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Development of A Scheme for Assessment of Demand Response Potential Using Distributed Sensor Networks for Residential Flat

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Abstract

Demand response, which is the change of electricity use of demand side during times of peak demand, is a cost-effective means of relieving the imbalance issues on the power grid. The residential ACs are excellent DR resources to deliver considerable power reduction without significantly affecting thermal comfort of residents. This research provides a scheme for assessment of demand response potential of residential ACs in flats. The essential part in the framework is the developed adaptive and self-learning building thermal model, which can be applied in residential buildings with different characteristics. GA algorithm is used as the model training method. The thermal model is used to predict the AC power consumption by introducing the predicted outdoor meteorological parameters. Reliable time series based outdoor temperature and solar radiation prediction methods are developed accordingly. AC power reduction and thermal comfort analysis with different indoor temperature set-points can be then performed. The scheme is implemented in a server which also collects the real-time measurements from the sensor block and the Hong Kong Observatory. The optimal control setting recommendation is then sent to the residents' mobile devices through Wifi.

Keywords – demand response; air conditioner; residential flat; GA algorithm

1. Introduction

Demand response (DR), is one important ingredient of the emerging smart grid paradigm [1]. DR programs are increasingly promoted to encourage power consumers to voluntarily alter or reduce the level of instantaneous demand in short time by providing time-based pricing or economic incentives. For instance, DR programs published by Regional Transmission Operators (RTOs) or Independent System Operators (ISOs) [2] often give customers load reduction incentives that are separate from, or additional to, their retail electricity rate, which may be fixed or time-varying.

Today's building sector accounts for over 30% of global energy consumption and is also a major contributor to the grid peak demand, e.g. 14% in California [3]. In large densely populated cities like Hong Kong, the high-density and high-rise residential flats are pervasive. A huge number of ACs work to provide a comfortable thermal environment, which usually creates significant peak demands in grid during summer [4]. Residential AC is an important demand response resource (DRR). Firstly, residential AC accounts for a large portion of energy consumption, e.g. up to 50% in the hot summer and cold winter zones in China [5]. Secondly, thermal capacity of building thermal mass, including both building envelope and indoor thermal mass, allows AC to be temporarily fully or partially shut down without immediate and substantial impact on the indoor thermal comfort. Lastly, with the widespread installation of smart meters, sensors and networks in residential flats, air conditioners can easily receive signals to generate response.

The basis for AC DR strategy development is the building thermal model, which characterizes the properties of building thermal mass and its behaviors. Based on the building thermal model, the analysis of building indoor thermal environment and AC power consumption can be conducted. The building thermal models have been proposed in many research works. RC (resistance and capacity) thermal network model using thermal resistance and capacity was developed for transient building thermal load prediction [6]. The estimation and optimization of parameters of 2R2C model and 3R2C model, which represent building internal thermal mass and envelope respectively, was developed [7, 8]. A procedure of identification of suitable RC thermal network model structure was also proposed [9].

Building thermal mass can function like batteries to store and release energy for peak demand limiting, energy management and demand response with low cost and less environmental pollution [10]. It can be used as passive thermal storage to store cooling energy by implementing AC control measures, such as decreasing indoor temperature set-point during off-peak period. The stored cooling will be released by increasing indoor set-point or shutting down AC during on-peak period [11]. Therefore, indoor temperature set-point reset and on/off control are two typical measures to reduce or shift the AC load. Meanwhile, the building thermal model is used to estimate the cooling demand and indoor temperature during the two control processes. Based on these two measures and building thermal model, different thermal solutions or control strategies have been developed, to maximize the net-benefit which represents the trade-offs between indoor thermal comfort and AC energy cost [12], or to minimize operation cost under dynamic pricing structures [13], or to minimize peak load [14]. In most cases, the control process was constrained by acceptable indoor thermal comfort requirements indicated by allowable values of indoor temperature.

This paper presents a scheme for assessment of DR Potential in residential flats to achieve energy and cost saving while maintaining acceptable indoor thermal comfort for residents. A self-learning and adaptive building thermal network model, which can be applicable in residential flats with different characteristics, is developed. The model is used to provide thermal characteristics of residential flats and predict energy consumption of AC units. A reliable time series based meteorological parameters prediction method is developed to provide input for the model. Energy consumption analysis can be performed under different indoor air temperature set-points accordingly. The optimal control setting without sacrificing indoor thermal comfort according to the requirement of ASHRAE 55 can be recommended.

2. Framework

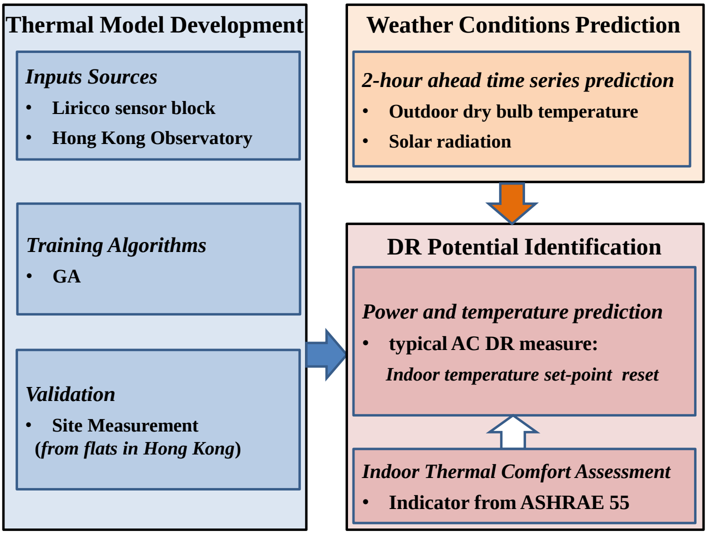

Figure.2.1 Schematic of the a scheme for assessment of demand response potential

As shown in Fig.2.1, the whole scheme includes three main steps: thermal model development, weather conditions prediction and DR potential identification.

A self-learning and adaptive grey-box thermal network model is developed firstly. The required inputs for the thermal model are provided by the sensor block comprising several environmental sensors and the website of Hong Kong Observatory in which the weather condition data are available. The sensor block is responsible for measurement of indoor thermal environment from the typical flats in Hong Kong. The indoor air temperature and humidity can be accurately measured. Heat dissipated by human body is determined from occupant presence detected by passive infrared (PIR) and Bluetooth module. The heat dissipated from lighting devices is also measured by background infrared measurement. GA algorithm is adopted to train the model for mutual verification and results comparison. The site measurement is used to train and validate the thermal model.

To predict AC energy consumption and indoor thermal environment under different control settings, reliable and accurate 2-hour ahead of outdoor dry bulb temperature and solar radiation prediction models are developed accordingly. Based on the developed thermal model and predicted weather condition, simplified thermal and energy performance analysis can be performed to identify the DR potential. The power reduction is realized by a typical DR measure, i.e. indoor temperature set-points reset. The indoor thermal comfort under different control settings is assessed by an indicator from ASHRAE 55.

3. Development and Validation of Thermal Network Model

3.1 Outline of the Building Thermal Model

A 3R2C+1R1C model is proposed in this study, as shown in Fig.3.1 in an electrical analogue pattern with resistance (R, m^2K/W) and capacity (C, $J/(m^2K)$). $R_{ext.1}$, $R_{ext.2}$, $R_{ext.3}$, $C_{ext.1}$, and $C_{ext.2}$ are assumed to consist of the thermal characteristics of the building envelope including walls and roofs. The heat transfer, i.e. heat gain from external sources, through walls, roofs and windows can be characterized accordingly. R_{im} and C_{im} are assumed to consist of the thermal characteristics of the building internal thermal mass including floors, partitions, furniture and etc.

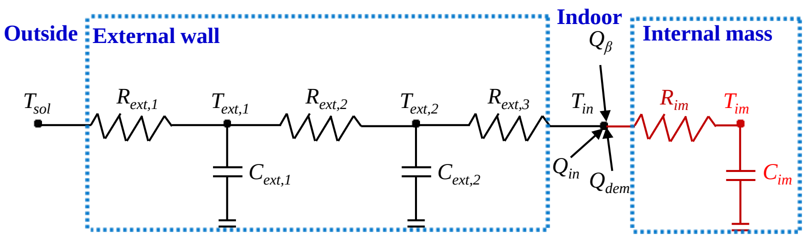

Figure.3.1 Schematic of 3R2C+1R1C thermal network model (3R2C+1R1C)

$R_{ext.1}$ is the resistance between external surface and the node 1 of equivalent unit area inside of envelope. $R_{ext.2}$ is the resistance between the node 1 and node 2 of equivalent unit area inside of envelope. $R_{ext.3}$ is the resistance between internal surface and the node 2 of equivalent unit area inside of envelope. The sum of the $R_{ext.1}$. $R_{ext.2}$ and $R_{ext.3}$ is the total heat transfer resistance of the whole envelope, which includes both convection and conduction resistance. $C_{ext.1}$ and $C_{ext.2}$ are the thermal capacity of node 1 and node 2. $T_{ext.1}$ and $T_{ext.2}$ are the temperatures of two nodes of equivalent unit area inside of the envelope. R_{im}, C_{im} and T_{im} are the thermal resistance, total thermal capacity and temperature of internal thermal mass respectively.

$$C_{in}\frac{dT_{in}(t)}{dt}=\frac{T_{ext,2}(t)-T_{in}(t)}{R_{ext,3}}+Q_{\beta}+Q_{\beta}-Q_{dem}+\frac{T_{im}(t)-T_{in}(t)}{R_{im}} \quad (1)$$

$$C_{ext,1}\frac{dT_{ext,1}(t)}{dt}=\frac{T_{sol}(t)-T_{ext,1}(t)}{R_{ext,1}}+\frac{T_{ext,1}(t)-T_{ext,2}(t)}{R_{ext,2}} \quad (2)$$

$$C_{ext,2}\frac{dT_{ext,2}(t)}{dt}=\frac{T_{ext,1}(t)-T_{ext,2}(t)}{R_{ext,2}}+\frac{T_{ext,2}(t)-T_{in}(t)}{R_{ext,3}} \quad (3)$$

$$C_{im}\frac{dT_{im}(t)}{dt}=\frac{T_{im}(t)-T_{in}(t)}{R_{im}} \quad (4)$$

where, Q_{β} is the heat gains from infiltration (W). Q_{in} is the sensible heat gain from indoor heat resources (W), e.g. human, equipment and lighting. Q_{dem} is the cooling demand (W) supplied by AC and it is zero when no AC is working. T_{sol} is the solar air temperature (°C), which is determined by the following equation:

$$T_{sol}=T_{out}+\frac{\alpha_{wall}\cdot I}{\alpha_{out}} \quad (5)$$

where, T_{out} is the outdoor dry bulb temperature (°C). I is the global solar radiation (W/m^2), α_{wall} is the wall absorption coefficient and α_{out} is the convective heat transfer coefficient of envelope external surface (W/m^2·K). The GA algorithm is used to identify the optimal values of parameters by minimizing the errors between the estimated indoor temperature result from the equations above and the measured temperature data collected from the real flats in Hong Kong. The optimized parameters are the resistances (R) and capacities (C) of the developed model that give the best fit with the reference data.

3.2 Validation of the Developed RC Model

One dormitory bedroom in Hong Kong was selected for validation of the developed RC model. The test period was from 12. Apr 00:00 to 22 Apr 23:50, in which the data of 7 days were used as training data and the data of left 4 days were used as validation data, as shown in Fig. 3.2. $T_{in,act}$ is the actual indoor temperature measured in the flat and $T_{in,RC}$ is the resulted indoor air temperature by RC model. The parameters identified by GA algorithm are: $R_{ext,1}$ = 0.053 m^{2}K/W, $R_{ext,2}$ = 0.078 m^{2}K/W, $R_{ext,3}$ = 0.178 m^{2}K/W, R_{im} = 0.026 m^{2}K/W, $C_{ext,1}$ = 286,208 J/m^{2}K, $C_{ext,2}$ = 311,695 J/m^{2}K, C_{im} = 642,127 J/m^{2}K.

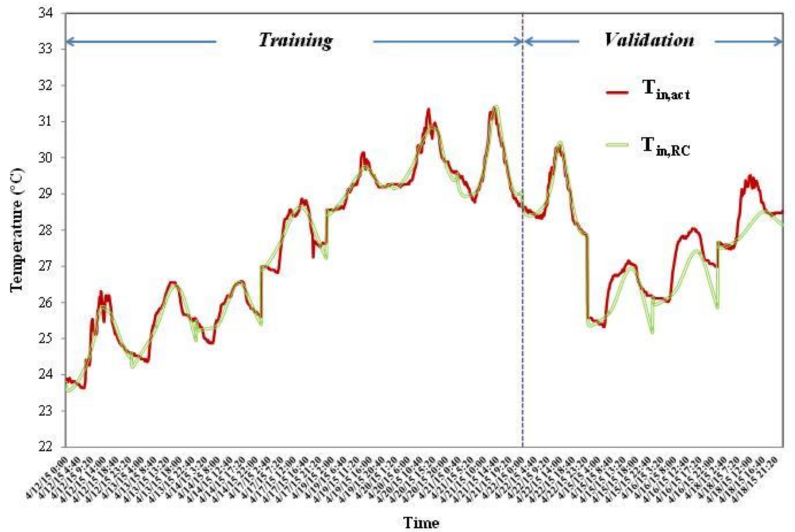

Figure.3.2 Training and validation results of dormitory bedroom by GA method

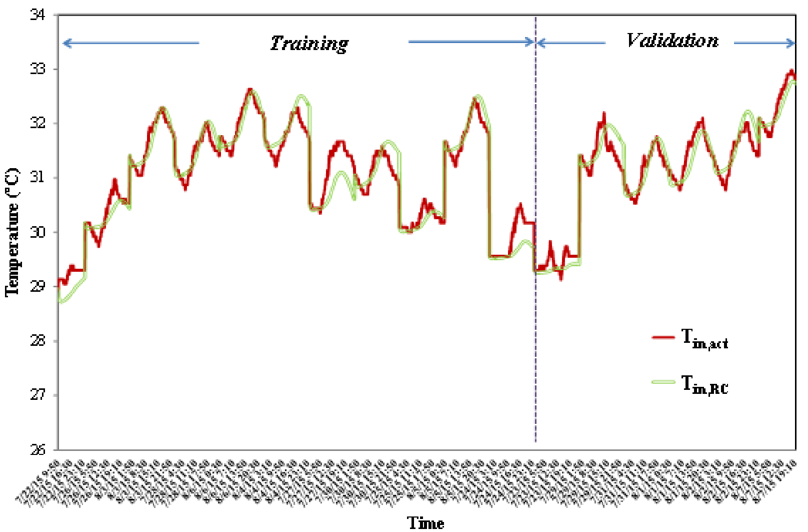

Fig. 3.3 Training and validation results of apartment by GA method

As shown in Fig. 3.2, the building indoor temperatures resulted by the model have satisfactory performance with high accuracy. It can be proved by the values of the accuracy indices as following: The mean absolute error

(MAE), mean absolute percentage error (RMSE) and root mean square error (RMSE) are 0.335°C, 1.20% and 0.479°C respectively.
Another apartment in Hong Kong was also selected for further validation of the developed RC model. The test period was from 22. Jul 9:50 to 7. Aug 19:40, in which the data of approximate 11 days were used as training data and the data of left around 6 days were used as validation data, as shown in Fig. 3.3. The parameters identified by GA algorithm are: $R_{ext,1}$ = 0.128 m^2K/W, $R_{ext,2}$ = 0.067 m^2K/W, $R_{ext,3}$ = 0.207 m^2K/W, R_{im} = 0.043 m^2K/W, $C_{ext,1}$ = 281,999 J/m^2K, $C_{ext,2}$ = 347,189 J/m^2K, C_{im} = 719,830 J/m^2K.
The values of the accuracy indices are following: the mean absolute error (MAE), mean absolute percentage error (RMSE) and root mean square error (RMSE) are 0.183°C, 0.59% and 0.230°C respectively. They prove that the accuracy of the model is quite good.

4. Development and Validation of Thermal Network Model

For evaluating control settings, the power consumption and indoor thermal environment with different control settings under realistic weather conditions are required. The prediction of weather conditions, particularly the outdoor air temperature and the solar radiation, are needed as inputs to the thermal model to predict the cooling demand, power consumption and indoor air temperature.
A 12-step ahead prediction, time step as 10 mins, of outdoor dry bulb temperature and solar radiation is set as target. The proposed modeling methods are autoregressive integrated moving average (ARIMA) and ARIMA with external inputs (ARIMAX). The model structure is defined by p (AR), d (difference) and q (MA). ARIMA (2,1,3) is selected as the modeling method to predict outdoor temperature, as shown in the following:

$$y_{Temp}^{t} - y_{Temp}^{t-1} = 1.26\times(y_{Temp}^{t-1} - y_{Temp}^{t-2}) - 0.30\times(y_{Temp}^{t-1} - y_{Temp}^{t-2}) - 1.01\times e^{t-1} \quad (6)$$

For prediction of solar radiation, the resulted optimal model structure for ARIMAX is (2,0,2), as shown in the following equation:

$$y_{Rad}^{t} = 1.99\times y_{Rad}^{t-1} - 0.99\times y_{Rad}^{t-2} - 0.85\times e^{t-1} + 0.05\times e^{t-2} - 0.011\times x^{t-1} \quad (7)$$

5. Demand Response Potential Identification

The function of the developed thermal network model is to estimate the cooling demand under different indoor temperature set-points. The required power consumption can be then calculated. The energy performance analysis can accordingly evaluate the DR potential of residential flats.
As shown in Fig.5.1, the 12-step ahead, i.e. 2 hours, predicted solar air temperature ($T_{sol,pre}$) is first resulted from the prediction model. It is the input

for the thermal network model. Based on the original indoor temperature set-point ($T_{in,set}$) and $T_{sol,pre}$, the corresponding cooling demand ($Q_{dem,set}$) is then resulted by thermal network model. According to the criteria of acceptable indoor thermal comfort from ASHRAE 55, an appropriate reset indoor temperature set-point ($T_{in,reset}$) is chosen to reduce the power consumption of AC unit. Based on $T_{in,reset}$ and $T_{sol,pre}$, the corresponding cooling demand ($Q_{dem,reset}$) is resulted. The COP estimator calculates cooling demand based on the outdoor temperature and predicted cooling demand. COP_{set} and COP_{reset} are resulted under $Q_{dem,set}$ and $Q_{dem,reset}$ respectively. The predicted power consumptions, i.e. $P_{in,set}$ and $P_{in,reset}$, under different indoor temperature set-points are then calculated to process the power consumption comparison.

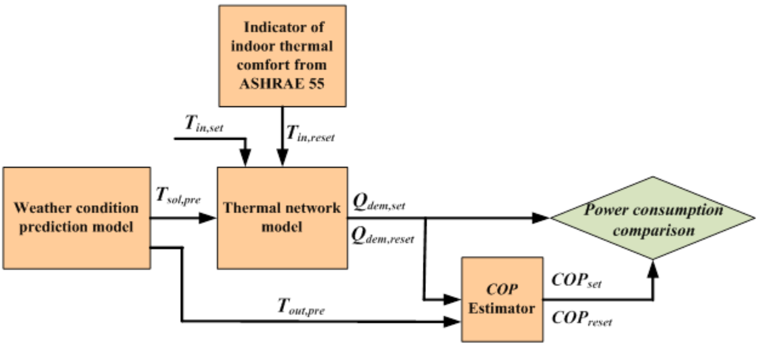

Fig. 5.1 Control logic diagram of indoor temperature set-point reset

The case of dormitory bedroom was used to demonstrate the energy reduction potential under different indoor temperature set-points. In accordance with the requirement of 90% acceptability of indoor thermal comfort from ASHRAE 55, the appropriate range of temperature was from around 22.2˚C to 26.7˚C since the prevailing mean outdoor air temperature was around 22˚C during the concerned period. Therefore, 22, 24 and 26˚C were selected as the indoor temperature set-points. The Fig. 5.2 shows the calculated cooling demand in the dormitory bedroom under these three set-points. The part load performance curve of AC unit was introduced from [15] to calculate the COP and the power consumption, as shown in Fig.5.3. The cooling capacity of the AC unit is 1650kW in this case. The energy consumptions of AC unit were 36 kWh, 26 kWh and 18 kWh for 11 days when the indoor temperature set-points were 22, 24 and 26ºC respectively. The corresponding costs were around 36, 26 and 18 HKD (around 1 HKD/kWh charged for residential flats in Hong Kong) respectively. It can be found that the power consumption was obviously reduced when the indoor temperature set-point increased by 4 degrees.

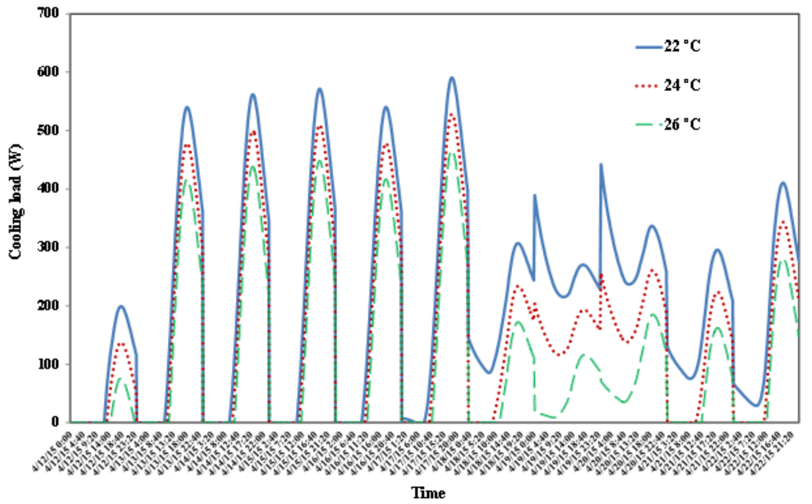

Fig. 5.2 Cooling demand under different indoor temperature set-points

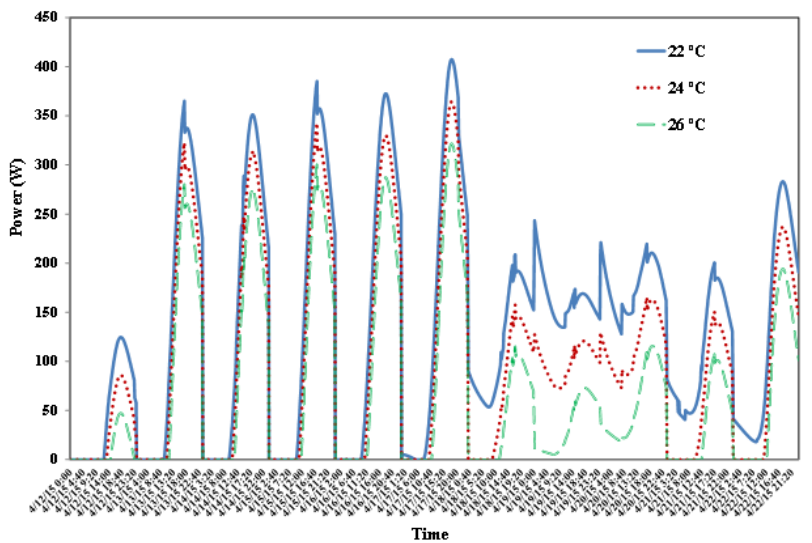

Fig. 5.3 AC Power consumption under different indoor temperature set-points

6. Conclusions

A scheme for assessment of DR potential of residential AC in flat is proposed in this research. A simplified and effective thermal and energy performance analysis is performed to identify the power reduction potential and saving opportunities for building residents based on the developed building thermal network model and weather condition prediction model. Significant cost and energy saving percentage can be obtained through the simple control measures, i.e. indoor temperature set-point reset, with the implementation of the server, sensor and network in residential flats.

Acknowledgement

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