A Dynamic Controller for Residential Energy Management at the Intersection of Occupant Thermal Comfort and Dynamic Electricity Price

Mostafa Meimand[1] and Farrokh Jazizadeh[2]

[1] Dept. of Civil and Environmental Engineering, Virginia Tech, 315B Patton Hall, 750 Drillfield Dr., Blacksburg, VA 24061. E-mail: mostafaem@vt.edu
[2] Dept. of Civil and Environmental Engineering, Virginia Tech, 200 Patton Hall, 750 Drillfield Dr., Blacksburg, VA 24061 (corresponding author). E-mail: jazizade@vt.edu

ABSTRACT

HVAC systems account for 50% of buildings' energy use and could play a critical role in energy management in buildings both for energy-saving, and demand-side management to reduce peak energy use. According to contextual demands of occupants, efficient control of HVAC systems could result in peak energy shaving and decreased energy costs in demand response programs. Accordingly, in this paper, we have introduced an agent-based model consisting of three agents: human agent, thermostat agent, and utility agent. In this model, the thermostat agent receives the real-time electricity price from the utility agent and aggregates thermal comfort profiles of the occupants from human agents. By considering these inputs, the thermostat agent employs a predictive model of a house and calculates the next setpoint of the HVAC system on energy cost and occupants comfort. Then, the thermostat agent signals the suggested setpoint to the thermostat of the building at each time step. For evaluating the proposed controller's performance, the electricity price profile from ERCOT, which supplies the state of Texas, is used as a signal from the utility agent. Realistic thermal comfort data were used to simulate the thermal preference of occupants represented as human agents. The evaluation was carried out in a co-simulation using a Python and EnergyPlus model of a residential unit. Our results show that the proposed controller reduces the peak energy by 5.5% to 10% and increases occupants' thermal satisfaction up to 12%. The main contribution of this paper is developing an agent-based model that humans, as the main stakeholders of the buildings, play a role in controlling HVAC systems for peak reduction and energy saving.

INTRODUCTION

Based on a report from U.S. Energy Information Administration, peak-to-average electricity demand ratio has been increased from 1.52 in 1993 to 1.78 in 2012 in the U.S. and New England (EIA 2014). Increasing the peak demand could stress the grid and cause blackouts during peak times in summer seasons (Strengers 2013). One of the low-cost strategies that have been proposed is curtailing or shifting loads on the demand side as a demand response strategy. In demand response, utility companies try to motivate and incentivize customers to change their energy use pattern during peak time (Shariatzadeh, Mandal et al. 2015). Demand response has been classified into two different approaches: incentive-based and price-based (Shariatzadeh, Mandal et al. 2015). In the incentive-based, customers authorize utility companies through a contractual agreement to control appliances such as dryers and washing machines (Haider, See et al. 2016). By employing incentive-based demand response, utility companies balance their energy supply and customers' demand. Another approach, which is the focus of this paper, is price-based programs in which utility companies increase the price of electricity during peak periods. By doing so, customers will be motivated to change their energy consumption behavior such as shifting deferrable loads to off-peak time or changing the thermostat. Previous studies have shown that implementation of demand response in residential buildings, which account for 27% of total energy use, could reduce the peak energy use considerably (EIA 2012, He, Wang et al. 2012, Afzalan and Jazizadeh 2018, Afzalan and Jazizadeh 2019, Afzalan and Jazizadeh 2020).

Heating, Ventilation, and Air Conditioning (HVAC) systems account for almost 50% of energy use for residential buildings to provide conditioned air for occupants comfort (EIA 2012). Dynamic control of HVAC systems based on demand variations and by temporal adjustment of system setpoint for reshaping the energy consumption profile could potentially result in peak shaving and aggregate energy-saving (Yoon, Baldick et al. 2014). In this paradigm, to account for thermal comfort of occupants, studies have commonly used a fixed range of temperature (e.g., 19˚C to 26˚C (Li 2018)). Although a common engineering solution, this approach does not consider occupants' thermal preferences and their diversity. To this end, a few studies have used indices such as Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfaction (PPD) to account for occupant thermal comfort (Li 2018). Although a target 90% of occupants would be satisfied if the PMV index is met for a thermal zone (ASHRAE 2017), recent studies have shown that at the individual level, only one-third of occupants are satisfied (Cheung, Schiavon et al. 2019).

Conventional methods of accounting for thermal comfort do not consider the variation across different groups of users. Smart thermostat technologies (e.g., Google Nest) have paved the way for learning occupant preferences from their interactions with the thermostat (Jazizadeh, Ghahramani et al. 2013, Jazizadeh, Ghahramani et al. 2014) or its proxy on a smartphone. Therefore, in this study, through an agent-based modeling paradigm, we have investigated a proposed controller thermostat for residential air conditioning systems that enables autonomous dynamic adjustment of setpoint by coordinating among human agents, a utility agent, and the thermostat agent. This controller centers around the concept of autonomous and human-in-the-loop (HITL) demand-response. In this concept, the thermostat agent learns the aggregated thermal comfort profile from the human agents and receives the real-time electricity price signal from the utility agent for efficient control. Furthermore, using a predictive model of the environment, the thermostat agent takes actions that result in energy saving and peak demand reduction. The performance of the proposed controller has been evaluated through a co-simulation using Python and an EnergyPlus model for a residential unit for different scenarios consisting of 1, 2, and 4 human agents to provide an insight into the impact of HITL demand-response compared to temperature-based control.

PREVIOUS STUDIES

Effective control of the HVAC systems could result in peak reduction and a balance between demand and supply in residential buildings (Yoon, Bladick et al. 2014). To this end, several HVAC controllers for residential buildings have been proposed in the literature. Yoon et al. (2014) developed a thermostat controller that dynamically adjusts the thermostat according to a dynamic electricity price profile to decrease energy use (Yoon, Baldick et al. 2014). In an example simulation, the controller was effective in reducing peak in summer by 12% and saving electricity cost by 20%. They also evaluated the efficiency of their proposed controller for different types of houses - small and large - and different weather conditions in Austin, TX, and Chicago, IL (Yoon, Bladick et al. 2014, Yoon, Baldick et al. 2016). The controller curtails the peak by 20.2% for the large house and 12.8% for the medium house. Vedullapalli and Schroeder (2019) developed a two model predictive controller for HVAC system and a battery in a residential building and save 13.5% annual saving of energy cost. Gupta and Ghose (2018) developed a dynamic controller for residential building that predicts price first and then changes the HVAC system setpoint based on the forecasted price. Although all the developed controllers benefit the customer by decreasing energy costs and curtailing energy peaks, they do not consider human preferences in the control loop. Although they investigated occupants' comfort level using predicted mean vote (PMV) and predicted percentage of dissatisfaction (PPD), occupant comfort level has not been integrated as a control variable in these controllers. Thus, these controllers cannot address differences between occupants' thermal preferences, while end-users are the main stakeholders that could decide on the trade-off between cost and comfort. Our proposed HITL controller seeks to address this aspect and investigate its impact. The agent-based model has been developed and evaluated for a single-family residential building and its performance were compared with two well-known control logics in the literature, a fixed setpoint logic and the Dynamic Demand Response Controller (DDRC) logic by (Yoon, Baldick et al. 2014).

METHODOLOGY

In Figure 1, we have presented the envisioned framework for a smart thermostat agent that coordinates with human agents and a service provider agent to: collect data, receive dynamic feedback, and optimize the performance by adjusting the setpoints. Human agents represent occupants by collecting their preference data and developing personal models to be used in aggerate comfort representations. In what follows, details of an example implementation of this framework have been elaborated.

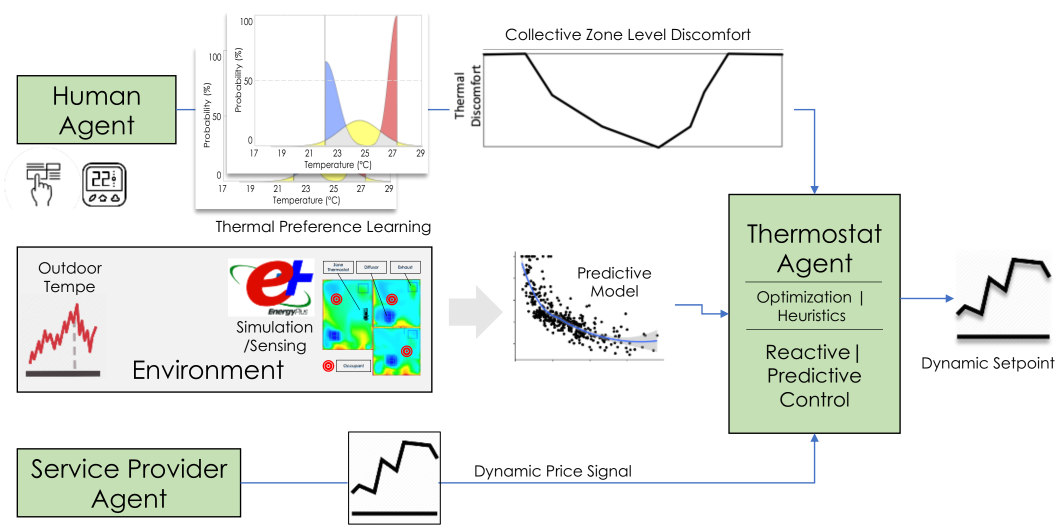

Figure 1. Overall framework of the model

Human agent. The human agent represents occupants that interact with the thermostat agent. Each occupant has a personal thermal comfort profile defined as a probability distribution quantifying how comfortable each individual feels for different ambient temperatures. For instance, Figure 2 (a) shows the thermal preference profiles of two occupants. The thermal preferences are 20.05°C and 27.31°C for agents #5 and #12, respectively. These profiles are derived from the interaction of each occupant with the thermostat interface. In this paper, 6 actual thermal votes data sets were gathered from (Jazizadeh, Ghahramani et al. 2014) and (Daum, Haldi et al. 2011). By employing a Bayesian network modeling approach, 15 profiles have been built. To this end, this approach is used to aggregate different probability distributions of feeling uncomfortably cold, uncomfortably warm, and comfortable into one probability distribution as shown in Figure 2 (a). More details could be found in (Jung and Jazizadeh 2020).

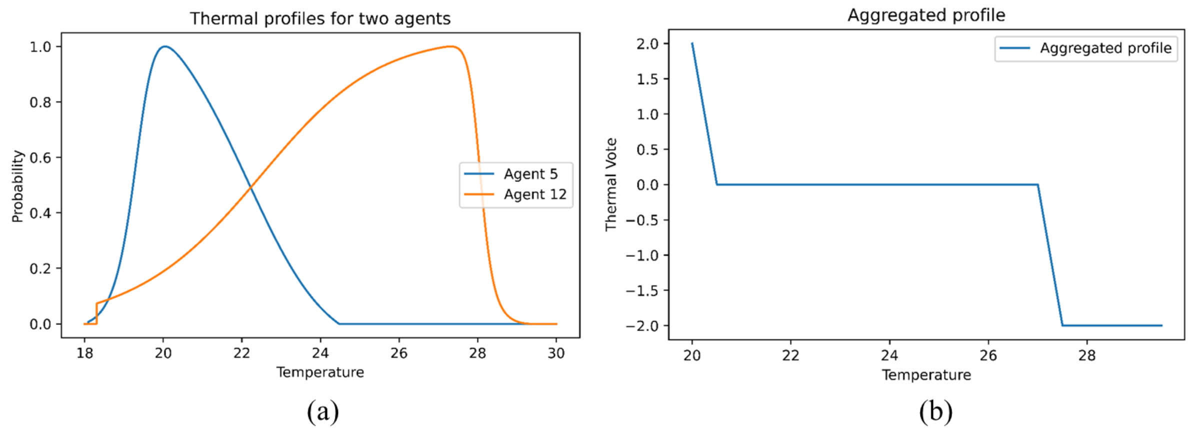

Figure 2. (a) Thermal comfort profiles for two agents, (b) Aggregated profile of the occupants

Typically, the number of occupants in a residential unit could be more than one. Thus, we used an aggregation strategy based on thermal comfort votes to build the aggregated comfort profile for all occupants that share a space. For each person, the thermal vote is +1 for all temperature values higher than his/her thermal preference and is -1 for all temperatures values lower than his/her thermal preference. Figure 3 (a) shows the pseudocode of the algorithm for aggregation of all occupants' thermal votes. For each temperature value, thermal votes of all occupants are summed up as $\widetilde{V_T}$, which represents aggregated profile of occupants. Figure 2 (b) shows the aggregated profiles that has been built based on Figure 3 (a) pseudocode.

Utility agent. As an energy management strategy, some utility companies increase the energy price during peak hours to incentivize customers to differ their loads to off-peak hours. In this paper, the utility agent provides a real-time electricity price to the thermostat agent. The electricity price that was used in this paper is the real-time electricity price from the Electric Reliability Council of Texas (ERCOT) for August, which is gauged every 15 minutes.

Thermostat agent. The main goal of the thermostat agent is to provide a control setpoint that decreases the peak demand without compromising the thermal satisfaction of occupants. The thermostat agent gets two signals: an aggregated thermal comfort signal from the human agent and the price signal from the utility agent. To drive the dynamic setpoint based on the real-time price of electricity, we adopted and modified the algorithm proposed by (Yoon, Baldick et al. 2014), called DDRC. In the original algorithm, a predictive model for energy consumption of HVAC system in a residential unit is used to identify a dynamic setpoint based on the dynamic price. In this paper, the residential unit that has been used for simulation is a single-family house from Residential Prototype Building Models developed by Pacific Northwest National Laboratory (PNNL) in Austin, Texas. The model has two thermal zones: living and attic zones. The HVAC system conditions the living zone only. The cooling system uses electricity only. The total area of the building is 3565.64 ft^2. The weather data that has been used in this study is typical meteorological year (TMY3) at Austin Mueller Municipal Airport, Austin, TX, USA. To decrease the complexity of the model in the control process, we used a simple representation of the building using a back-box modeling scheme. This model has been only used in the control algorithm and the high-fidelity EnergyPlus model of the building was used for validation. The black-box model was developed using the data from EnergyPlus model and by changing the thermostat setpoints and calculating their corresponding energy consumption. Figure 4 shows the results of changing setpoint against change in HVAC energy consumption with a Pearson correlation coefficient of -0.97.

Variables:
- N: number of occupants
- T: Temperature
- P_i: Thermal Preference of occupant i
- $V_{i,t}$: Thermal vote of occupant i at temperature t
- $\widetilde{V_T}$:Aggregated thermal profile

For *1 to N* do:
- if $T < P_i$ then
  - $V_{i,T} = -1$
- if $T > P_i$ then
  - $V_{i,T} = +1$
- if $T = P_i$ then
  - $V_{i,T} = 0$

For *all temperature* do:

$$\widetilde{V_T} = \sum_{i=1}^{N} V_{i,T}$$

(a)

Variables:
- $\widetilde{V_T}$:Aggregated thermal profile from human agent
- TS: number of timesteps
- $Setpoint_{DDRC}$: Setpoint suggested by DDRC
- $Setpoint_{Final}$: Revised setpoint
- P_t = Real-time price at time t from utility agent

for t = *1 to TS* do:
- $Setpoint_{DDRC} = \Delta T_{cool} = a \cdot HVAC_{cool} \cdot 2\Delta P$
- if $\widetilde{V_T}$ ($Setpoint_{DDRC}$) > 0
  - $Setpoint_{Final} = Setpoint_{DDRC} + 1$
- elseif $\widetilde{V_T}$ ($Setpoint_{DDRC}$) < 0
  - $Setpoint_{Final} = Setpoint_{DDRC} - 1$
- elseif $\widetilde{V_T}$ ($Setpoint_{DDRC}$) = 0
  - $Setpoint_{Final} = Setpoint_{DDRC}$

end for

(b)

Figure 3. (a) Pseudocode of the aggregation, (b) Control strategy

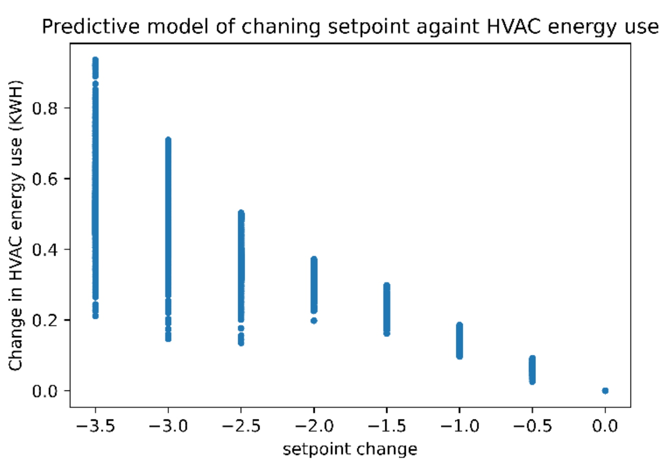

Figure 4 - Changing setpoint against HVAC energy usage

$$HVAC_{cool} = -0.145 * \Delta T - 0.004 \qquad \text{Equation (1)}$$

Equation (1) shows the linear regression model that associates change in HVAC energy use with setpoint change. In this equation, ΔT is the change of setpoint. The DDRC controller receives a price threshold set by occupants, which was set to be 0.04 ($/kWh) in this paper. By calculating the difference between real-time price and price threshold (ΔP), the setpoint is changed (ΔT_{cool}) using equation (2).

$$\Delta T_{cool} = a \cdot HVAC_{cool} \cdot 2\Delta P \qquad \text{Equation (2)}$$

where a is a correlation coefficient between outdoor temperature and price during August in Texas. a is 2.254 based on our analysis. Although this controller in the original publication has shown to decreases energy peak by 12% and decreases energy cost by 10.8%, it does not consider human preferences in the control process. Thus, our contribution focuses on integrating occupants' personal comfort into the control loop. Figure 3 (b) shows our proposed control strategy. $\widetilde{V_T}$ shows the aggregated comfort profile in each temperature from Figure 2 (b). Positive $\widetilde{V_T}$ means, occupants collectively prefer a higher temperature and vice versa. Therefore, the DDRC driven setpoint is either increased or decreased (by one unit) in case of a positive and negative $\widetilde{V_T}$, respectively. The rationale behind changing by one unit is we move the setpoint suggested by DDRC to a setpoint where occupant comfort more aggregately. The efficiency of this controller has been evaluated in a co-simulation of python-EnergyPlus environment. At each time step, the EnergyPlus model received the suggested setpoint from thermostat agent along with weather data and building ambient conditions and a simulation was run at 15-minute intervals to return indoor temperature to the thermostat agent to calculate the next step setpoint.

To investigate the efficiency of the controller, all 15 profiles have been used to have a wide range of thermal preference profiles in our simulations. We evaluated the proposed control strategy for different multi-occupancy scenarios consisting of one, two, and four occupants. The total number of combinations for each scenario has been shown in Table 1. We evaluated all single-occupant scenarios and randomly chose 30 cases for two and four occupant scenarios.

$$N_{agent} = C(n,k) = \frac{n!}{k!(n-k)!} \qquad \text{Equation (3)}$$

Table 1 - Number of iterations for different multi-occupancy scenarios

Number of occupants	Total number of combinations	Number of samples
1	$C(15,1) = 15$	15
2	$C(15,2) = 105$	30
4	$C(15,4) = 1365$	30

DATA ANALYSIS AND RESULTS

Table 2 shows the result of the analysis. The proposed controller's total energy usage and total energy cost are higher than DDRC's for all scenarios. However, the average percentage of satisfaction (measured using individual thermal comfort profiles) is higher than DDRC's by 16% for one occupant scenario (*p*-value of t-test = 0.058) and 14% for the two-occupant scenarios (*p*-value of t-test = 0.019) and the same for four occupants scenarios. Compared to a fixed setpoint strategy, the DDRC controller reduced the peak by 15% while the proposed controller reduced the peak by 9% for one occupant, 8% for two occupants, and 6% for four occupants. In terms of total energy cost, compared with the DDRC controller, depending on different multi-occupancy scenarios, the occupants pay $19 to $23 per month to achieve higher thermal satisfaction. Increasing the number of occupants decreases the standard deviation for energy usage, average daily peak, and total energy cost. The higher number of occupants causes less flexibility in controlling the thermostat for energy saving, peak shaving, and decreasing cost.

Table 2 – Results of evaluations

Different Controllers	Total energy usage (std) KWH	Average daily peak (std) KWH	Total energy cost (std) $	Average percentage of satisfaction
Fixed Setpoint	855.50 (-)	4.18 (0.30)	187.80 (-)	68%
DDRC	787.80 (-)	3.54 (0.30)	140.14 (-)	64%
one occupant	810.55 (159.68)	3.81 (0.47)	159.03 (17.6)	80%
two occupants	821.48 (72.26)	3.83 (0.30)	158.82 (9.25)	78%
four occupants	841.32 (63.41)	3.93 (0.30)	163.79 (4.95)	68%

CONCLUSION

In this study, we presented an agent-based model that facilitates the coordination among human agents, thermostat agents, and utility agents to reduce energy cost and shave energy consumption peak while accounting for occupants personalized thermal preferences in the control loop. In this agent-based modeling framework, the thermostat agent receives a price signal from the utility company, and uses an aggregated comfort profile learned from human-thermostat interactions. By employing a low-fidelity, black-box predictive model of the building, as well as the input from human agents and the utility agent, the thermostat agent dynamically controls the HVAC system's setpoint. The agent-based model has been implemented and validated in a python-EnergyPlus co-simulation environment for a residential building in Austin, TX and for different realistic comfort profiles, representing a diverse set of occupants and different occupancy combinations. Our results show that the proposed controller could curtail the peak demand by 5.5% to 10% depending on the number of occupants while increasing occupants' thermal satisfaction up to 12%.

AKNOWLEDGEMNT

This material is based in part upon work supported by the National Science Foundation under grant #1663513. Any opinions, findings, and conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

REFERENCES

Afzalan, M. and F. Jazizadeh (2018). Efficient integration of smart appliances for demand response programs. Proceedings of the 5th Conference on Systems for Built Environments, ACM.

Afzalan, M. and F. Jazizadeh (2019). "Residential loads flexibility potential for demand response using energy consumption patterns and user segments." Applied Energy **254**: 113693.

Afzalan, M. and F. Jazizadeh (2020). "A Machine Learning Framework to Infer Time-of-Use of Flexible Loads: Resident Behavior Learning for Demand Response." IEEE Access **8**: 111718-111730.

ASHRAE (2017). Thermal Environmental Conditions for Human Occupancy. A. ASHRAE, GA.

Cheung, T., S. Schiavon, T. Parkinson, P. Li and G. Brager (2019). "Analysis of the accuracy on PMV – PPD model using the ASHRAE Global Thermal Comfort Database II." Building and Environment **153**: 205-217.
Daum, D., F. Haldi and N. Morel (2011). "A personalized measure of thermal comfort for building controls." Building and Environment **46**(1): 3-11.
EIA. (2012). "Residential Buildings Energy Consumption Survey: Energy Usage Summary."
EIA. (2014). "Peak-to-average electricity demand ratio rising in New England and many other U.S. regions."
Haider, H. T., O. H. See and W. Elmenreich (2016). "A review of residential demand response of smart grid." Renewable and Sustainable Energy Reviews **59**: 166-178.
He, Y., B. Wang, J. Wang, W. Xiong and T. Xia (2012). "Residential demand response behavior analysis based on Monte Carlo simulation: The case of Yinchuan in China." Energy **47**(1): 230-236.
Jazizadeh, F., A. Ghahramani, B. Becerik-Gerber, T. Kichkaylo and M. Orosz (2013). Personalized Thermal Comfort Driven Control in HVAC Operated Office Buildings. ASCE International Workshop on Computing in Civil Engineering (IWCCE) Conference.
Jazizadeh, F., A. Ghahramani, B. Becerik-Gerber, T. Kichkaylo and M. Orosz (2014). "Human-Building Interaction Framework for Personalized Thermal Comfort-Driven Systems in Office Buildings." Journal of Computing in Civil Engineering **28**(1): 2-16.
Jazizadeh, F., A. Ghahramani, B. Becerik-Gerber, T. Kichkaylo and M. Orosz (2014). "User-led decentralized thermal comfort driven HVAC operations for improved efficiency in office buildings." Energy and Buildings **70**: 398-410.
Jung, W. and F. Jazizadeh (2020). "Energy saving potentials of integrating personal thermal comfort models for control of building systems: Comprehensive quantification through combinatorial consideration of influential parameters." Applied Energy **268**.
Li, Y., Jaime De La Ree, and Yanfeng Gong (2018). The smart thermostat of HVAC systems based on PMV-PPD model for energy efficiency and demand response. 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2).
Sandip kr. Gupta, T. G., Kalyan Chatterjee (2018). Droop Based Dynamic Demand Response Controller for HVAC Load. 20th National Power Systems Conference (NPSC).
Shariatzadeh, F., P. Mandal and A. K. Srivastava (2015). "Demand response for sustainable energy systems: A review, application and implementation strategy." Renewable and Sustainable Energy Reviews **45**: 343-350.
Strengers, Y. (2013). The Global Challenge of Encouraging Sustainable Living.
Vedullapalli, D. T., Ramtin Hadidi, and Bill Schroeder. (2019). Optimal Demand Response in a building by Battery and HVAC scheduling using Model Predictive Control. IEEE/IAS 55th Industrial and Commercial Power Systems Technical Conference (I&CPS).
Yoon, J. H., R. Baldick and A. Novoselac (2014). "Dynamic Demand Response Controller Based on Real-Time Retail Price for Residential Buildings." IEEE Transactions on Smart Grid **5**(1): 121-129.
Yoon, J. H., R. Baldick and A. Novoselac (2016). "Demand response control of residential HVAC loads based on dynamic electricity prices and economic analysis." Science and Technology for the Built Environment **22**(6): 705-719.
Yoon, J. H., R. Bladick and A. Novoselac (2014). "Demand response for residential buildings based on dynamic price of electricity." Energy and Buildings **80**: 531-541.