Building thermal model development of typical house in U.S. for virtual storage control of aggregated building loads based on limited available information

Borui Cui*, Jeffrey Munk, Roderick Jackson, David Fugate, Michael Starke

Oak Ridge National Laboratory, One Bethel Valley Road, Oak Ridge, TN 37831, USA

Abstract:

A building thermal model is an essential component for achieving optimal control of a building's heating, ventilation, and air conditioning (HVAC). A self-learning grey-box model has been developed by implementing data-driven techniques and utilizing limited available information about the building. In previous research, detailed foreknown knowledge/information, e.g. physical and thermal properties of building materials, as well as sufficient number of observation points, e.g. indoor temperature sensors in different zones, are available for making the decision of model structure and parameters searching range easier. The availability of measured data and a narrowed searching range of model parameters, e.g. resistance and capacity for each wall, made the adopted algorithms quickly achieve near optimal values, which closely approximate the actual heat transfer of a building. Meanwhile, the details of pre-processing of the key inputs were seldom explained. Compared to the previous research, in this study, the available information is assumed to be limited which can fill the requirement for large scale virtual storage control of real residential community in near future, where it may be impractically or over time-consuming to acquire the detailed information for each single house. The developed model is validated by comparing the results to measured data in a recently-built home typical of the southeastern United States.

Keywords:

building thermal model; demand response; typical house in the U.S.; virtual storage;

1. Introduction
1.1 Background of Research

Residential and commercial building sectors account for approximately 37% and 36% of total U.S. electricity consumption respectively. Together, these sectors account for 73% of national electricity consumption [1]. Meanwhile, as of 2011, there were over 132 million housing units in the U.S., and of those 87% had air conditioning (AC) units. In the southern United States, the percentage of homes with air conditioning approaches 100% [2]. These AC units tend to exacerbate peak demand issues. For example, during the 2011 summer peak in the ERCOT (Electric Reliability Council of Texas) grid, over 50% of the total electrical load was from homes [3], whose loads were primarily driven by their air conditioning systems.

Further compounding the challenge of power delivery is the increasing use of renewable energy sources (RES). The use of RES has been recognized as a solution to the energy problems and critical to for achieving a low-carbon, sustainable society [4]. Despite their advantages, a main challenge needs to be overcome; the widespread use of RES inserts uncertainty into the grid, due to their stochastic output profile which strongly depends on local weather conditions [5]. Integration of RES into the electricity grid can be enhanced by demand response (DR) programs, which can help to reduce electricity generation from fossil fuels by adjusting the demand to the present availability of fluctuating RES [6].

Given their relatively large energy use, AC units in residential buildings are an obvious candidate for DR. Additionally, they have other characteristics that meet the requirements for successful implementation of DR. First, the operation of AC (systems) can be temporarily curtailed without immediate and significant impact on building occupants due to the thermal capacity of the building's mass, including both the mass of building envelope and the furnishings [7]. Second, the ramp time and response time of AC power consumption change can match the requirements of different scale of DR products, including regulation, ramping services, contingency and etc.. Third, with the wide spread installation of smart meters, sensors, and networks in residential building, AC units can easily receive signals to generate response [8]. The AC DR strategies can be split two basic categories: direct load control (DLC), in which utilities send signals directly to loads instructing them to alter their operation , and indirect load control (ILC), which is accomplished through various pricing mechanism [9].

The following part introduces the existing AC DR and optimal control strategies and essential building thermal model development research.

1.2 Literature Review

Model predictive control (MPC) is widely used in the AC DR research. It is a promising control strategy that is a capable of addressing all the criteria and has shown results for achieving higher efficiency in buildings. MPC can provide a potential building energy saving of 16–41% [10] compared to the commonly used rule-based building HVAC controllers. Other advantages of MPC for building HVAC systems include robustness, tunability, and flexibility [11]. A nonlinear model predictive control (NMPC) was designed and implemented in a well monitored house, with over 100 sensor points to measure indoor environmental parameters, including temperatures of different zones, and ambient conditions, including solar radiation on walls different orientations. The results show that there is a 30.1% measured energy reduction compared with the conventional scheduled temperature set-points [12]. A hybrid model predictive control (HMPC) strategy was developed and implemented to control solar-assisted AC system in a solar decathlon house in in Australia. The whole system features a Photovoltaic-Thermal (PVT) system and a phase change material (PCM) active storage unit, integrated with a standard ducted AC system. The experimental results demonstrate the high performance of energy saving with using the HMPC [13]. A Hierarchical MPC method was proposed in simulated building integrated with microgrid, where building heating/cooling is coordinated with renewable energy production, storages state of charge and volatile electricity pricing from grid. The used building model is a state-space model with only one single state and multiple inputs of different disturbances, e.g. hourly solar radiation and internal heat gains [14].

The performance of these above control techniques relies heavily on the quality of building model, which characterizes the properties of building thermal mass and its behaviour. Generally, the building thermal models can be classified into three categories: detailed physical models, black-box models and grey-box models. The detailed physical models have been widely used in the simulation softwares, e.g. EnergyPlus and DOE-2 [15]. A simplified model is regressed by the exhaustive abundant data resulted from prototype building models in EnergyPlus, which are well known in terms of detailed physical and thermal parameters, for prediction of DR potentials [8]. One popular black-box/date-driven model structure is ARX (autoregressive with exogenous outputs) family of models [16]. One ARX in conjunction with a RC building thermal model, with pre-known parameters values, to forecast AC power consumption was developed. The appropriate identification of inputs from the proposed options for ARX model was provided and the corresponding performances were validated in terms of the accuracy of simulated AC power [17]. RC (resistance and capacity) thermal network model is a typical grey-box model which has simplified structure with certain physical meanings for generation of acceptable and reliable results. An over-simplified building model was proposed to simulate the thermal load for MPC control in a simulated residential building [18]. The total cooling supply from AC was considered as a constant and directly introduced as the input. Another RC model with 44 inputs was developed and validated in EnergyPlus platform to analyse the impacts from parameters uncertainties on simulated peak cooling load [19].

1.3 Gap and Objectives

Some previous research was based on the adequate required information and measured data from experiments of real buildings [12,13] or simulated building in detailed simulation platforms, e.g. EnergyPlus [8, 19] for realization of the training processes and further optimal inputs selection process or sensitivity analysis. However, for practical implementation of advanced control technique, e.g. MPC, in plentiful houses of a community, it may be not practical to install multiple sensors and collect very detailed information from each single house.

A reduced-order and simplified model is necessary for MPC control [16]. Accurate complicated or high-order dynamic models are readily available, e.g. models in simulation software such as EnergyPlus and TRNSYS, but may not be generally suitable for optimization and control. They tend to make it difficult for algorithms to converge to an optimal solution in time when the models are implemented in MPC control. However, the building thermal models in some previous research [14, 18] were oversimplified. One state was formulated only, which equivalently assumed that the temperatures of different elements, such as air, wall surface and roof, in the house were identical. This assumption is not practical and probably cannot embody the delay and thermal storage effects from walls and roof due to the missing thermal resistances and capacitances.

Based on the above gaps, this paper therefore presents a building thermal model development method based on limited available information of typical houses in the U.S. A simplified grey-box model with appropriate assumptions and structure is developed to predict the indoor temperature for 24-hour horizon. It is a first-order model which can be easily applied in large-scale control. The less amount of required inputs for the model is readily available from local local weather stations. The limited information for estimation of model parameters are from 2006 IECC (International Energy Conservation Codes) [20]. The thermal storage effects from wall, attic and internal thermal mass are also fully considered. The model parameters are identified by particle swarm optimization (PSO) method.

2. Project Aims and Requirements of Simplified Building Thermal Model

The inherent flexibility and wide distribution of existing houses makes their deployment as "battery" or virtual storage devices which are an attractive, low-cost investment option enables smaller, 'right-sized' installation of grid-scale storage. During the cooling season, the battery is fully charged when the indoor temperature is at the lowest temperature allowed by the occupant and fully discharged when the indoor temperature is at the highest temperature allowed by the occupant. The efficiency and capacity of the HVAC system coupled with the thermal characteristics, weather, and internal loads dictate the charging and discharging rate of the "battery."

In previous research, the use of available battery capacities in houses to provide grid services, such as DR, is typically employed by shutting off a homeowner's AC during peak load periods. The homeowners are compensated or benefitted by participation in the program or the price differences in dynamic price structures. However, this one-size-fits-all approach does not take full advantage of individual house's potential of virtual thermal storage. How battery, in single house, is characterized as well as how it can be aggregated and used to provide flexibility is subject to many factors, such as battery capacities, individual comfort preference and control constraints.

This project aims to develop technologies for transforming buildings into active participants in operation of a more-stable and economically efficient electric grid by exposing their inherent virtual storage capabilities and operational flexibility through improved characterization, control and integration with transactive mechanisms. To optimal control house loads as virtual storages, the ability to forecast how the state of battery will change with and without charging or discharging events is essential. This ability to forecast AC power use and indoor temperature over several hours, which allows complete charging, e.g. precooling, discharging, e.g. load shedding, and recovery cycles to be predicted and planned.

An appropriate building thermal model is needed for this requirement. While complex building models can provide very good accuracy, they also require a substantial amount of information about the building itself. At the utility or even community scale it is not feasible to expect that this information will be obtainable in a cost-effective manner. Due to the need of deploying this building model at large scale, a simplified building model was developed using limited information about the house.

3. Description of Typical House in U.S.

As shown in Fig.1, the reference building being modelled in this research is a typical single family detached house in southeast region of U.S. It was built in 2008 and located in Knoxville, Tennessee and is part of a large subdivision of similar homes built around the same time. The physical and thermal properties are under the building code of IECC 2006 [20]. The construction and thermal efficiency of the home are typical of the region and age of the home. The home energy rating score (HERS) value is a metric used to compare the expected energy use of different homes. The building being modeled in this paper achieved a HERS score of 101, which is very close to RESNET's reference value of 100(representing a 2004 IECC built home) [21]. Additional information can be found in [22].

The house was unoccupied to eliminate the uncertainty and variability introduced with human occupants. However, the major appliances: refrigerator, oven, dishwasher, clothes washer, dryer, lighting, and shower were run on a schedule based on the typical usage as outlined in the Building America House Simulation Protocol [23]. The sensible and latent gains associated with human respiration, perspiration, and heat generation were simulated with a human emulator. Sensible gains from miscellaneous electrical loads (MELs) were simulated with electric heaters.

4. Building Thermal Model Development

A grey-box model is proposed to simulate the thermal performance in typical U.S. houses in southeast region. For in-situ measurement and application, the developed model requires relatively less training efforts, e.g. 3 weeks of historic operation data with different indoor temperature set-points. The available information is assumed to be limited which meets the requirement for large scale virtual storage control of real residential community in the near future.

4.1 Outline of Mathematical Model

A 4R4C model is proposed in this study, as shown in Fig.2. It is in an electrical analogue pattern with resistance (R, K/W) and capacitance (C, J/K). Building physical properties affecting thermal transfer are mainly those of exterior wall, roof and internal mass, which are handled separately in this model. The developed model can therefore reflect thermal status and response of different building component. It is worth noting that only sensible load is considered in this model. Meanwhile, all resistances and capacitances are assumed to be time-invariant.

The heat transfer in the building model is described using the following equations:

(1)

$$C_w \frac{dT_{Wall}(t)}{dt} = \frac{T_{sol,w}(t) - T_{wall}(t)}{R_{w/2}} - \frac{T_{wall}(t) - T_{in}(t)}{R_{w/2}}$$

(2)

$$C_{in} \frac{dT_{in}(t)}{dt} = \frac{T_{wall}(t) - T_{in}(t)}{R_{w/2}} + \frac{T_{attic}(t) - T_{in}(t)}{R_{attic}} + \frac{T_{im}(t) - T_{in}(t)}{R_{im}} + C_1 Q_{IHL,i} + C_2 Q_{AC,i} + C_3 Q_{solar,\,i}$$

(3)

$$C_{attic}\frac{dt_{attic}(t)}{dt}=\frac{T_{sol,r}(t)-T_{attic}}{R_{roof}}-\frac{T_{attic}(t)-T_{in}(t)}{R_{attic}}$$

(4)

$$C_{im}\frac{dT_{im}(t)}{dt}=-\frac{T_{im}(t)-T_{in}(t)}{R_{im}}+C_1Q_{IHL,m}+C_2Q_{AC,m}+C_3Q_{solar,m}$$

C_w, C_{attic}, C_{im}, and C_{in} are the thermal capacitances of exterior wall, air in attic, internal mass and indoor air respectively. R_w, R_{attic}, R_{roof} and R_{im} are the thermal resistance of exterior walls, attic floor, roof and internal mass respectively.

Building internal mass includes floors, interior partitions, furniture, etc. It absorbs radiant heat through the windows and from occupants, lighting, etc. It then releases (or absorbs) heat gradually to the air via convection [24]. It is necessary to consider the building internal mass independently since the effect of building internal mass on cooling/heating energy consumption and indoor temperature is significant. The area of internal mass is difficult to calculate and thus assumed to be the floor area although the actual area of internal mass is larger than the floor area.

Q_{IHL} is the sensible heat gains from indoor heat resources (W), e.g. human, equipment and lighting, which is calculated from (5):

$$Q_{IHL}=W_{house}-W_{AC}-W_{WH}-W_{dryer}-W_{garage}-W_{ex,1}$$

where, W is the power consumption (W). The subscripts *house, AC, WH, dryer, garage* and *ex,l* mean the whole house, AC, water heater, dryer, garage and exterior lights respectively. It is assumed that all power used by the house with the exceptions noted above is converted to sensible heat.

Q_{AC} is the total cooling capacity (W) of AC as shown in the following equations. Where, W_{AC} is the power of AC outdoor unit (W). *COP* is the dynamic coefficient of performance, as shown in (7), which is the product of rated COP and COP adjustment function resulted from regression of the historic data of a single speed heat pump.

(6)

$$Q_{AC} = W_{AC}COP$$

(7)

$$COP = 3.516\left(1.194 - 0.00589T_{out} - 0.0000411T_{out}^2\right)$$

The solar radiation through window is characterized by Q_{solar} (W) in the following:

(8)

$$Q_{solar} = F_{win}(t)I(t)A_{win,tot}SHGC$$

where, I is the direct normal solar irradiance (W/m^2). $A_{win,tot}$ is the total window area (m^2). SHGC is the solar heat gain coefficient of windows. F_{win} is the area-weighted average of view factors of windows with different orientations, which are calculated using a solar calculator spreadsheet developed by NOAA [25]:

(9)

$$F_{win}(t) = \frac{\sum_{i=1}^{4} A_{win,i}F_i(t)}{\sum_{i=1}^{4} A_{win,i}}$$

Subscript i indicates the orientations, i.e. east, south, west and north. A_{win} is the general area of window (m^2). Fi is the view factor for windows with different orientations.

Since one assumption in this research is that the available information is limited in terms of numbers of measure points, e.g. one indoor temperature data measurement available only in this paper, and specific properties of building materials, the effective heating/cooling gain coefficients C1, C2 and C3 are introduced as one main innovation. C_1, C_2 and C_3 are used to adjust Q_{IHL}, Q_{AC} and Q_{solar} for unknown factors. All C_1, C_2 and C_3 are assumed to be unknown and need to be identified by searching algorithm illustrated in Sub-section 4.2.

For Q_{IHL}, the unknown factors include sensible heat ratio (SHR) of internal loads, e.g. latent heat resulted from cooking, and possible exhausted energy use, e.g. range hood operation during cooking. For Q_{AC}, unknown factors include SHR with typical range of 0.6 to 0.8 and the installed inefficiencies such as long refrigerant lines, low indoor airflow, dirty coils, improper refrigerant charge, etc., which are estimated at 10-20%. For Q_{solar}, the unknown factors include the bug screens, blinds/curtains, and shading.

Portions of C_1Q_{IHL}, C_2Q_{AC} and C_3Q_{solar}, i.e. $C_1Q_{IHL,i}$, $C_2Q_{AC,i}$ and $C_3Q_{solar,i}$, are transmitted to indoor air directly by convection and the rest, i.e. $C_1Q_{IHL,m}$, $C_2Q_{AC,m}$ and $C_3Q_{solar,m,}$, are absorbed by internal thermal mass where the subscripts i and m indicate the indoor air and internal mass. They are calculated by the following equations:

(10)

$$C_1Q_{IHL,i} = Sp_1 \times C_1Q_{IHL}$$

(11)

$$C_1Q_{IHL,m} = (1 - Sp_1) \times C_1Q_{IHL}$$

(12)

$$C_2Q_{AC,i} = Sp_2 \times C_2Q_{AC}$$

(13)

$$C_2Q_{AC,m} = (1 - Sp_2) \times C_2Q_{AC}$$

(14)

$$C_3Q_{solar,i} = Sp_3 \times C_3Q_{solar}$$

(15)

$$C_3Q_{solar,m} = (1 - Sp_3) \times C_3Q_{solar}$$

where, Sp_1, Sp_2 and Sp_3 are the convection fractions for C_1Q_{IHL}, C_2Q_{AC} and C_3Q_{solar} respectively. All Sp_1, Sp_2 and Sp_3 are assumed to be unknown and need to be identified by searching algorithm illustrated in Sub-section 4.2.

The effects of solar radiation on walls and roof are considered by calculation of $T_{sol,w}$ and $T_{sol,r}$ respectively, which are the sol-air temperatures, shown in the followings:

(16)

$$T_{sol,w} = \frac{\alpha_w}{h(t)} F_w(t) I(t) + T_{out}$$

(17)

$$T_{sol,r} = \frac{\alpha_r}{h(t)} F_r(t) I(t) + T_{out}$$

where, α is the absorption coefficient of wall and roof. T_{out} is outdoor dry bulb temperature (°C). *h* is convective heat transfer coefficient of roof and exterior wall surfaces (W/m^2 K), which is calculated by the correlation between *h* and wind speed developed from ASHRAE Handbook [26]:

(18)

$$h = xV_{wind} + y$$

where, V_{wind} is the wind speed (m/s). x and y are the regression coefficients.

F_w and F_r in (16) and (17) are the area-weighted averages of view factors of exterior walls and roofs with different orientations.

where, A_{wall} is the general area of each wall (m^2). Fi is the view factor for walls with different orientations. Subscript j indicates the orientations, i.e. north and south, of roof.

(19)

$$F_w(t) = \frac{\sum_{i=1}^{4} A_{wall,i} F_i(t)}{\sum_{i=1}^{4} A_{wall,i}}$$

(20)

$$F_r(t) = \frac{\sum_{j=1}^{2} F_j(t)}{2}$$

A comparison among F_r, F_w and F_{win} in Sep 1, 2012 is shown in Fig.3 for illustration purpose.

A summary of the required information as model inputs are listed in Table 1. Three main data sources are required. The weather data are assumed to be available from observatory directly. The building plans are available from building plans or general estimations for calculation of solar radiation and sol-air temperature. The measured or estimated data include the whole house power, HVAC power, water heater power, dryer power and power use in unconditional spaces.

4.2. Parameters Identifications

The searching process for optimal values of the undetermined parameters in this model is a nonlinear optimization process. Given a set of parameters, the grey-box model can predict the indoor air temperature (T_{in}) profile. An objective function is used to evaluate the fitness between the predicted results and measured data collected from the reference building during the training period. The objective function J of such optimization is to minimize the integrated root-mean- square-error (RMSE), as defined in Eq.

(21):

$$J(R_w, R_{roof}, R_{attic}, R_{im}, C_w, C_{im}, C_{attic}, C_{in}, C_1, C_2, C_3, Sp_1, Sp_2, Sp_3) = \sqrt{\frac{\sum_{K=1}^{N}(T_{in,act} - T_{in,simu})^2}{N-1}}$$

where, $T_{in,act}$ is the measured building indoor dry bulb temperature. $T_{in,simu}$ is the indoor temperature resulted from the model. The parameters are identified by particle swarm optimization (PSO) method. The searching ranges for C_w, C_{attic} and all the R are referred to the recommended parameters values of buildings in zone 4 from IECC [20]. C_{im} can be assumed to a be in the range of 100 to 450 (KJ/K m^2) [19]. The lower and upper limits for each R and C are 1/3 and 3 times the recommended values respectively. The ranges of C_1, C_2 and C_3 are estimated based on experiences and the ranges of Sp_1, Sp_2 and Sp_3 are referred to [26].

The model development is written and the PSO package is imported in RStudio [27], which is a free and open-source integrated development environment (IDE) for R.

5. Model Validation

The data collected from the reference building in different consecutive time periods with various operation conditions, e.g. different schedules of AC indoor temperature set-points, as well as different outdoor weather conditions are used to train and validate the model. The data collected from Sep 1 to Sep 26, 2012 are used for training session. The indoor temperature set-point was scheduled as 20°C from 9 a.m. to 1 p.m., around 27.8°C from 1 a.m. to 7 p.m. and around 25.6°C from 7 p.m. to 9 a.m. of next day. The data collected from Sep 1 to Sep 26, 2012 are used for training and results are shown in Fig.4.

$T_{in,act}$ is the measured indoor temperature and $T_{in,simu}$ is the indoor temperature from the model for a 24-hour prediction horizon. The resulting parameters identified by PSO are: R_w = 0.00852 K/W, R_{attic} = 0.0344 K/W, R_{roof} = 0.000311 K/W, R_{im} =0.00661 K/W, C_w = 9,719,515 J/K, C_{attic} = 501,509 J/K, C_{im} = 19,999,128 J/K, C_{in} = 6,666,569 J/K, C_1 = 0.732, C_2 = 0.495, C_3 = 0.0500, Sp_1 = 0.913, Sp_2 = 0.111, Sp_3 = 0.920.

The data collected from Jul 1 to Jul 24, 2011and from Oct 1 to Oct 20, 2011 are used for validation. The results are shown in Fig.5 and Fig.6.

From Jul 1 to Jul 7, the indoor temperature set-point was set as 25.6°C. From Jul 8 to Jul 24, the setpoint was scheduled as 29.4°C from 12 p.m. to 5 p.m., around 28.3°C from 5 p.m. to 7 p.m. and around 25.6°C from 7 p.m. to 12 p.m. of next day. For Oct, the set-point was around 24.4°C.

To quantify the deviations of the predicted data from the measured data in both training session and validation sessions, three indices are used to evaluate the deviations: mean absolute error (MAE), mean absolute percentage error (MAPE) and RMSE:

(22)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left| T_{in,act}(t) - T_{in,simu}(t) \right|$$

(23)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{T_{in,act}(t) - T_{in,simu}(t)}{T_{in,act}(t)} \right|$$

(24)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i-1}^{n} \left(T_{in,act}(t) - T_{in,simu}(t) \right)^{2}}$$

Table 2 lists the three accuracy indices of the developed model in training and validation sessions. It can be found that the developed model has satisfactory performance in prediction of the building indoor temperature under different scenarios.

6. Conclusion

A simplified grey-box model with appropriate assumptions and complexity is developed based on limited available information from a typical building in the southeast region of the U.S. The model has excellent performance in prediction of building indoor temperature for a 24-hour horizon. Due to the simplified structure and reduced number of inputs, it can be readily adopted in popular optimal virtual storage or DR control, e.g. MPC, of multiple building loads to provide grid services.

Some features in the developed modelling method can be promoted and directly applied in modelling of other houses in U.S.: The first-order building model structure which considers the non-homogeneous heat transfer features of exterior wall, roof and internal mass separately. Second, the identification method of the view factors. Third, the broad searching ranges of RC and other coefficients, which includes all the possible values of equivalent R and C of typical houses in specific regions of the U.S.

Acknowledgments

The research presented in this paper was funded by the United States Department of Energy, Energy Efficiency and Renewable Energy Office, Building Technology Office under the grid modernization program.

References

[1] DOE. Buildings energy data book tech rep. U.S. Department of Energy; 2011.

[2] Cole, W.J., Powell, K.M., Hale, E.T., Edgar, T.F. Reduced-order residential home modeling for model predictive control. Energy and Buildings 2014; 74: 69-77.

[3] Wattles P. ERCOT demand response overview & status report. InProc. AMIT-DSWG Workshop AMI’s Next Front. Demand Response 2011 Aug 30 (pp. 1-25).

[4] Mitra S., Sun L., Grossmann I.E. Optimal scheduling of industrial combined heat and power plants under time-sensitive electricity prices. Energy 2013; 54: 194–211.

[5] Korkas, C.D., Baldi, S., Michailidis, I., Kosmatopoulos, E.B. Occupancy-based demand response and thermal comfort optimization in microgrids with renewable energy sources and energy storage. Applied Energy 2016; 163: 93-104.

[6] Christantoni, D., Oxizidis, S., Flynn, D., Finn, D.P. Implementation of demand response strategies in a multi-purpose commercial building using a whole-building simulation model approach. Energy and Buildings 2016: 131: 76-86.

[7] Cui, B.R., Wang, S., Yan, C.C., Xue, X., 2015. Evaluation of a fast power demand response strategy using active and passive building cold storages for smart grid applications. Energy Conversion and Management 2015; 102: 227-238.

[8] Yin, R., Kara, E.C., Li, Y., DeForest, N., Wang, K., Yong, T., Stadler, M. Quantifying flexibility of commercial and residential loads for demand response using setpoint changes. Applied Energy 2016; 177: 149-164.

[9] Johnson, B.J., Starke, M.R., Abdelaziz, O.A., Jackson, R.K. and Tolbert, L.M., A dynamic simulation tool for estimating demand response potential from residential loads. In Innovative Smart Grid Technologies Conference (ISGT), IEEE Power & Energy Society; February 2015.

[10] Afram, A. and Janabi-Sharifi, F. Theory and applications of HVAC control systems–A review of model predictive control (MPC). Building and Environment 2014; 72:343-355.

[11] Maasoumy, M., Razmara, M., Shahbakhti, M., Vincentelli, A.S. Handling model uncertainty in model predictive control for energy efficient buildings. Energy and Buildings 2014; 77: 377-392.

[12] Dong, B., Khee, P.L. A real-time model predictive control for building heating and cooling systems based on the occupancy behavior pattern detection and local weather forecasting. Building Simulation 2014; 7(1): 89-106.

[13] Fiorentini, M., Wall, J., Ma, Z., Braslavsky, J.H., Cooper, P. Hybrid model predictive control of a residential HVAC system with on-site thermal energy generation and storage. Applied Energy 2017; 187: 465-479.

[14] Lešić, V., Martinčević, A., Vašak, M. Modular energy cost optimization for buildings with integrated microgrid. Applied Energy 2017; 197: 14-28.

[15] Crawley, D.B., Lawrie, L.K., Pedersen, C.O., Winkelmann, F.C. Energy plus: energy simulation program. ASHRAE journal 2000; 42 (4): 49-56.

[16] Cole, W.J., Powell, K.M., Hale, E.T., Edgar, T.F. Reduced-order residential home modeling for model predictive control. Energy and Buildings 2014; 74: 69-77.

[17] Touretzky, C.R., Patil, R. Building-level power demand forecasting framework using building specific inputs: development and applications. Applied Energy 2015; 147: 466-477.

[18] Sharma, I., Dong, J., Malikopoulos, A.A., Street, M., Ostrowski, J., Kuruganti, T., Jackson, R. A modeling framework for optimal energy management of a esidential building. Energy and Buildings 2016; 130: 55-63.

[19] Domínguez-Muñoz, F., Cejudo-López, J.M. and Carrillo-Andrés, A. Uncertainty in peak cooling load calculations. Energy and Buildings 2010; 42(7): 1010-1018.

[20] International Energy Conservation Codes (IECC) – 2006 IECC Prescriptive Requirements-Available at:
https://www.energycodes.gov/sites/default/files/documents/ta_2006_iecc_prescriptive_requirements.pdf

[21] RESNET. Understanding the HERS® Index. Accessed 4/26/2017. Available at :http://www.hersindex.com/understanding.

[22] Christian, J. E., A.C. Gehl, P.R. Boudreaux, J. R. New. Campbell Creek TVA 2010 First Year Performance Report. Oak Ridge National Laboratory. 2010 August. No.: ORNL/TM-2010/206.

[23] Hendron, R. and Engebrecht, C. Building America house simulation protocols. Golden, CO: National Renewable Energy Laboratory; 2010.

[24] Xu, X.H. and Wang, S.W. A simplified dynamic model for existing buildings using CTF and thermal network models. International Journal of Thermal Sciences 2008; 47(9): 1249-1262.

[25] National Oceanic and Atmospheric Administration (NOAA). Solar Calculation Details – Available at: https://www.esrl.noaa.gov/gmd/grad/solcalc/calcdetails.html.

[26] ASHRAE. ASHRAE Handbook: Fundamentals (SI Edition). Atlanta, GA: American Society of Heating, Refrigerating and Air-conditioning Engineers; 2013.

[27] Rstudio-Open source and enterprise-ready professional software for R. Available at: https://www.rstudio.com/

Fig.1. A view of reference house in Tennessee

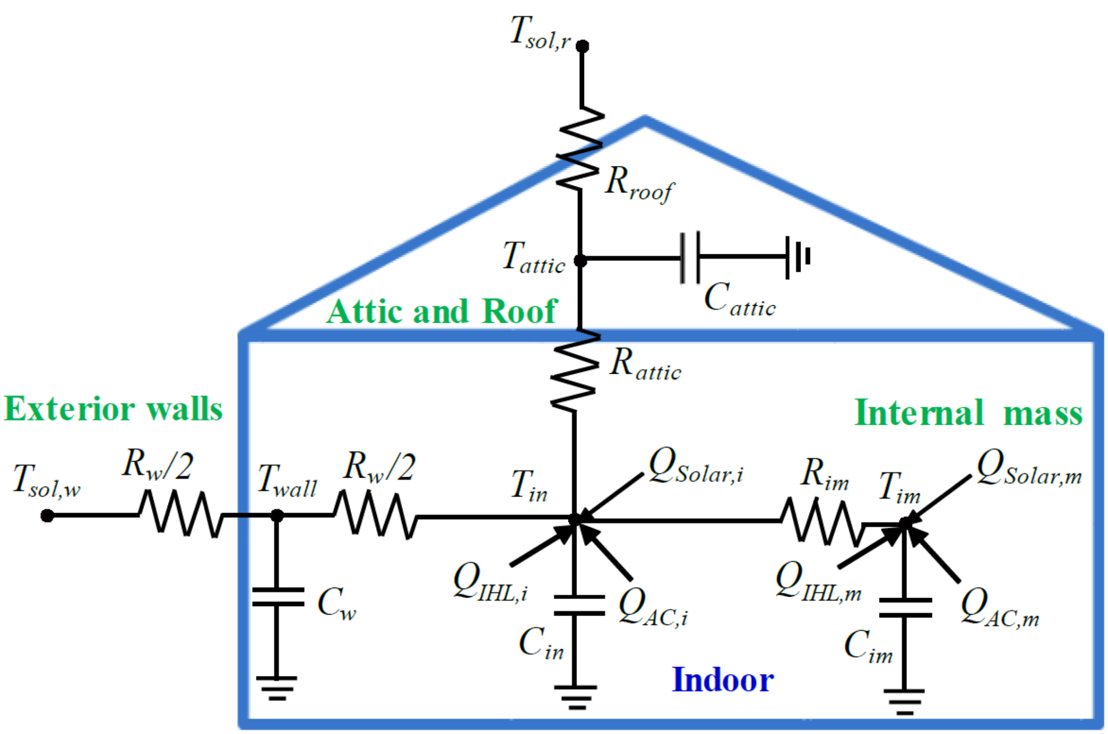

Fig.2. Schematics of the simplified building thermal network model (4R4C)

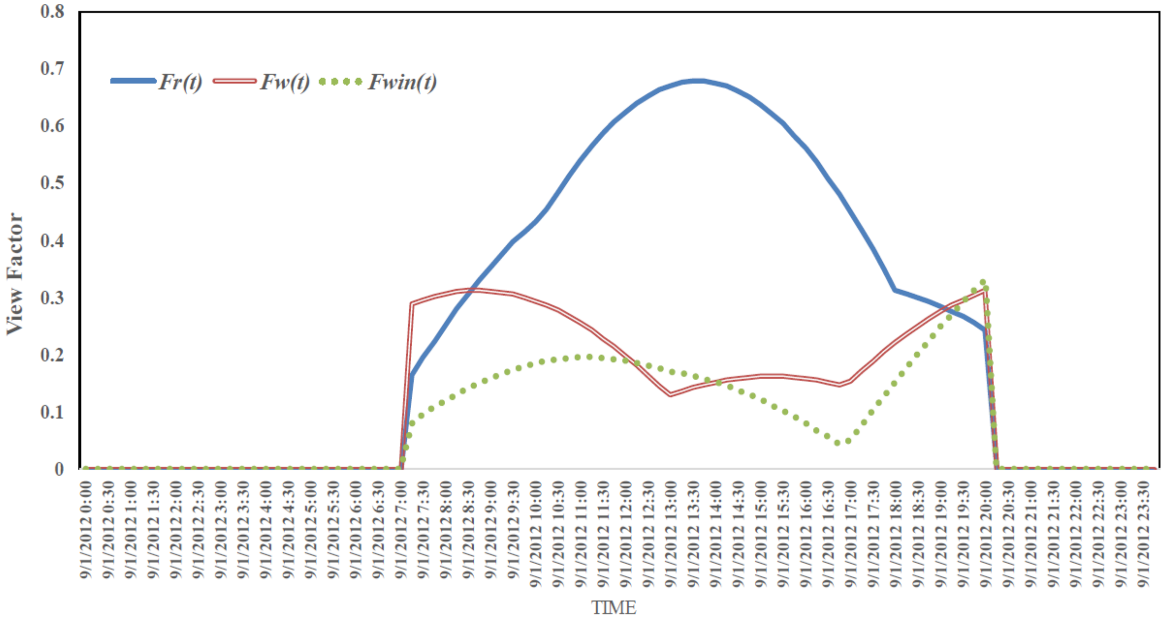

Fig.3 Comparison of view factors in a typical day in September

Table 1 Data/information required for the model inputs

Source	Data/Info	Involved model inputs
Weather data/forecast (available from observatory)	Outside Temperature	$T_{solar,w}$, $T_{solar,r}$
	Direct Normal Irradiance	$T_{solar,w}$, $T_{solar,r}$, Q_{solar}
	Wind Speed	$T_{solar,w}$, $T_{solar,r}$
Building properties (available from building plans or general estimations)	Wall Area	$T_{solar,w}$
	Wall Absorptivity	$T_{solar,w}$
	Wall Area by Face	$T_{solar,w}$
	Building Orientation	$T_{solar,w}$, $T_{solar,r}$, Q_{solar}
	Roof Absorptivity	$T_{solar,r}$
	Roof Orientation	$T_{solar,r}$
	Window Area by Face	Q_{solar}
	Window SHGC	Q_{solar}
	Rated HVAC COP	Q_{AC}
Measured or Estimated	Whole House Power	Q_{IHL}
	HVAC Power	Q_{IHL}, Q_{AC}
	Water heater Power	Q_{IHL}
	Dryer Power	Q_{IHL}
	Power use in unconditioned spaces (exterior and garage plug loads and lights)	Q_{IHL}

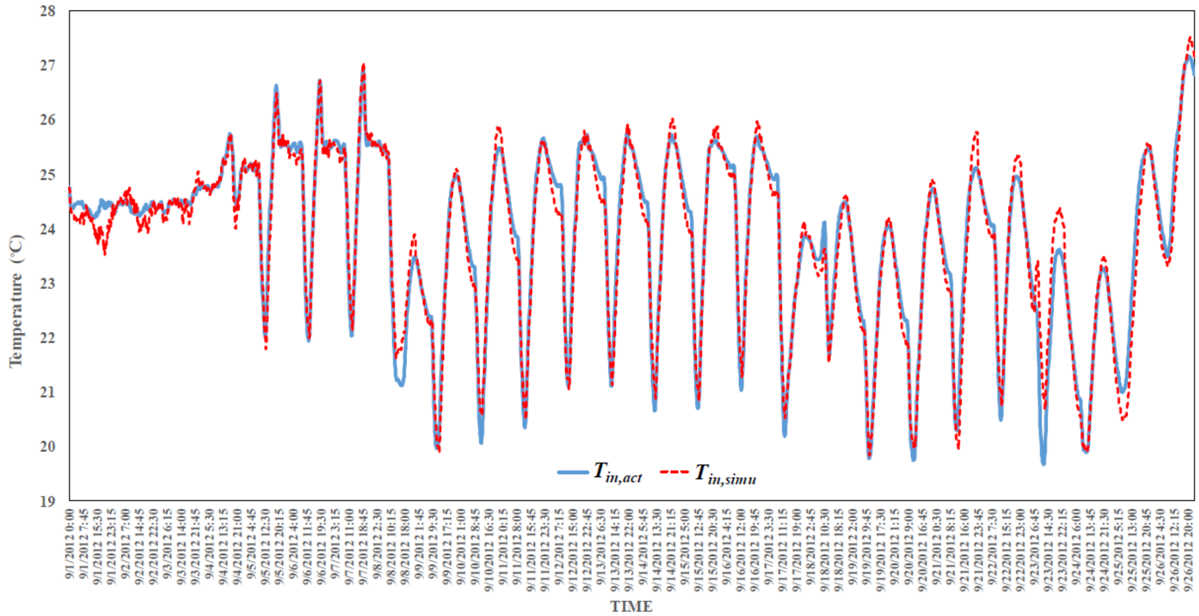

Fig.4. Training results from Sep 1, 2012 to Sep 20, 2012

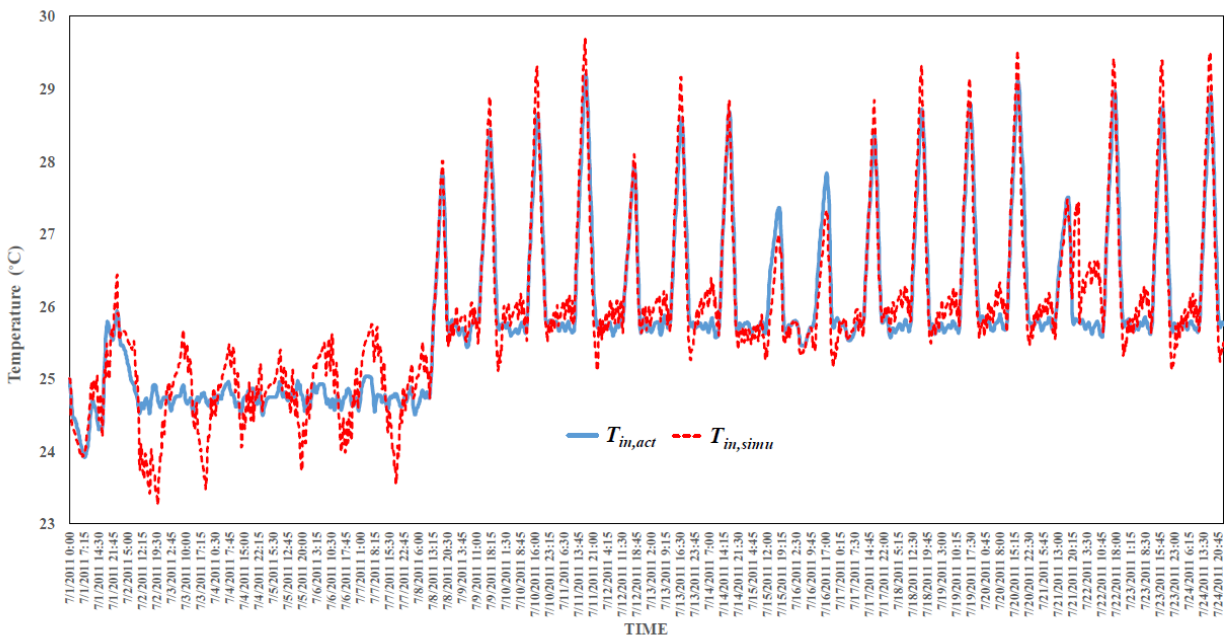

Fig.5. Validation results from Jul 1, 2011 to Jul 24, 2011

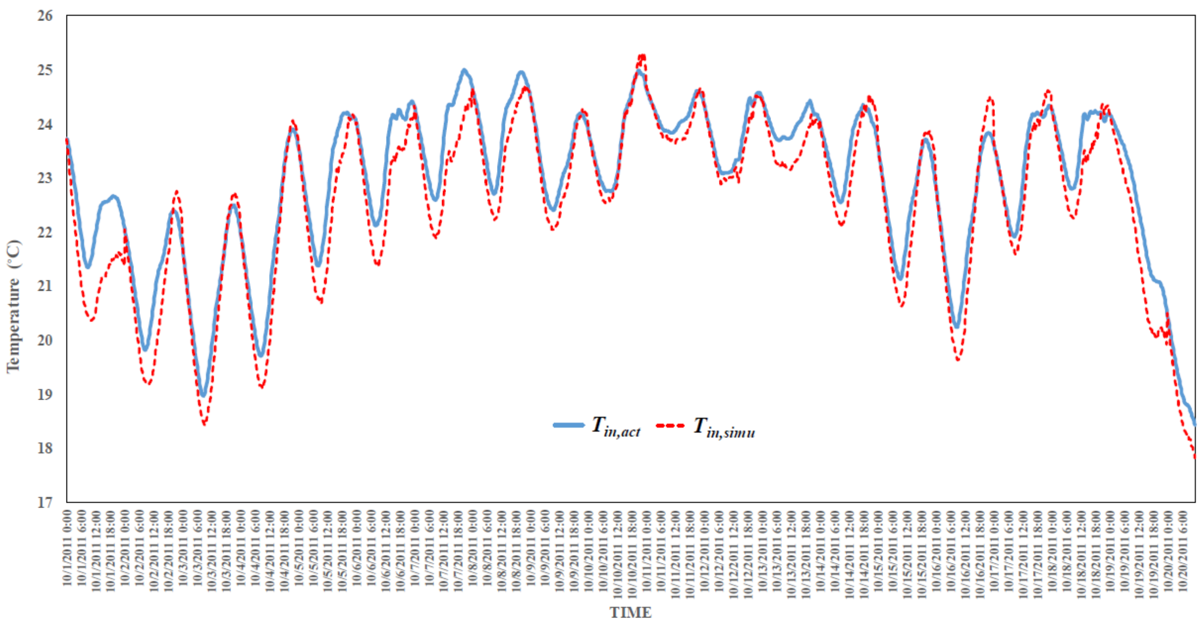

Fig.6. Validation results from Oct 1, 2011 to Oct 20, 2011

Table 2 Accuracy indices of the developed model

Time	Training/Validation	MAE	MAPE	RMSE
Sep 1,2012 to Sep 26,2012	Training	0.209°C	0.90%	0.292°C
Jul 1, 2011 to Jul 24 2011	Validation	0.300°C	1.16%	0.388°C
Oct 1,2011 to Oct 20,2011	Validation	0.425°C	1.94%	0.528°C