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Investigation of the Demand Response Potentials of Residential Air Conditioners Using Grey-box Room Thermal Model

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Abstract

This paper investigates demand response (DR) potentials of residential air conditioners (AC) under different control strategies using a grey-box room thermal model. The proposed resistance-capacitance (RC) thermal model combines the essential prior knowledge of room thermal characteristics with data-driven techniques. With the aim of saving the optimization time and improving the reasonableness of the search results, undetermined parameters were physically estimated prior to the identification with nonlinear optimization method. A typical residential bedroom in Hong Kong was chosen to test the room thermal model. The root mean square errors (RMSE) between the sampled and predicted data sets for training and validation sessions were 0.25 ℃ and 0.28 ℃ respectively. After coupling the room RC thermal model and an empirical AC energy consumption model, we can get AC power reductions under different control strategies during the DR period. The simulation results show that the temperature set-point reset control strategies enable the power consumption to decrease during the DR event, and the peak reduction increases when the set-point is set higher. Besides, the precooling control strategy can help to further reduce the electric power.

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Keywords: Residential air conditioner; Demand Response; Grey-box room thermal model; Smart Grid

1. Introduction

Smart grid is an intelligent electric system that integrates with advanced communication and control technologies, and upgrades the power grid to be cleaner and more efficient, reliable, resilient and responsive. In smart grid, demand response enables consumers to reduce or shift their electricity usage during peak periods in response to time-based rates (e.g., Time-of-Use Pricing, Critical Peak Pricing and Real Time Pricing) or other forms of financial incentives. With the increasing saturation and penetration rate of the Advanced Metering Infrastructure (AMI), the potential peak reduction from retail and wholesale demand response programs had reached to 57,029 MW in total in 2013, accounting for 7.3 percent of non-coincident peak load in U.S. [1, 2]. As to the residential sector, demand response resources provided by residential customers ramped up from 5,803 MW in 2006 to 8,600MW in 2012 due to the wide deployment of AMI and the dynamic electricity pricing schemes [3]. In Hong Kong, a high density city, the electricity consumption of residential buildings accounted for 26 percent of all electricity consumption in 2013, in which the electricity consumed by space conditioning represented 31% [4]. A typical evening peak usually occurs between 18:00 and 20:00 in summer because people go back home and turn on their home air conditioners. Residential air conditioners can make significant contributions to power reduction during this peak periods.

In recent years, smart household monitoring, communication and automated control technologies and products, e.g. smart meters, and home energy management system (HEMS), have been developed and deployed rapidly. This can provide large amount of measured data, like indoor air temperature and power consumption, and facilitate the use of the data-driven techniques for home energy management [5-7]. In this paper, an improved grey-box room thermal model was developed to investigate the demand response potentials of residential air conditioners in Hong Kong. The model can be integrated in the smart home energy management system to control the energy consumption during normal and DR periods.

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2. Development of grey-box room thermal model

Building thermal RC models have been widely investigated [5-7]. This study focus on the individual room thermal model considering that a huge number of small air conditioners are installed in the high-rise residential buildings in modern high density cities like Hong Kong and Shanghai. Many previous researchers studied the demand response of residential buildings in an aggregated approach using simplified RC models [8-11]. The grey-box room thermal model proposed in this study integrates physical principles of room thermal responses and data-driven optimization technique. Model training data are assumed to be available from smart home system and local observatory.

2.1. Improved RC model

The physical description of a grey-box model should be neither too simple nor too complex. It should capture the key and most thermal behaviors of targeted room to keep its robustness to different operating conditions. But for the sake of computation time, the model should not be too complicated. Fig.1 illustrates the components included in the model and the heat fluxes exchanged between them. The model mainly involves four nodes: outdoor environment, building envelop, indoor air, and internal thermal mass.

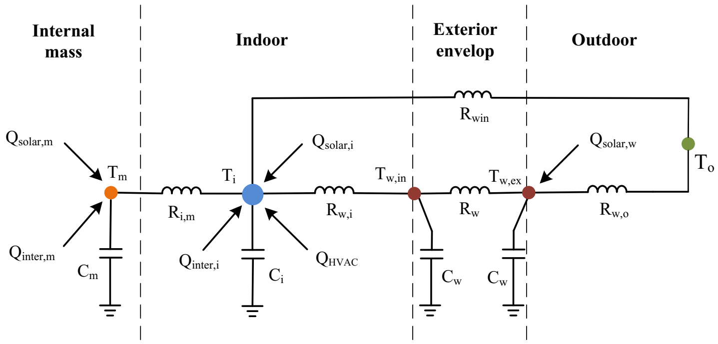

Fig. 1. Schematic of grey-box thermal model of residential buildings (5R4C)

The exterior building envelop consists of opaque walls and transparent windows. Considering the climate in Hong Kong, most residential buildings are constructed with light-weight wall and without thermal insulation. Therefore, it is reasonable to consider the external wall as one thermal resistance and two equal thermal capacities [12]. Note that a portion of solar radiation through the window is directly transmitted into indoor air, and the rest is absorbed by internal mass constituted by floor, ceiling, partitions, and furniture. The bulk of internal mass absorbs the solar radiation through the windows and heat from indoor heat sources, then gradually transfers the heat into the space by convection. The energy balances for the external/internal wall surfaces, the indoor air and the internal thermal mass are given by the following equations:

$$C_w \frac{dT_{w,ex}}{dt} = \frac{T_o - T_{w,ex}}{R_{w,o}} + \frac{T_{w,in} - T_{w,ex}}{R_w} + Q_{solar,w} \tag{1}$$

$$C_w \frac{dT_{w,in}}{dt} = \frac{T_{w,ex} - T_{w,in}}{R_w} + \frac{T_i - T_{w,in}}{R_{w,i}} \tag{2}$$

$$C_i \frac{dT_i}{dt} = \frac{T_m - T_i}{R_{i,m}} + \frac{T_{w,in} - T_i}{R_{w,i}} + \frac{T_o - T_i}{R_{win}} + Q_{solar,i} + Q_{inter,i} + Q_{HVAC} \tag{3}$$

$$C_m \frac{dT_m}{dt} = \frac{T_i - T_m}{R_{i,m}} + Q_{solar,m} + Q_{inter,m} \tag{4}$$

$$Q_{solar,w} = \alpha A_w I_{solar} \tag{5}$$

$$Q_{solar,m} = f_{solar,m} \times SHGC \times A_{win} I_{solar} \tag{6}$$

$$Q_{solar,i} = f_{solar,i} \times SHGC \times A_{win} I_{solar} \tag{7}$$

$$Q_{inter,i} = f_{inter,i} Q_{inter} \tag{8}$$

$$Q_{inter,m} = f_{inter,m} Q_{inter} \tag{9}$$

where R and C represent the overall heat resistance and capacity; T denotes temperature; subscripts *i, o, w, in, ex, win* and *m* indicate indoor air, outdoor air, exterior wall, internal wall surface, external wall surface, window and internal mass respectively; $Q_{solar,w}$, $Q_{solar,i}$ and $Q_{solar,m}$ are solar heat gains absorbed by external wall surface, indoor air and internal mass respectively; $Q_{inter,i}$ and $Q_{inter,m}$ are internal heat gains absorbed by indoor air and internal mass; I_{solar} denotes global solar radiation; A denotes geometric area; f denotes the radiative/convective split for heat gain; α denotes absorptance of surface for solar radiation; *SHGC* denotes solar heat gain coefficient. To improve the accuracy of the model, the mathematical representation of the improved RC model incorporates more physical parameters compared with other RC model structures, such as SHGC, α, and f. The values of SHGC and α depend on the materials, structures and processes of the glasses and external wall surface [13]. The radiative/convective splits for different heat gain types vary to some extent [13].

2.2. Parameter identification

Accuracy and computation efficiency are two major considerations in developing grey-box models using data-driven techniques. In this study, physical estimation of the model parameters was first conducted to narrow the search space of the optimization problem.

2.2.1 Estimation of the model parameters

In Hong Kong, U-value of exterior wall ranges typically from 2.2 to 2.9 W/(m^2·K), and average U-value of single glazed windows is 5.6 W/(m^2·K). Considering the average wind speed of 7.2 m/s during the summer months in Hong Kong, an average external wall surface resistance is recommended as 0.036 (m^2·K)/W, or the convective heat transfer coefficient equals 27.8 W/(m^2·K) [14, 15]. Typical range for interior surface heat transfer coefficient is from 0.12 to 0.2 (m^2·K)/W [13]. Thermal resistances, i.e. R_w, R_{win}, $R_{w,o}$, $R_{w,i}$, and $R_{i,m}$, are all overall thermal transfer values, and can be calculated by the Eq. (10). The thermal capacities in model including C_i, C_w, and C_m play functions of dampening the effects of heat, which would otherwise result in an instantaneous change in corresponding objects. It is noted that the thermal capacities used in the grey-box model may be effective or equivalent thermal capacities, not always equal the physical ones. For example, C_i used in GridLAB-D equals three times the volumetric capacitance of the interior air volume [16]. The building internal mass (e.g. partitions, furniture, carpet etc.) can be summed to a lumped thermal mass C_m, ranging from 100 to 450 kJ/(K·m^2) [17, 18]. Thermal capacity of half exterior wall can be calculated by the Eq. (11).

$$R = \frac{1}{A \times U} \tag{10}$$

$$C_w = \frac{\sigma_w A_w \rho_w c_w}{2} \tag{11}$$

where σ_w denotes the wall thickness; A_w denotes the wall area; ρ_w denotes the wall density.

2.2.2 Nonlinear optimization of the parameters

Searching the best values of the undetermined parameters of the grey-box model is a nonlinear optimization process, and the whole identification was processed using the Nonlinear Least Squares in the MATLAB platform.

During the regression, given a set of R and C, the grey-box model can generate the predicted the profile of indoor air temperature, then we can evaluate the fitness between the prediction results and measured data arising from smart sensors by the objective function. The optimal set of R and C can make the indoor air temperature prediction fit the measured profile well each day. The optimization objective is to minimize the integrated root-mean-square error defined as:

$$J(C_w, C_i, C_m, R_{win}, R_w, R_{w,o}, R_{w,i}, R_{i,m}) = Minimize\sqrt{\frac{1}{N}\sum_{i=1}^{N}(T_{model,i} - T_{sample,i})^2} \tag{12}$$

where $T_{model,i}$ is the model predicted indoor air temperature; $T_{sample,i}$ is the actual measured indoor air temperature; C_w, C_i, C_m, R_w, R_{win}, $R_{w,o}$, $R_{w,i}$, $R_{i,m}$ are the unknown parameters of the grey-box model. The Trust Region algorithmic strategy [19] was employed to search the optimal set of parameter values.

3. Test of the room thermal model using field measurements

One residential bedroom in Hong Kong was chosen to test the grey-box room thermal model. The geometric dimension of the room is 4.8m long, 3.6m wide, and 3m high. It has only one exterior wall which embedded with single glazed windows. The Window-Wall-Ratio (WWR) is 0.2 and the type of glass is clear. The absorption coefficient of the external wall surface is 0.8, and the solar heat gain coefficient (SHGC) of the glass is 0.7. Considering the interior shading and types of internal heat gains, the radiative/convective splits for both solar heat gain through windows and internal heat gains are 0.5/0.5 [13]. A smart sensor was installed in the room to record the indoor air temperature with the interval 10 minutes. As for the outdoor weather data, both outdoor air temperature and horizontal global solar radiation are obtained from the nearby Hong Kong Observatory with the interval of 1 minute.

In order to get the feasible search ranges of the parameters, an estimation procedure was conducted first using the specific geometric parameters and general building thermal parameters in Hong Kong. The search range of each parameter is set as 1±30% of the corresponding estimated value. Then the measured data from 27 July 2015 to 31 July 2015 were used to train the optimal parameters of the grey-box model. The estimated and identified values of R and C are shown in Tab. 1. Fig 2-a shows the outdoor weather condition during the training session. Fig 2-b depicts the sampled and modelled indoor air temperature profiles.

Table 1. Estimated and identified values of R and C for the bedroom grey-box thermal model.

	C_w (J/K)	C_i (J/K)	C_m (J/K)	R_{win} (K/W)	R_w (K/W)	$R_{w,o}$ (K/W)	$R_{w,i}$ (K/W)	$R_{i,m}$ (K/W)
Estimated values	1,850,688	187,868	25,488,000	0.0643	0.0463	0.0033	0.0106	0.0014
Identified values	2,221,000	225,400	30,590,000	0.0450	0.0531	0.0023	0.0075	0.0009

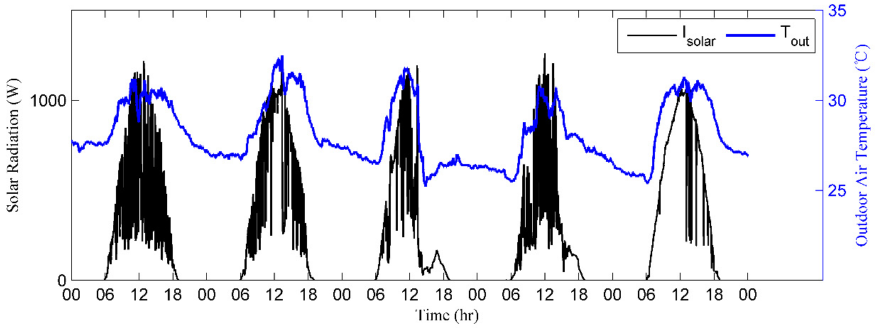

Fig. 2-a. Outdoor weather conditions during training session (27 Jul 2015 - 31 Jul 2015)

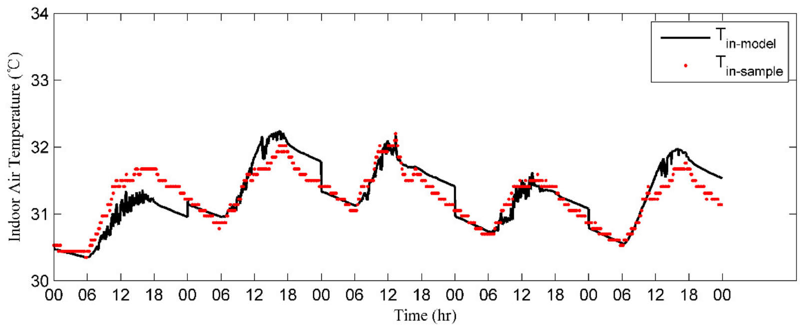

Fig. 2-b. Simulated and sampled indoor air temperature during training session (27 Jul 2015 - 31 Jul 2015)

Then during the next five days (1 August 2015- 5 August 2015), a validation was made using the model and the identified R and C. The outdoor weather condition and comparison between sampled and simulated data during validation session are shown in the Fig. 3-a and Fig. 3-b respectively. The modelling performance during the training and validation sessions are listed in Tab. 2.

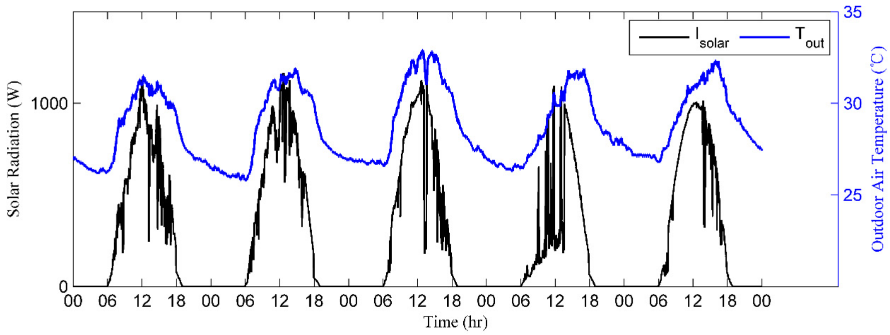

Fig. 3-a. Outdoor weather conditions during validation session (1 Aug 2015 - 5 Aug 2015)

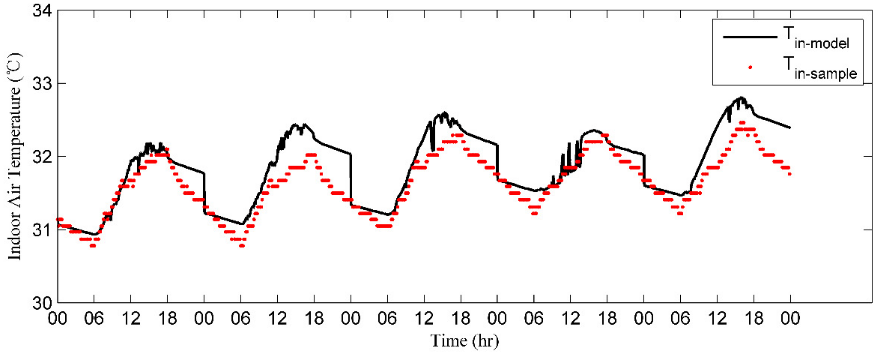

Fig. 3-b. Simulated and sampled indoor air temperature during validation session (1 Aug 2015 - 5 Aug 2015)

Table 2. Evaluations of the deviation between measured data and prediction results from grey-box the model.

Sessions	Performance metrics		
	MAE	MAPE	RMSE
Training session	0.1968	0.63%	0.2475
Validation session	0.2276	0.72%	0.2849

4. Estimation of DR potentials under different AC control strategies using grey-box room thermal model

To investigate the energy saving and peak reduction potentials for a specified residence during DR events, apart from the building thermal model, a residential air conditioner energy consumption model is also needed. The DOE-2 [20], a widely used and accepted building energy analysis program, provides characteristic curves for cooling capacity and energy input ratio of room air conditioners, as shown in Eq. (13) – (14).

$$Cap_{real} = (-0.0051T_{o,db} + 1.489)Cap_{nom} \tag{13}$$

$$EIR_{real} = (0.0107T_{o,db} - 0.0136)EIR_{nom} \tag{14}$$

Where the *EIR* refers to energy input ratio, which is the inverse of *COP*; *Cap* denotes the cooling capacity, W; $T_{o,db}$ is dry-bulb temperature of outdoor air, °F; subscript *nom* indicate AC nominal operating condition.

The control algorithm of the AC is on/off control, and the state depends on the deviation of the indoor air temperature from thermostat set-point, as shown in Eq. (15)-(16), in which δ denotes the dead-band.

$$s = 1,\ T_i > T_{set} + \delta/2 \tag{15}$$

$$s = 0,\ T_i \leq T_{set} - \delta/2 \tag{16}$$

The peak reduction potential of one air conditioner with nominal cooling capacity 2.8 kW and nominal COP 2.5 was investigated on a typical hot summer day (i.e., 1 August 2015). For the room air conditioner, the DR control strategies refer to vary the temperature set-points of the AC when or before the electricity network reaches a peak demand (18:00 to 20:00). Tab. 3 provides a summary of different control strategies used during predefined periods, and there is one baseline case and five DR cases.

Table 3. Indoor air temperature set-points schedules in different control strategies.

	Control Strategies				
	0:00 - 8:00	8:00 - 17:00	17:00 - 18:00 *(Precooling Period)*	18:00 - 20:00 *(DR Period)*	20:00 - 24:00
Baseline Case	24	OFF	OFF	24	24
DR Case 1	24	OFF	OFF	25	24
DR Case 2	24	OFF	OFF	26	24
DR Case 3	24	OFF	25	25	24
DR Case 4	24	OFF	26	26	24
DR Case 5	24	OFF	26	25	24

Fig. 4 illustrates the simulated daily AC electric power consumption shapes under different operation cases. The simulated results were also analyzed, as shown in the Tab. 4. When thermostat set-point is reset from 24℃ to 25℃/26℃ during DR period, a peak reduction of 0.2 kW and 0.63 kW can be respectively achieved by DR case 1 and DR case 2. Combining the set-point reset strategy with precooling strategy (e.g. DR case 3, 4, and 5), the peak demand reduction will rise to some extent. Compared with the DR case 1, the peak demand reduction in DR case 3 goes up from 0.2 kW to 0.41 kW. Similarly, the precooling measure enables the demand reduction increase from 0.63 kW in DR case 2 to 0.82 kW in DR case 4. Comparing the DR case 3 and DR case 5, we can find that the set-point during the precooling period have impact on the demand reduction during the DR period. When the set-point during the precooling session increases from 25℃ to 26℃, the AC contribution to peak demand reduction will decrease from 0.41kW to 0.3 kW. In conclusion, the temperature set-point reset control strategy do reduce the peak demand during the DR event, and the precooling control strategy can help to further the power reduction.

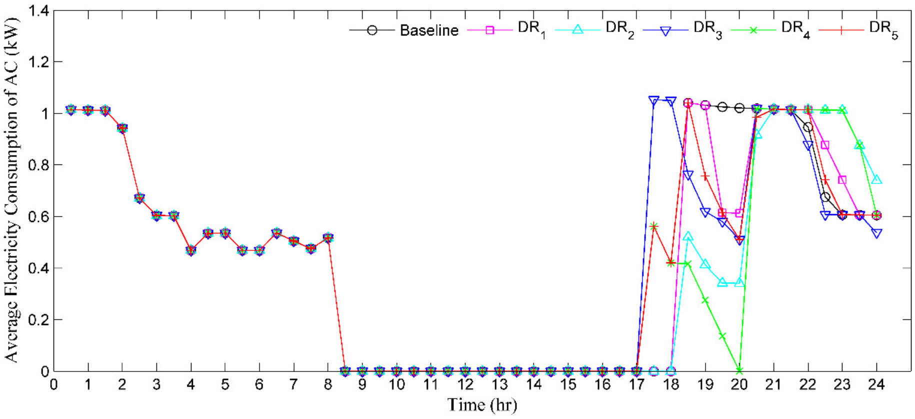

Fig. 4. AC energy consumption shapes with different control strategies

Table 4. AC electricity consumption pattern in different control strategies.

	Electricity Consumption (kWh)			Average power reduction during DR period (kW)	Power reduction percentage during DR period
	Precooling period	DR period	All-day		
Baseline Case	0	2.06	10.49	0	0.00%
DR Case 1	0	1.66	10.28	0.2	19.42%
DR Case 2	0	0.8	9.79	0.63	61.17%
DR Case 3	1.05	1.24	10.62	0.41	39.81%
DR Case 4	0.49	0.42	9.87	0.82	79.61%
DR Case 5	0.49	1.46	10.43	0.3	29.13%

5. Conclusion

In the present paper, we developed an improved RC room thermal model and investigated the peak reduction potentials of residential AC under different DR strategies in Hong Kong. The grey-box room thermal model can be trained by making full use of indoor environment data collected and stored in smart home energy management system. For a typical room in Hong Kong, the root mean square errors for the training and validation data sets were 0.25 ℃ and 0.28 ℃ respectively. It is worth mention that prior to the nonlinear optimization of R and C values, estimations were done to guarantee the reasonableness of the identified parameter values and to save the CPU time for regression. The simulation results show that AC power consumption can be reduced by adopting the temperature set-point reset and precooling strategies.

The RC room thermal model proposed in this paper can capture the essential thermal dynamics in the air-conditioned room and has a simple structure at the same time. After being trained with the data collected from the smart home energy management system, it can be used for supervisory control purpose to save the energy and cost for residents. Besides, the utility companies can use the model to estimate the electric power baseline and DR potentials in large scale, then make some incentive policies accordingly. The AC used in this research is with single-speed compressor, and its energy consumption model is a simplified empirical steady-state model. However, more and more variable-speed air conditioners are produced and installed in residential buildings nowadays. In the future work, we will focus on studying the dynamical modeling and control of inverter residential AC and investigating their power reduction potentials during DR events.

Acknowledgements

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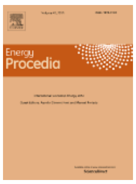

Biography

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