, total radiative heat from solar radiation through windows, from occupants, lights etc. is distributed evenly between the two nodes of building internal mass (i.e., $Q_{\mathrm{r},1} = Q_{\mathrm{r},2}$). The area of internal mass is difficult to calculate and thus assumed to be the floor area although the actual area of internal mass including internal wall, furniture etc. is larger than the floor area. The actual effect of the internal mass will be explained by the parameters to be identified.

The properties of exterior walls and roof are relatively easy to obtain. They are used to compute CTF coefficients for heat transfer calculation. The model parameters, $C_{\mathrm{im},1}$, $R_{\mathrm{im},1}$, $C_{\mathrm{im},2}$, $R_{\mathrm{im},2}$ of the building internal mass can be optimized by minimizing the difference between the measured cooling load and the model predicted cooling load using operation data, while the CTF coefficients of building envelopes are calculated in advance. The cost function (J) of such optimization employs the root-mean-square error. This is a typical nonlinear optimization problem. Genetic algorithm (GA) is employed for the parameter identification of the simplified 2R2C building internal mass [24]. Fig. 2 shows schematically the flowchart of the GA estimator developed for the parameter optimization of the 2R2C building internal mass model. Eq. (9) represents the fitness function (f) in genetic algorithm, which is the reciprocal of the cost function. The description of the genetic algorithm for parameter identification and the parameters of the genetic algorithm used can be found in Ref. [24].

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

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

where, Q_{act} is the actual measured cooling/heating load, Q_{est} is the model predicted cooling/heating load, $C_{\mathrm{im},1}$, $R_{\mathrm{im},1}$, $C_{\mathrm{im},2}$, $R_{\mathrm{im},2}$ are the parameters of 2R2C model.

The measured cooling/heating load (Q_{act}) is calculated using *the return and supply water temperature difference and the water flow rate* retrieved from BMS. To predict the building cooling/heating load using the simplified building energy model, *indoor air temperature and humidity, outdoor air temperature and humidity, fresh air flow rate, solar radiation, occupancy and internal gains* are needed. The means to collect these data for the parameter identification of the internal mass are described in Section 3.1.

3. Model validation

The parameter optimization for the *CTF + 2R2C* model is similar to that for the *3R2C + 2R2C* model presented in Ref. [24]. The building and the operation data for the validation of this *CTF + 2R2C* model are identical to those for the validation of the previously proposed *3R2C + 2R2C* model. However, for readers to follow the work clearly and easily, the basic information of the building as well as data collection are also given here. For more details, Ref. [24] can be referred.

3.1. Brief of the building and collection of operation data

The building in Hong Kong as shown in Fig. 3 is used for model validation. This building is for commercial office usage consisting of a main building of 50 floors and an attached building of 7 floors. For the main building, the first and second floors are served as shopping centers. The third, fourth and fifth floors are restaurants. The sixth floor is used for chiller plant. The commercial offices are located from the 7th to 49th floors with 2262 $\mathrm{m^2}$ (58 × 39 m) per floor except that the 15th, 31st, 48th floors are for refuge use. The 50th floor is used as banquet hall. For the attached building, the first and second floors are also served as shopping center. The other floors are used for offices with 1738 $\mathrm{m^2}$ (22 × 79 m) per floor, and the roof is covered with a swimming pool. The basements are used as garage. The area of south, north, west and east walls are 8075, 8088, 6624 and 6896 $\mathrm{m^2}$. The ratio of window to wall of the building is approximately 25%. The gross floor area with air-conditioning is about 116 160 $\mathrm{m^2}$. This gross floor area is taken as the total internal mass area. The building construction and simplification measures for convenience of modeling are not presented for conciseness. More detailed information can be found in [24].

The building is air-conditioned with the chilled water from the 6th floor chiller plant except that the banquet hall on the 50th floor is air conditioned by a separate air-cooled package

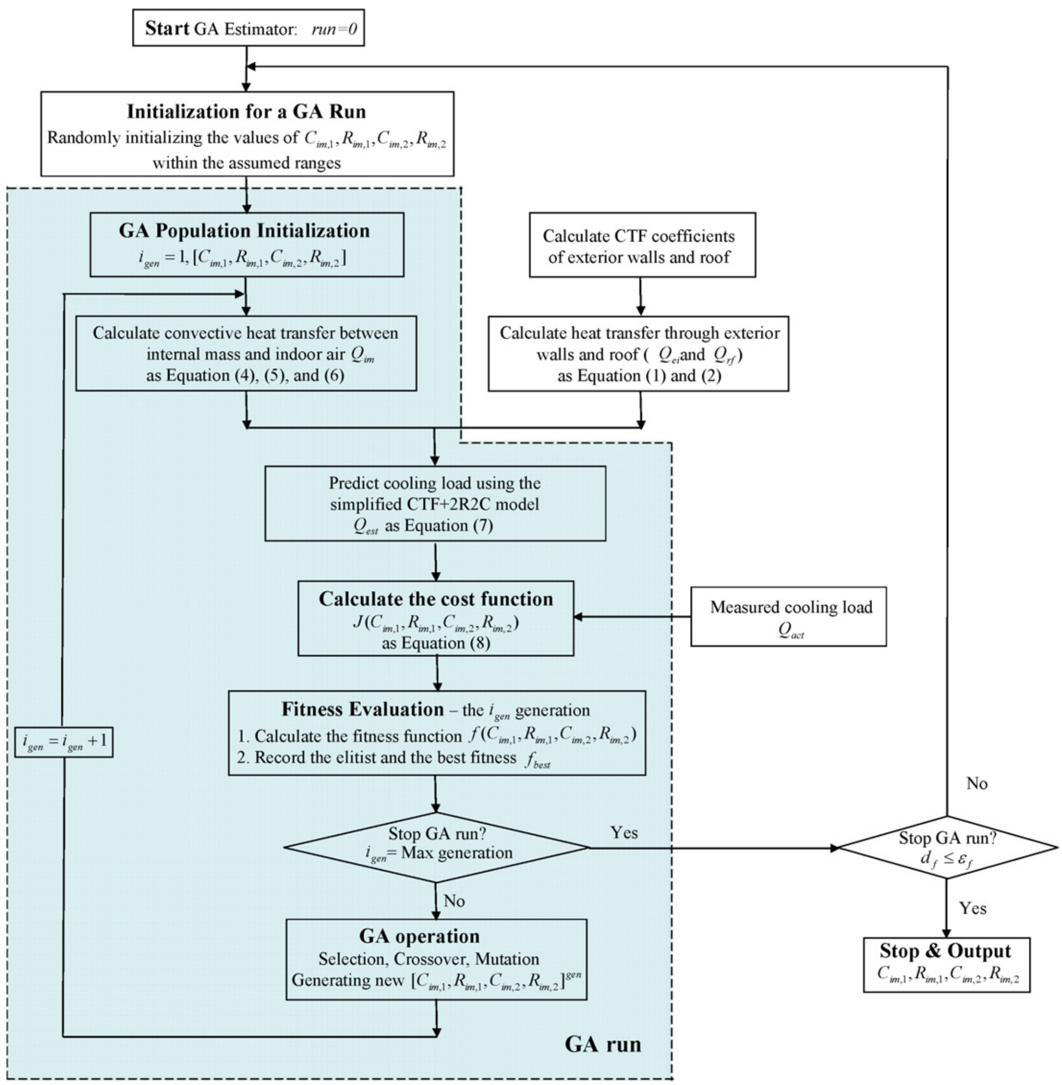

Fig. 2. GA estimator for parameter identification and optimization.

unit. Most of the air conditioning terminals are AHUs located in the core areas. In some floors, FCUs (fan coil units) are separately installed to provide cooling load for communication rooms or computer rooms to keep the temperature at set points when AHUs are shut down at night, on weekends and public day.

A site survey was conducted and original design information was collected to build the complete profiles of the occupancy, the use of lighting and equipments, fresh air and infiltration. The occupancy load and the internal load from lighting and equipments were estimated according to the rules established on the basis of site survey and according to a previous research on Hong Kong buildings [10] as briefed as follows. The normal occupancy periods of office, shopping center and restaurant are from 8:00 am to 6:00 pm, from 10:30 am to 10 pm, and from 6:30 am to 10 pm or late respectively. The densities of occupancy for the three places are approximately 9, 4.5 and 2 m^2 per person respectively. The design equipment powers for these three places are 25, 30 and 55 W/m^2 respectively. The design lighting powers are 25, 70 and 35 W/m^2 respectively. The normal patterns of occupancy, equipment power load and lighting power load are not presented here. They can be found in Ref. [24]. The offices, shopping centers and restaurants are supplied with fixed amount of fresh air with the ventilation rate of 10, 7 and 7 L/s per person respectively in the occupancy periods. Although the building is tight most with fixed windows, the infiltration rate is considered as 0.1 ach (air change time) in the occupied period and 0.5 ach in the unoccupied period.

The return air temperature of AHUs and actual cooling load of the building were measured and recorded by BMS. The outdoor air temperature and humidity were measured by BMS as well. An average return air temperature was taken as the uniform indoor air temperature (i.e., "measured" temperature). This temperature was used for cooling load prediction.

Hourly horizontal global solar radiation was obtained from Hong Kong Royal Observatory for use. It was decomposed into direct normal solar radiation and diffusive solar radiation with the relationship established by Lam and Li [12] for Hong Kong. The direct normal solar radiation and diffuse solar radiation were used to calculate "solar air temperature" on different ex-

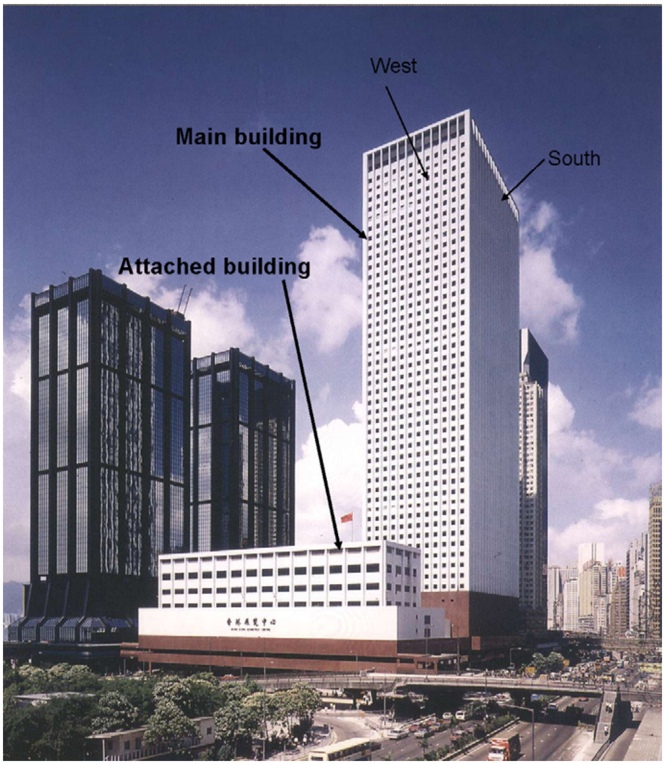

Fig. 3. A view of the building used for model validation.

terior wall surfaces as well as the solar radiation transmitted through windows. The solar radiation through windows were calculated in detail and decomposed to convective heat and radiative heat since the windows have inside shade.

3.2. Results and comparisons

The *CTF* + *2R2C* model of existing buildings was validated in the real high-rising commercial office building in Hong Kong. Two weeks' operation data in summer season were used to identify the optimal parameters of the 2R2C model in the *CTF* + *2R2C* model. This model was further validated using other two weeks' summer operation data and one week' winter operation data with the identified thermal parameters.

It is worthy to mention that the sampling time for the operation data of the supply and return chilled water temperatures, chilled water flow rate as well as indoor air temperature was half of an hour. The interval time of simulation was also half of an hour. The CTF coefficients of exterior walls and roof were computed in the interval of half of an hour for heat transfer calculation using frequency-domain regression method [22,23,27]. For heat transfer calculation, these differential equations of the 2R2C model were solved numerically using explicit Runge–Kutta algorithm. All the procedures were programmed using Fortran language.

In the parameter identification case of the *CTF* + *2R2C* model, the searching scopes of these parameters of the simplified 2R2C building internal mass model should be determined in advance. The determination of the searching scopes can be found in Ref. [24]. The weather conditions including outdoor air temperature and horizontal global solar radiation for the identification case are presented in Fig. 4. Most of the days were sunny and cloudy. Some days were in sunny periods with a few showers. In the identification process, only the cooling loads during office hours were used to calculate the root mean square error as Eq. (8) for parameter identification since the temperatures measured in non-office hours cannot well represent the true indoor air temperature (this point will be explained later). These temperatures were needed for cooling load calculation.

The optimized parameters of the 2R2C model in the *CTF* + *2R2C* model are $C_{\mathrm{im},1} = 649\,365\ \mathrm{J/(m^2\,K)}$, $C_{\mathrm{im},2} = 77\,605\ \mathrm{J/(m^2\,K)}$, $R_{\mathrm{im},1} = 0.29971\ \mathrm{m^2\,K/W}$, $R_{\mathrm{im},2} = 0.02789\ \mathrm{m^2\,K/W}$. This result is almost the same to the optimal parameters of the 2R2C model in the previously proposed *3R2C* + *2R2C* model. They are as follows: $C_{\mathrm{im},1} = 648\,729\ \mathrm{J/(m^2\,K)}$, $C_{\mathrm{im},2} = 73\,793\ \mathrm{J/(m^2\,K)}$, $R_{\mathrm{im},1} = 0.29942\ \mathrm{m^2\,K/W}$, $R_{\mathrm{im},2} = 0.02818\ \mathrm{m^2\,K/W}$ [24]. Using the optimized parameters of the simplified *CTF* + *2R2C* model, the cooling load was predicted with "measured" indoor air temperature and other measurements. The comparison between the model predicted and actually measured cooling loads is presented in Fig. 5. The predicted cooling load using the simplified *3R2C* + *2R2C* model is also presented for reference. It shows that the predicted cooling load using the simplified *CTF* + *2R2C* model well followed the dynamic profile of the actually measured cooling load. The predicted cooling load profiles using both models (i.e., *CTF* + *2R2C* model and *3R2C* + *2R2C* model) almost overlapped.

For the consecutive two weeks, the 3rd day was public holiday (Wednesday), the 6th day and 13th day were Saturday (only half of the days were in office hours), the 7th day and 14th day were Sunday. The root mean square error (*RMSE*) as Eq. (10) is used to evaluate the prediction performance of different models. The relative *RMSE* (*ReRMSE*) is also used when relative error is concerned. $Q_{\mathrm{act,m}}$ is the maximum actually measured cooling load. The *RMSE* using the *CTF* + *2R2C* model is 1198 kW for the data points of office hours of 8:00 am ∼ 18:00 pm while the *RMSE* using the *3R2C* + *2R2C* model is 1237 kW. The relative errors (*ReRMSE*) using both models are 9.39% and 9.69% respectively with the maximum cooling load 12 762 kW. When all the data points including that in office hours and non-office hours were used, the *RMSE* using the *CTF* + *2R2C* model and the *3R2C* + *2R2C* model are 1335 kW, 1354 kW respectively.

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N}[Q_{\mathrm{act}}(k) - Q_{\mathrm{est}}(k)]^2}{N-1}} \tag{10}$$

$$ReRMSE = \frac{100}{Q_{\mathrm{act,m}}}\sqrt{\frac{\sum_{k=1}^{N}[Q_{\mathrm{act}}(k) - Q_{\mathrm{est}}(k)]^2}{N-1}} \tag{11}$$

For a deeper look into the cooling load prediction performance of the simplified models, the averaged daily cooling load profiles are also presented in Fig. 6. It is noted that 5 days were excluded (i.e., the 3rd day (public day), the 6th, 7th, 13th, and 14th days (weekend days)). This figure further reveals that both models can provide almost the same cooling load predictions. At the same time, these predicted cooling loads in office

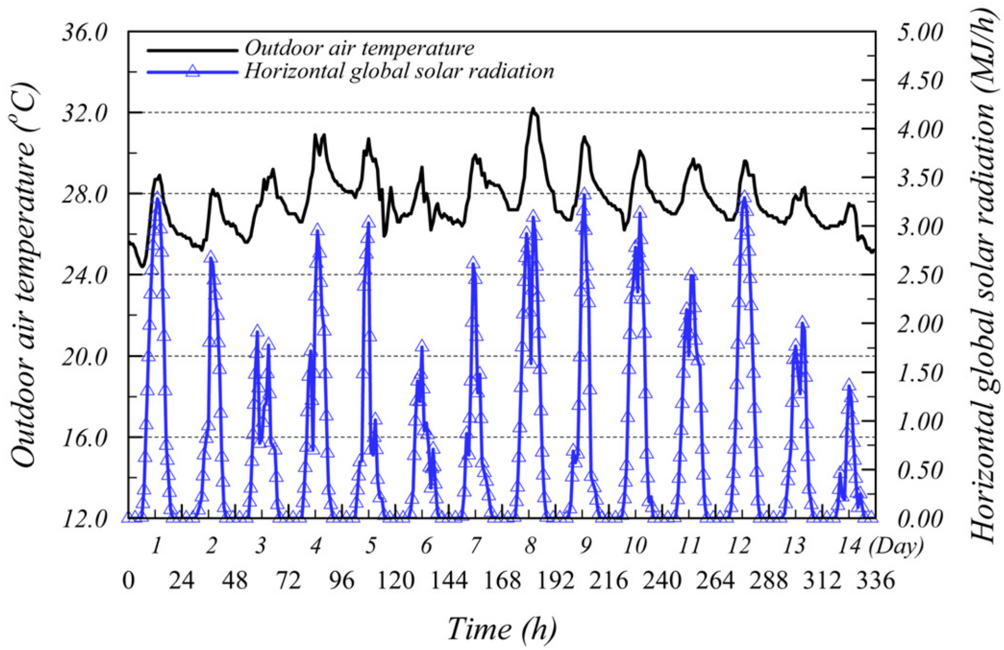

Fig. 4. Outdoor air temperature and horizontal global solar radiation (parameter identification case).

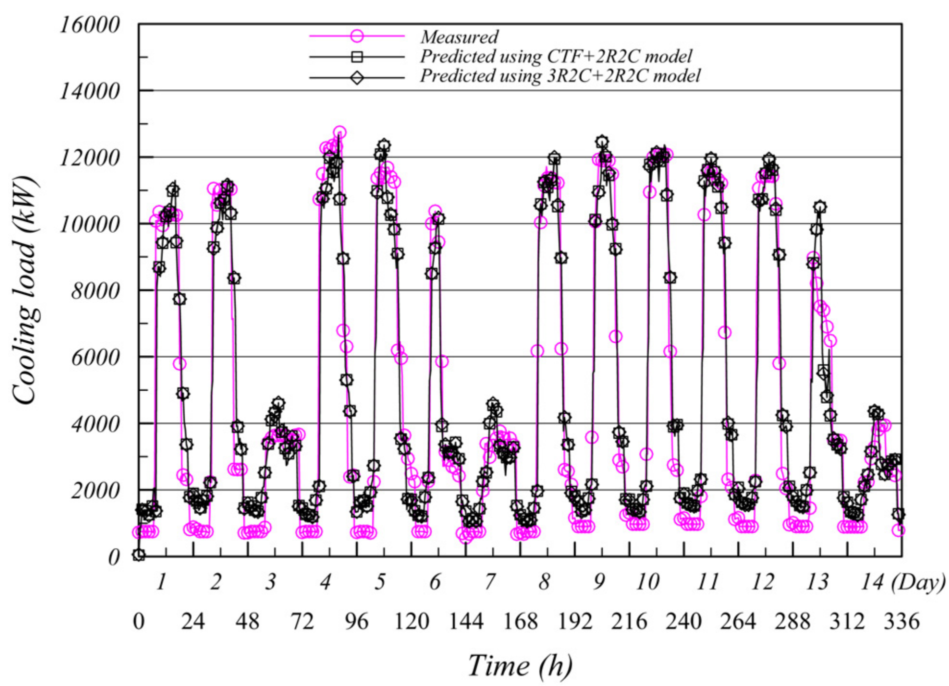

Fig. 5. Model predicted cooling loads vs actually measured cooling load (parameter identification case).

hours agreed well with the actual measurement. During the non-office hours, the model trended to significantly over-predict the cooling load. It can be explained that the "measured" uniform indoor air temperature, which was used for cooling load prediction, is higher than the actual temperature in non-office hours (this point will also be explained later).

A sensitivity study was also conducted to evaluate the effects on the model performance of changes in input parameters. It was found that the model error were most sensitive to the magnitude of the internal gains. Fig. 7 presents the predicted averaged daily cooling load profiles using different internal heat gains. The internal heat gains including occupancy, equipments and lightings described in Section 3.1 is referred as benchmark. 1.2 times, 0.8 times, 1.5 times and 0.5 times the benchmark were used to identify the parameters of the *2R2C* model respectively. Then, these identified parameters were used to predict the cooling loads using these coincident internal heat gains respectively. It is obvious that the internal heat gains have a great effect on cooling load prediction. This is not surprise, since large buildings are generally dominated by internal heat gains.

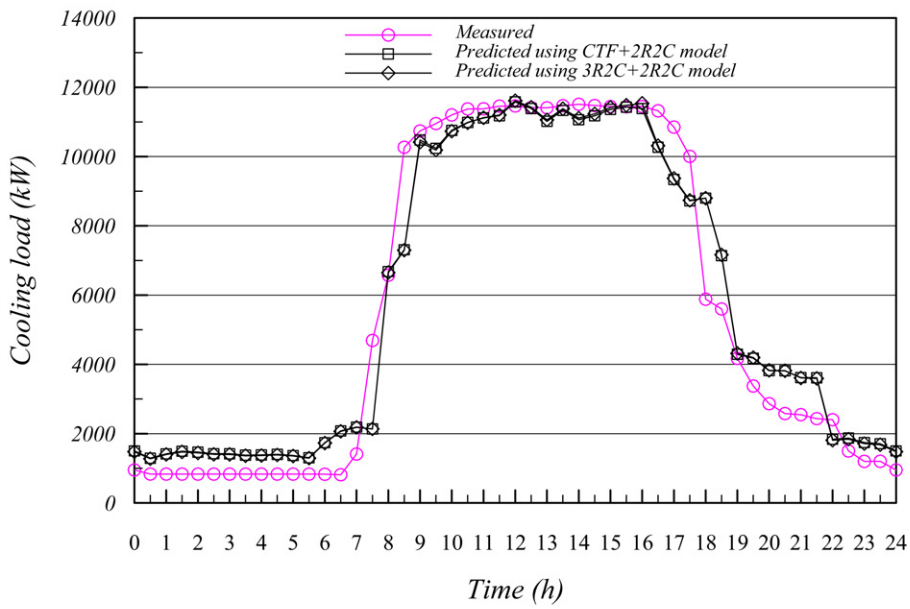

Fig. 6. Model predicted averaged daily cooling loads vs actually measured averaged daily cooling load (parameter identification case).

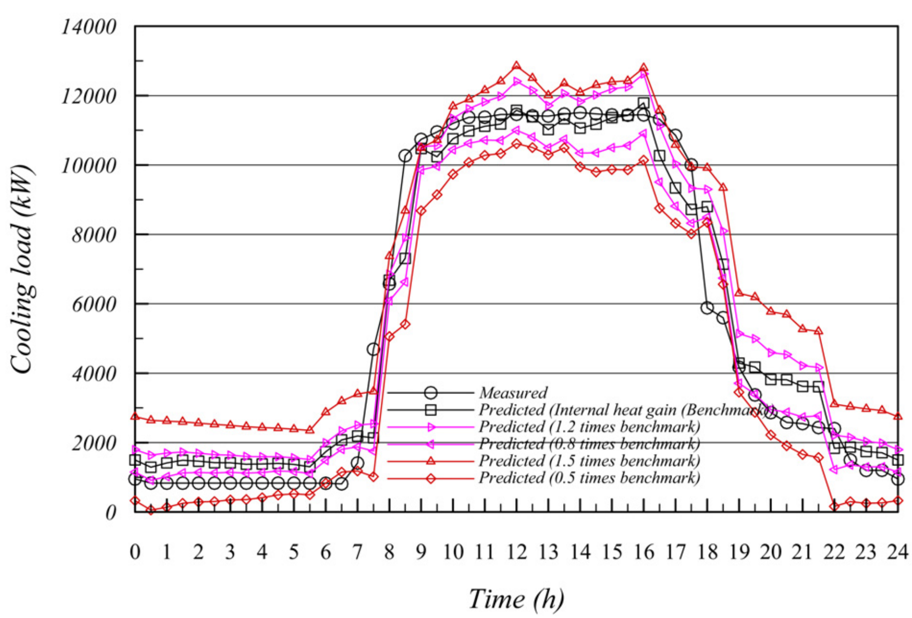

Fig. 7. Model (*CTF* + *2R2C* model) predicted averaged daily cooling loads using different internal heat gains and actually measured averaged daily cooling load (parameter identification case).

Accurate estimation of the occupancy, the use of equipment and lighting coincident with the real situation is also important for the model development.

This study also investigated the impacts of another modeling assumption for internal mass on modeling efforts and the cooling load prediction as well as indoor temperature prediction. This assumption is to merge all the internal mass in the air node (i.e., C_{in}) while building envelopes are modeled using CTF models. All the radiative heat from solar radiation through windows, from occupants, lights etc. is absorbed directly by the air node. This model is called the *simplest model* thereafter. Different capacitances (C_{in}) of the air node were adjusted manually to match the cooling load prediction of the simplest model with the actual measurement. Only the results using three manually adjusted capacitances are presented in Fig. 8 to demonstrate the calibration efforts (the operation data in the identification case was used). The first capacitance is 7270 J/(m^2 K), which is one percent of the total identified capacitance of the above 2R2C model of internal mass. The second and the third are 72.70 J/(m^2 K) and 10 J/(m^2 K) respectively. The capacitance of the air node was also identified automatically instead of manually using genetic algorithm as described earlier. The identified value is 26.39 J/(m^2 K).

When $C_{in} = 7270\ \mathrm{J/(m^2\,K)}$, the predicted cooling load was extremely unreasonable as shown in Fig. 8. When $C_{in} = 72.70\ \mathrm{J/(m^2\,K)}$ and $C_{in} = 10\ \mathrm{J/(m^2\,K)}$, the predicted cool-

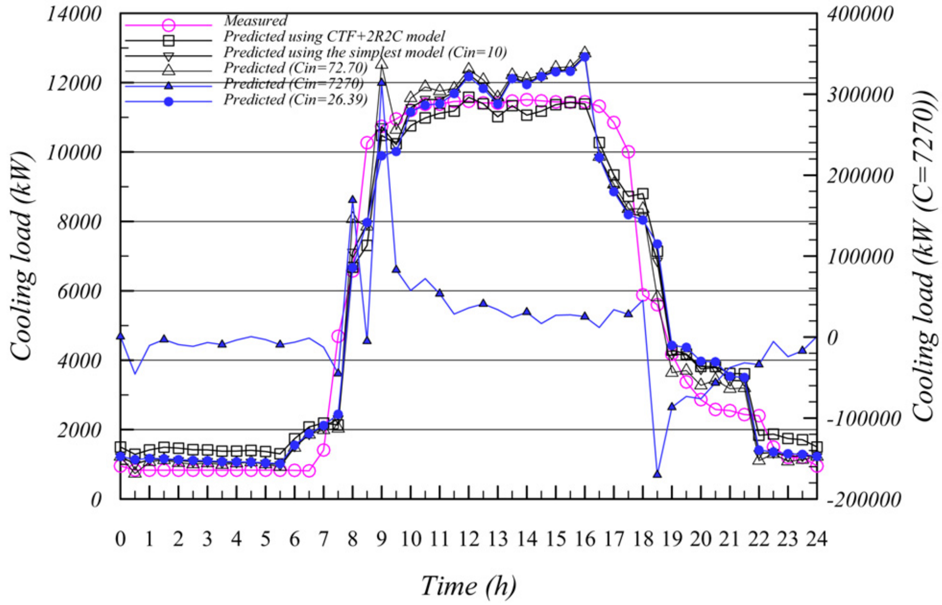

Fig. 8. Actually measured and predicted averaged daily cooling loads using the $CTF + 2R2C$ model and the simplest model with different thermal capacitances (parameter identification case).

ing loads agreed the actual measurement approximately. The *RMSE* using the simplest model with the above both capacitances are 1548 kW and 1403 kW for the data points of office hours, significantly higher than the *RMSE* of 1198 kW when using the $CTF + 2R2C$ model. The relative errors (*ReRMSE*) using the simplest model with the above both capacitances are 12.13% and 10.99% respectively while the relative errors using the $CTF + 2R2C$ model is 9.39%. When the optimal parameter $C_{in} = 26.39\ \text{J}/(\text{m}^2\,\text{K})$ was used for this simplest model, the *RMSE* of the predicted cooling load is 1396 $\text{J}/(\text{m}^2\,\text{K})$ with the relative errors of 10.94%. It seems that the manually adjusted capacitance $C_{in} = 10\ \text{J}/(\text{m}^2\,\text{K})$ is the near-best value as far as the prediction error is concerned. However, the accuracies of the cooling load prediction using the simplest model with the identified optimal parameter and the manually adjusted near-best parameter are lower (at least 1.6%) than that using the second-order model of internal mass (i.e., 2R2C). In addition, the optimal capacitance value of the air node is far from the actual capacitance value of building internal mass. Using these capacitances of the simplest model, the indoor air temperature can also be predicted given the measured cooling load. The predicted indoor temperature of this model using the optimal parameter $C_{in} = 26.39\ \text{J}/(\text{m}^2\,\text{K})$ is presented in Fig. 10. The predicted temperature is far from the measurement. Therefore, the internal mass and internal air are considered separately and the internal mass is assumed to be a second-order model. Such consideration and assumption can result in more accurate performance prediction than the assumption that all the internal mass is merged in the air node. As far as the parameter identification using genetic algorithm automatically is concerned, the calibration efforts of both models (the simplest model and the $CTF + 2R2C$ model) were almost the same. The experience also shows that tuning the thermal capacitance (air node) of the simplest model manually was time-consuming.

Using the given cooling load, the uniform indoor air temperature can also be predicted using the identified parameters of building internal mass model based on heat balance. Fig. 9 presents the model predicted indoor air temperatures and the "measured" uniform indoor air temperature in the consecutive fourteen days. Fig. 10 is the model predicted averaged daily temperatures and the "measured" averaged daily indoor temperature. The daily temperature is the average of the temperature in the nine office days. These figures show both models provided almost the same temperature prediction. The predicted temperature in office hours agreed well with the actually "measured" values. The RMSE of the predicted temperature in office hours using the $CTF + 2R2C$ model and the $3R2C + 2R2C$ model are 0.20 °C and 0.21 °C respectively. In non-office hours, the model predicted indoor air temperature was noticeably higher than the "measured" uniform indoor air temperature. It is because, in office hours, the air was circulating and the measured return air temperature in the return air chamber could well represent the indoor air temperature. However, in non-office hours, the measured return air temperature was obviously lower than the real indoor air temperature in summer season because the air was stagnant and the measured return air temperature in the return air chamber (in core area) was not affected (i.e. heated up) significantly by the outside weather condition. Therefore, the model predicted indoor air temperature could represent the uniform indoor air temperature more accurately compared with the "measured" uniform indoor air temperature in non-office hours.

To validate the accuracy and applicability of the developed simplified $CTF + 2R2C$ model, it was used to predict the cooling load with the "measured" uniform indoor air temperature in other two operation periods. One was also in summer season lasting for two weeks (i.e., summer validation case), the other was in winter season lasting for one week (i.e., winter validation

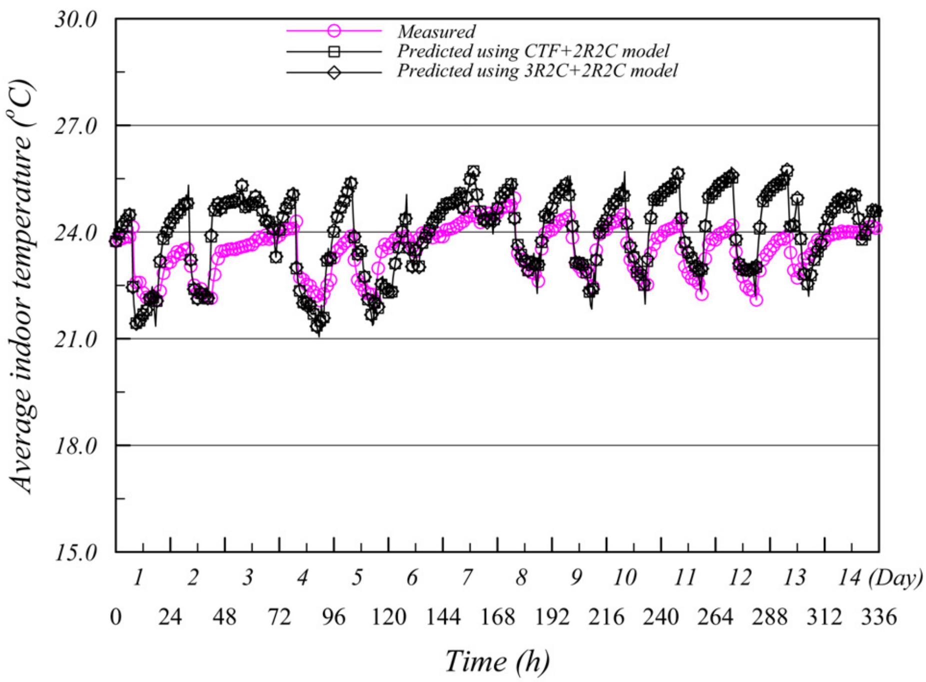

Fig. 9. Model predicted indoor air temperatures vs "measured" uniform indoor air temperature (parameter identification case).

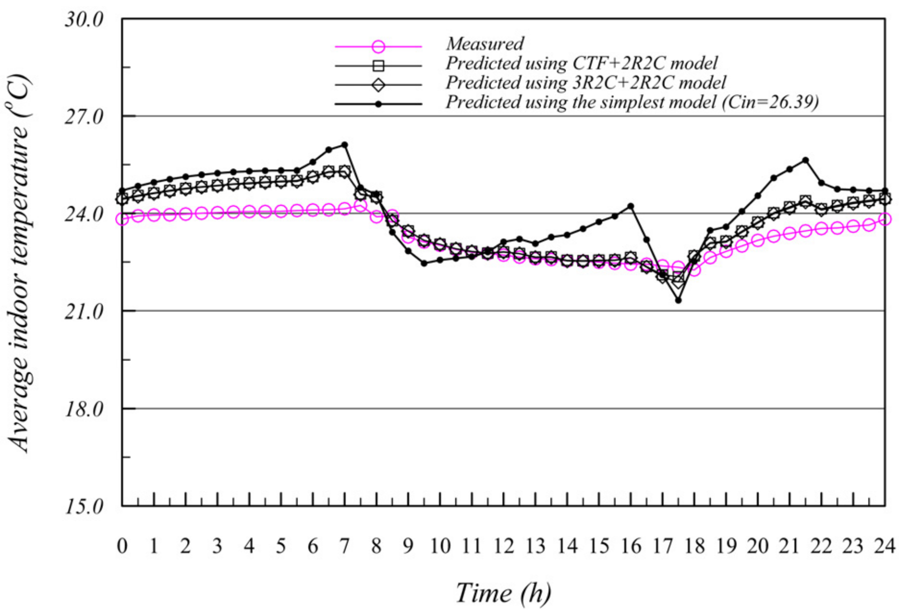

Fig. 10. Model predicted averaged daily indoor air temperatures vs "measured" averaged daily indoor air temperature (parameter identification case).

case). The internal heat gains used in both cases were the same as that used in the parameter identification case. The weather conditions for both validation cases are not presented. Readers can find the information in Ref. [24].

The predicted cooling load using the $CTF + 2R2C$ model and the actually measured cooling load for the summer season (i.e., summer validation case) are presented in Fig. 11. The averaged daily cooling load profiles are presented in Fig. 12. At the same time, the results using the $3R2C + 2R2C$ model are also presented for reference. These results show that the predicted cooling load using the $CTF + 2R2C$ model is almost the same to that using the $3R2C + 2R2C$ model. Both profiles also agreed well with the profile of the actually measured cooling load in office hours. The *RMSE* using the $CTF + 2R2C$ model is 1190 kW for the data points of office hours of 8:00 am ∼ 18:00 pm while the *RMSE* using the $3R2C + 2R2C$ model is 1193 kW. The actually measured maximum cooling load is 12 087 kW. The relative errors (*ReRMSE*) using both models are also good with 9.85% and 9.87% respectively. With the measured cooling load, the uniform indoor air temperature was also predicted using the simplified models. Fig. 13 presents the predicted averaged daily temperature profiles using the $CTF + 2R2C$ model and

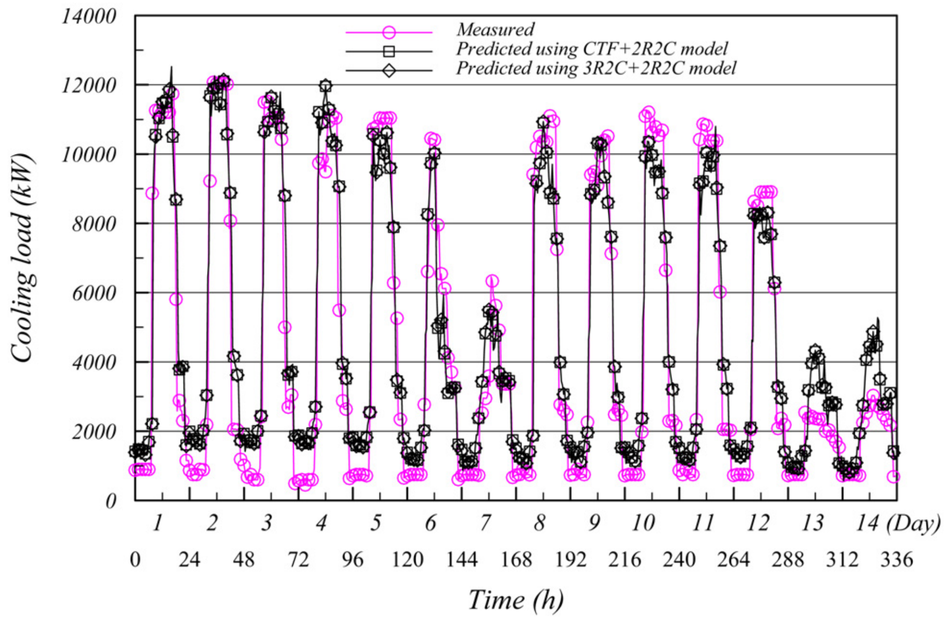

Fig. 11. Model predicted cooling loads vs actually measured cooling load (summer validation case).

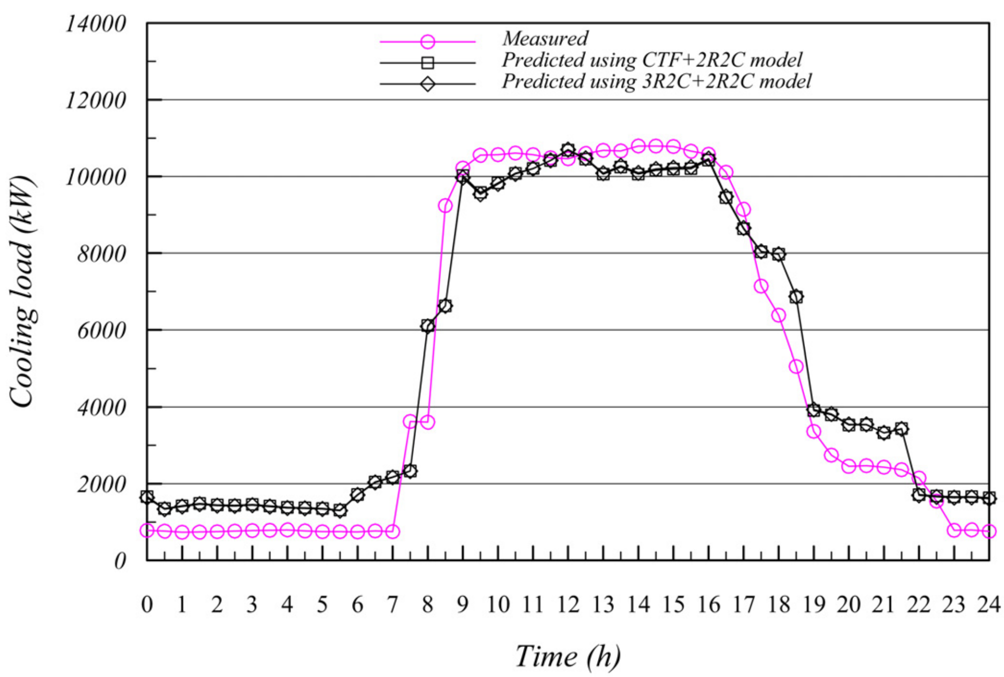

Fig. 12. Model predicted averaged daily cooling loads vs actually measured averaged daily cooling load (summer validation case).

the *3R2C* + *2R2C* model, and the "measured" averaged daily indoor temperature profile. The model predicted temperature showed the dynamic trends of indoor air temperature change correctly. In the office hours, the *RMSE* using both models is 0.58 °C. This figure also displays the "measured" indoor air temperatures in the non-office hours (at night) were much lower than the predicted uniform indoor air temperatures. The situation was similar to that stated in the parameter identification case.

The predicted cooling load using the *CTF* + *2R2C* model and the measured cooling load for one week in winter season (i.e., winter validation case) are presented in Fig. 14. The averaged daily cooling load profiles (including the data in the first five days) are presented in Fig. 15. Fig. 16 is the model predicted averaged daily temperature profile and the averaged daily indoor air temperature profile. At the same time, the results using the *3R2C* + *2R2C* model are also presented in these figures for comparison. Figs. 14 and 15 show that the *CTF* + *2R2C* model over-predicted the cooling load in the office hours. The predicted indoor temperature is also higher than the "measured" uniform indoor air temperature in the office hours as shown in Fig. 16. The *RMSE* using both models in office hours is 0.86 °C.

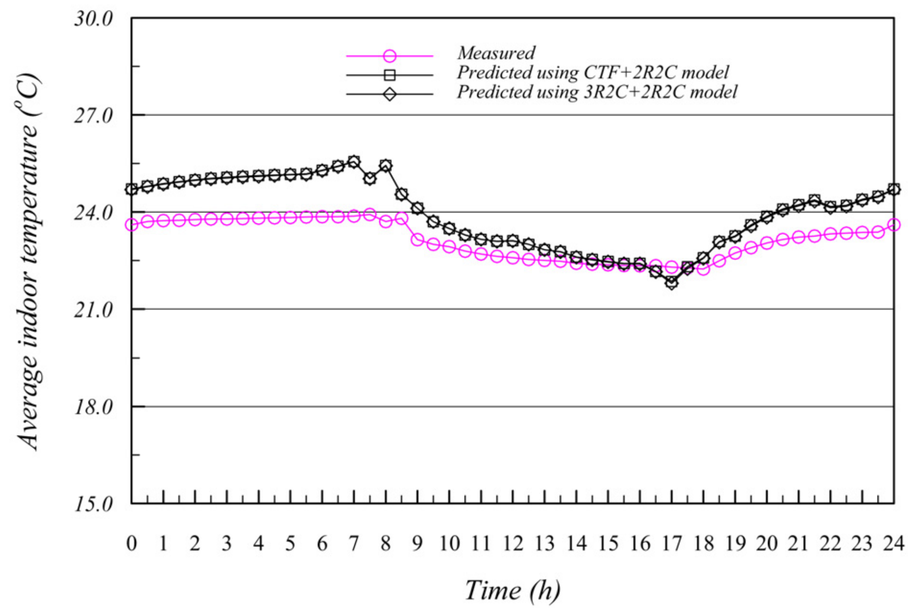

Fig. 13. Model predicted averaged daily indoor air temperatures vs "measured" averaged daily indoor air temperature (summer validation case).

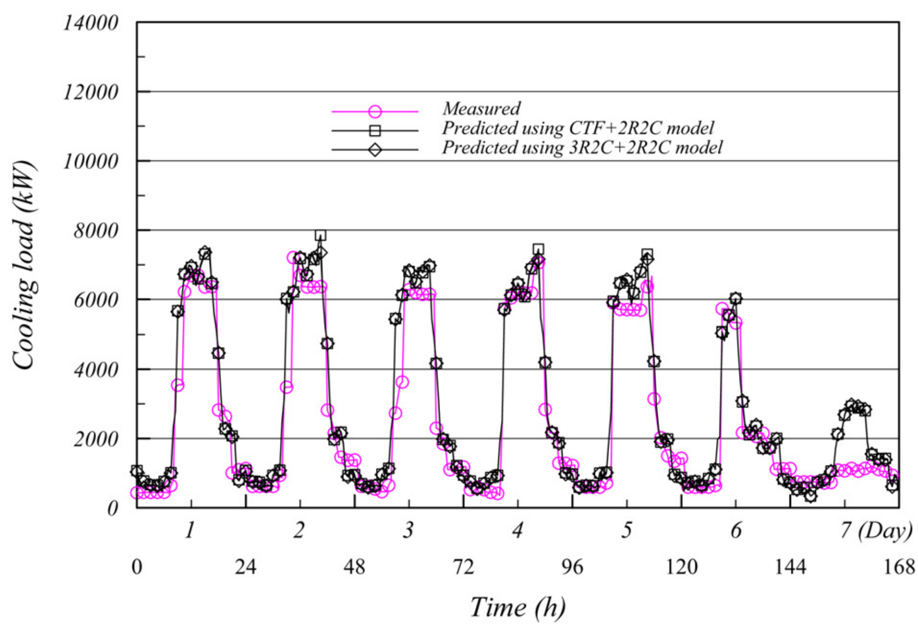

Fig. 14. Model predicted cooling loads vs actually measured cooling load (winter validation case).

It can be explained by that the input internal heat gains might differ from (be higher than) the real situation. In this winter validation case, the input internal heat gains are the same to those used for the parameter identification case. The real internal heat gains in the one week of the winter validation case might have differed from the description of the internal heat gains presented in Section 3.1. This discrepancy between the measurement and the model prediction is not the defects of the simplified models.

In summary, the simplified $CTF + 2R2C$ model can predict the thermal performance of existing buildings such as cooling load and indoor air temperature (and free floating temperature) for practical applications with good accuracy. The cooling load and indoor air temperature predicted using this model are almost identical to those predicted using the previously proposed $3R2C + 2R2C$ model. These results further demonstrate the validity and applicability of the $3R2C + 2R2C$ model. These models have extensive applicability under different operation conditions by capturing the dynamic characteristics of building system correctly. Both models (i.e., $CTF + 2R2C$ model in this paper and the previously proposed $3R2C + 2R2C$ model [24]) are effective and efficient approaches for dynamically modeling the heat transfer process of existing buildings.

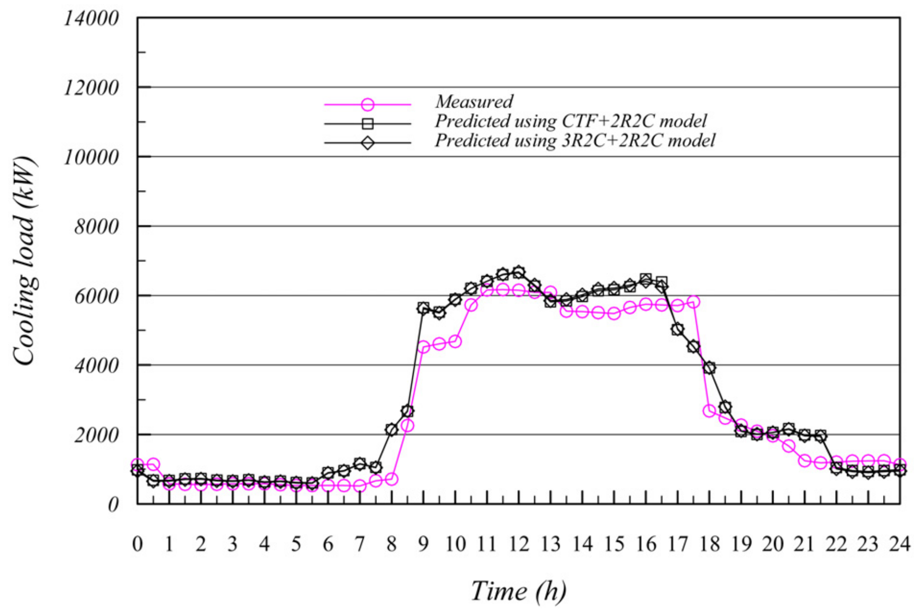

Fig. 15. Model predicted averaged daily cooling loads vs actually measured averaged daily cooling load (winter validation case).

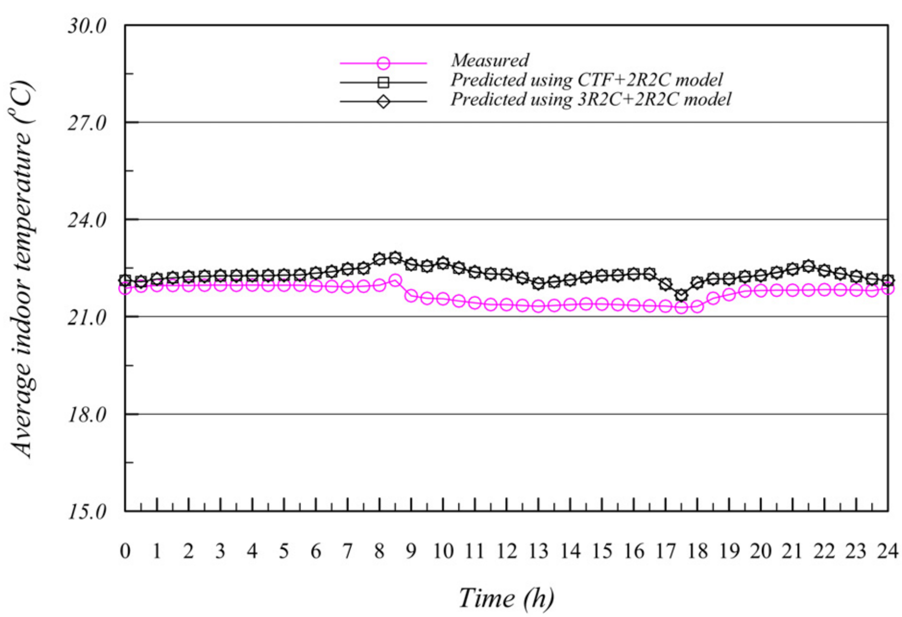

Fig. 16. Model predicted averaged daily indoor air temperatures vs "measured" averaged daily indoor air temperature (winter validation case).

4. Conclusion

This paper presents an alternative simplified building energy model (i.e., *CTF + 2R2C* model) for dynamic thermal performance estimation of existing buildings by combining CTF models of building envelopes and 2R2C thermal network model of building internal mass. Coefficients of the CTF models of building envelopes can be deduced based on their detailed description of physical properties. The building internal mass is simplified as a grey model with the structure of a second-order thermal network model (2R2C). This simplification can simplify the description of building internal mass including internal wall, partition, furniture etc. The parameters of this grey model can be identified and optimized effectively and efficiently using genetic algorithm with short-term monitored operation data. The quantification of the building internal mass with lumped thermal network can benefit the prediction of building dynamic thermal performance for advanced and optimal controls.

The simplified building model was verified in a high rising commercial office building under different operation conditions. Test results demonstrate that this *CTF + 2R2C* model predicted the cooling load with about ten percent relative root mean square error (*ReRMSE*) by comparing to the actual measurement. This model can also provide indoor air temperature prediction of good accuracy in office hours. In the non-office hours, the model predicted indoor air temperature is more accurate to represent the real uniform indoor air temperature by comparing with the "measured" uniform indoor air temperature. The results using this $CTF + 2R2C$ model were also compared to those using the $3R2C + 2R2C$ model in Ref. [24]. This $CTF + 2R2C$ model of existing buildings provides an alternative approach for users to dynamically model existing buildings for building thermal or energy analysis when they would like to use CTF model of building envelope. This study also investigated the effects of different modeling assumptions for internal mass and internal air on the modeling efforts and the thermal performance prediction. The results demonstrates the presented $CTF + 2R2C$ model with genetic algorithm for parameter identification can result in more accurate performance prediction than the simplified model merging internal mass in the air node.

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