An Evaluation of the HVAC Load Potential for Providing Load Balancing Service

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***Abstract*—This paper investigates the potential of providing intra-hour load balancing services using aggregated heating, ventilating, and air-conditioning (HVAC) loads. A directload control algorithm is presented. A temperature-priority-list method is used to dispatch the HVAC loads optimally to maintain customer-desired indoor temperatures and load diversity. Realistic intra-hour load balancing signals are used to evaluate the operational characteristics of the HVAC load under different outdoor temperature profiles and different indoor temperature settings. The number of HVAC units needed is also investigated. Modeling results suggest that the number of HVAC units needed to provide a ± 1-MW load balancing service 24 hours a day varies significantly with baseline settings, high and low temperature settings, and outdoor temperatures. The results demonstrate that the intra-hour load balancing service provided by HVAC loads meets the performance requirements and can become a major source of revenue for load-serving entities where the two-way communication smart grid infrastructure enables direct load control over the HVAC loads.**

***Index Terms*—Air conditioning, ancillary service, demand response, direct load control, HVAC, load balancing, load following, regulation service, renewable integration, smart grid, thermostatically controlled appliances.**

I. INTRODUCTION

MORE THAN 10 000 MW of new wind power was added to the U.S. electrical grid in 2009, almost 40% of the grid's newly installed capacity [1]. Many studies have examined the technical feasibility of and issues related to using wind energy to generate 20% of the nation's electricity by 2030 [2], [3].A major operational issue identified is that both the ramp-rate and magnitude of the regulation and load following requirement are expected to increase significantly. In meeting increased ramp and capacity requirements, the regulating generators may be unable to operate close to their preferred operating points, resulting in lower efficiencies. Faster regulating movements also increase mechanical stress on these generators, shortening their lifetimes and increasing the wear-and-tear cost.

Pumped-hydro power plants, batteries, flywheels, distributed generation resources, and demand-side management (DSM) are flexible energy options that could provide the needed fast-response ancillary services [4], [5]. Of these options, DSM is the least studied and most underutilized. Since 2006, markets for regulation service from DSM programs have opened in Pennsylvania, New Jersey, the Maryland Interconnection, and the PJM Interconnection LLC (PJM), but because of the strict telemetry requirement, all the participants of these programs have been large industrial customers [6].

However, the deployment of the smart grid will enable communication and control between buildings and utility control centers. Therefore, this paper demonstrates that thermostatically controlled appliances (TCAs) can provide load balancing capacity when aggregated, which may enable small residential or commercial customers to participate in ancillary service markets in the future. The TCAs include residential heating, ventilation, and air-conditioning (HVAC) systems; electric water heaters; and refrigerators.

There are two control methods in DSM: indirect load control and direct load control. In indirect load control, the power consumption of loads is controlled manually by the customers or automatically by the appliances, with consideration given to information such as real-time electricity tariffs and frequency deviation in power systems. For example, the set point control of TCAs according to the real-time electricity tariff affects end users less than load shedding. However, the relationship between varying numbers of the external parameters (e.g., electricity tariffs) and power consumption is very complicated. Not only is the relationship nonlinear, but the power consumption may oscillate because of the lack of load diversity after the control is initiated [7].

In direct load control [8]–[11], the power consumption of loads is controlled directly by a utility or a system operator, regardless of the customers' preference. It is easy to adjust the demand precisely, but it is hard to gain customer acceptance if their comfort settings are compromised. Therefore, strong financial incentives must be provided. Regulation and load following services are both high value ancillary services compared to peak shaving and load shifting, but the control objects must be available, controllable, and observable. Thus, direct load control has been selected in this study to demonstrate the applications of providing regulation and load following services using TCAs.

Suitable aggregated TCAs for regulation application: a) are frequently in operation because regulation is required at all times; b) have a high capacity to obtain an appreciable response with few appliances; and c) have broad temperature setting ranges because a short-term temperature-setting violation may be necessary to maintain the quality of service. Therefore, electric water heaters (EWHs) and HVAC loads are selected for evaluation. A study of the direct control of EWHs to adjust

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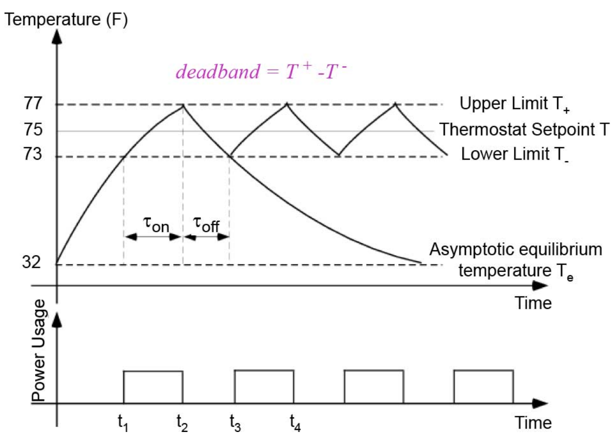

Fig. 1. Thermal behavior of an HVAC unit.

their power consumption to follow regulation signals has been published in Kondoh [12]. This paper presents the direct control of HVAC units to follow the regulation and load following signals. Although both EWHs and HVAC units store thermal energy, EWH energy consumption is governed frequently by random hot water consumption, while HVAC consumption is governed by ambient temperature changes. Therefore, the thermal dynamics of the HVAC unit must be modeled properly to simulate the unit's electricity consumption when responding to ancillary service signals under the restriction to minimize end user discomfort, considering the outdoor temperature changes.

Callaway proposes a system identification approach based on Fokker-Planck diffusion models to design a direct control strategy to manage large populations of HVAC units [13]. An extended optimal centralized control strategy with comfort-constraints is proposed by Parkinson *et al.* [14]; Wang implemented this method on a simulation test bed to investigate the regulation and load shifting service supported by HVAC units to offset the intermittency of renewable resources in a self-regulating distribution system [15]. The identification computation burden for large-scale aggregated power dynamics needs to be solved by a suitable improvement for this approach. The temperature priority list method introduced in this paper applied a simplified HVAC model at the central controller to forecast room temperatures on a per-minute basis and correct the forecasts using measured room temperatures every 15 min. The communication and computation burdens are therefore greatly reduced. Simulation results showed that the load balancing services provided are satisfactory and customer comfort is not compromised significantly.

This paper presents the simplified HVAC model in Section II and introduces the control algorithm for providing ancillary services in Section III. The modeling results are discussed in Section IV. The conclusions and future work are summarized in Section V.

II. MODELING METHODOLOGIES

To model the electricity consumption of an HVAC unit, it is critical to model the unit's heat transfer process (as shown in Fig. 1), considering ambient temperature changes. This section introduces the thermal dynamic equations.

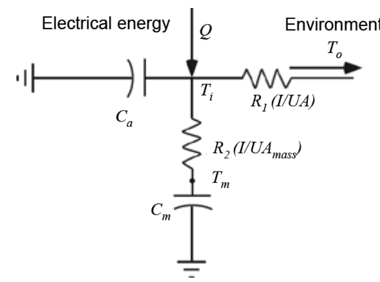

Fig. 2. ETP model of a residential HVAC unit.

A. Thermal Dynamics Models of an HVAC Unit

A simplified equivalent thermal parameters (ETP) model [16]of a residential HVAC unit is shown in Fig. 2. Simplified modeling is well-suited for simulating residential and small commercial buildings. However, it may be unsuitable for large commercial buildings with multizone central heating and cooling systems.

C_a	air heat capacity ($\mathrm{Btu}/^\circ\mathrm{F}$ or $\mathrm{J}/^\circ\mathrm{C}$);
C_m	mass heat capacity ($\mathrm{Btu}/^\circ\mathrm{F}$ or $\mathrm{J}/^\circ\mathrm{C}$);
Q	heat rate for HVAC unit ($\mathrm{Btu/hr}$ or W);
UA	standby heat loss coefficient ($\mathrm{Btu}/^\circ\mathrm{F}\cdot\mathrm{hr}$ or $\mathrm{W}/^\circ\mathrm{C}$);
R_1	$1/\mathrm{UA}$;
R_2	$1/\mathrm{UA}_{\mathrm{mass}}$;
T_o	ambient temperature ($^\circ\mathrm{F}$ or $^\circ\mathrm{C}$);
T_i	air temperature inside the house ($^\circ\mathrm{F}$ or $^\circ\mathrm{C}$);
T_m	mass temperature inside the house ($^\circ\mathrm{F}$ or $^\circ\mathrm{C}$).

A state space description of the ETP model is

$$\begin{aligned}
\dot{x} &= Ax + Bu \\
y &= Cx + Du \\
\dot{x} &= \begin{bmatrix} \dot{T}_i \\ \dot{T}_m \end{bmatrix} \quad x = \begin{bmatrix} T_i \\ T_m \end{bmatrix} \quad u = 1 \\
A &= \begin{bmatrix} -(\frac{1}{R_2 C_a} + \frac{1}{R_1 C_a}) & \frac{1}{R_2 C_a} \\ \frac{1}{R_2 C_m} & -\frac{1}{R_2 C_m} \end{bmatrix} \\
B &= \begin{bmatrix} \frac{T_0}{R_1 C_a} + \frac{Q}{C_a} \\ 0 \end{bmatrix} \\
C &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad D = \begin{bmatrix} 0 \\ 0 \end{bmatrix}.
\end{aligned} \tag{1}$$

The space heating unit model can be simplified further by considering an equivalent model that matches the measured turn-on time, τ_{on}, and turn-off time, τ_{off}, under a range of ambient temperatures, T_o. When the heater is turned off, the room temperature, T_{room}, at time t is described by

$$T_{\mathrm{room}}^{t+1} = T_o^{t+1} - (T_o^{t+1} - T_{\mathrm{room}}^{t})e^{-\Delta t/RC}. \tag{2}$$

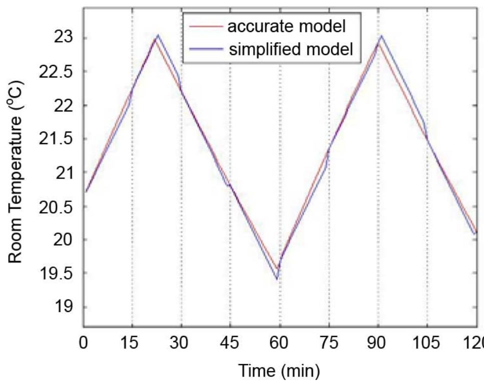

Fig. 3. Space heating unit behavior modeled by the simplified model and tuned by measurements.

When the heater is turned on, the room temperature at time t is described by

$$T_{\text{room}}^{t+1} = T_o^{t+1} + QR - (T_o^{t+1} + QR - T_{\text{room}}^{t})e^{-\Delta t/RC} \quad (3)$$

T_{room}	room temperature (°C);
C	equivalent heat capacity (J/°C);
R	equivalent thermal resistance (°C/W);
Q	equivalent heat rate (W);
t	time (minute);
Δt	time step (1 minute);
T_o	ambient temperature (°C).

Note that parameters, R, C, and Q are curve fitting parameters that fit the performance curve produced by the precise physical model represented by (1) or by measurements. Because the room temperature variation is controlled within a narrow temperature band of 2–4 °C, the simplified model produces satisfactory results and significantly simplifies the forecasting process required to create the temperature priority list for a large number of HVAC units in seconds. Fig. 3 also shows how the forecasted room temperatures are tuned by measurements every 15 min.

Six temperature profiles with daily average temperatures, T_{ave}, ranging from -10 °C to 15 °C, are used to model different weather conditions, as shown in Fig. 4. Customer thermostat settings, T_{set}, are set at 21 °C. Temperature deadbands are set to 2 °C or 4 °C for comparison, where $deadband = T^{+} - T^{-}$.The mean values of C, R, and Q are set to 3599.3 J/°C, 0.1208 $^\circ\text{C}/W$, and 400 W, respectively. The R, C, and Q parameters for the HVAC units are randomized for different HVAC units to create load diversity. An initialization process sets the initial room temperature and randomizes the on and off status of each HVAC unit for a few hours. An example of the initialization process is shown in Fig. 5.

B. Construction of the HVAC Baseline Output

An aggregated baseline output of the HVAC units, P_{baseline}, must be provided to grid operators so that deviations from the baseline output can be measured as load balancing services (e.g., regulation up and regulation down services).

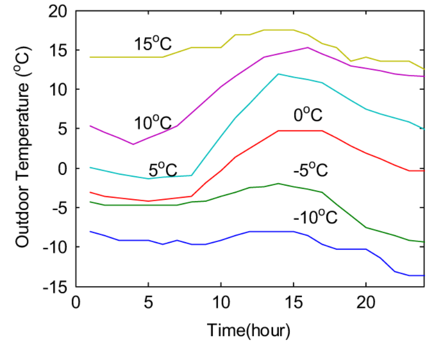

Fig. 4. Outdoor temperature profiles.

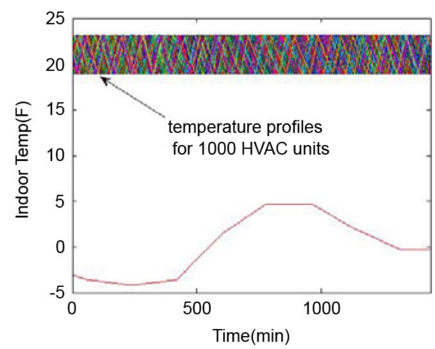

Fig. 5. HVAC initialization process ($T_{\text{ave}} = 0$ °C).

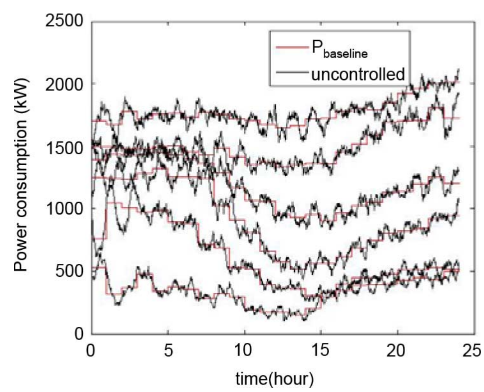

Fig. 6. Construction of HVAC baseline loads using six sets of outdoor temperature profiles (temperature profiles: $T_{\text{ave}} = -10, -5, 0, 5, 10, 15$ °C).

To create a baseline load, all participating HVAC units are modeled in an uncontrolled mode using next-day outdoor temperature forecasts. The uncontrolled model means that HVAC thermostats turn the HVAC units on and off. The aggregated HVAC power output (black lines in Fig. 6) are averaged to an hourly load profile as the day-ahead (red lines in Fig. 6). Note that the baseline load profiles vary with different thermostat settings and different numbers of controlled HVAC units, as illustrated in Figs. 7 and 8. In general, more HVAC units and wider deadband settings provide greater load balancing capacity.

C. Construction of the Control Signal

Realistic intrahour load balancing signals are used to evaluate the performance of the aggregated HVAC load for ancillary services. Two types of load balancing signals [3] are used: the area control error (ACE) signal, P_{ACE}, and load following signal,

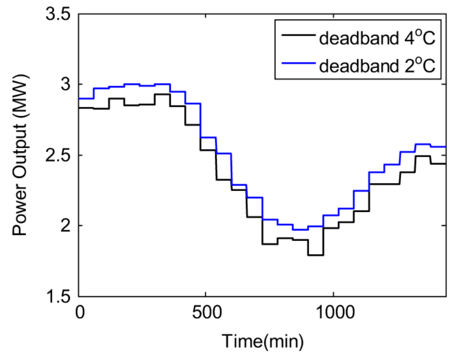

Fig. 7. Construction of hourly HVAC baseline loads using different temperature deadbands ($T_{\text{ave}} = 0\ ^\circ\text{C}$; 1000 HVAC units).

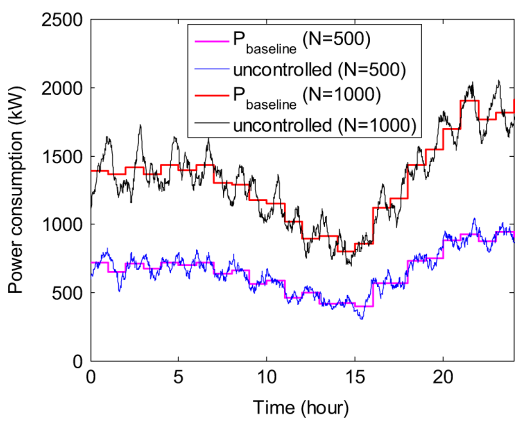

Fig. 8. Construction of hourly HVAC baseline loads using different number of HVAC units ($T_{\text{ave}} = 0\ ^\circ\text{C}$).

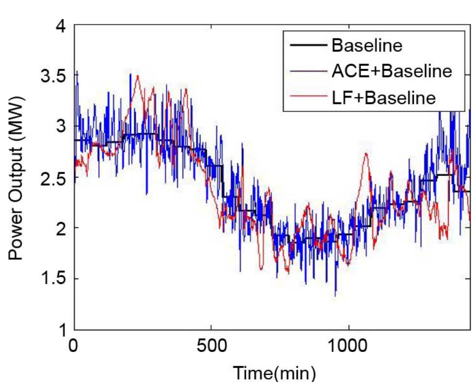

Fig. 9. Construction of control signals ($T_{\text{ave}} = 0\ ^\circ\text{C}$, 1000 HVAC units).

P_{LF}. Both are scaled to 1-min signals normalized to ± 0.2, ± 0.6, and ± 1 MW for a baseline load constructed by 1000 controlled HVAC units when T_{ave} varies from $-10\ ^\circ\text{C}$ to $15\ ^\circ\text{C}$ to model performance under different weather conditions. Note that ACE signals are similar to regulation signals and vary much faster than the load following signals.

The control signals, P_c^{LF} and P_c^{ACE}, are calculated as

$$P_c^{\text{LF}} = P_{\text{baseline}} + P_{\text{LF}} \tag{4}$$

$$P_c^{\text{ACE}} = P_{\text{baseline}} + P_{\text{ACE}}. \tag{5}$$

Examples of load following and ACE control signals are shown in Fig. 9.

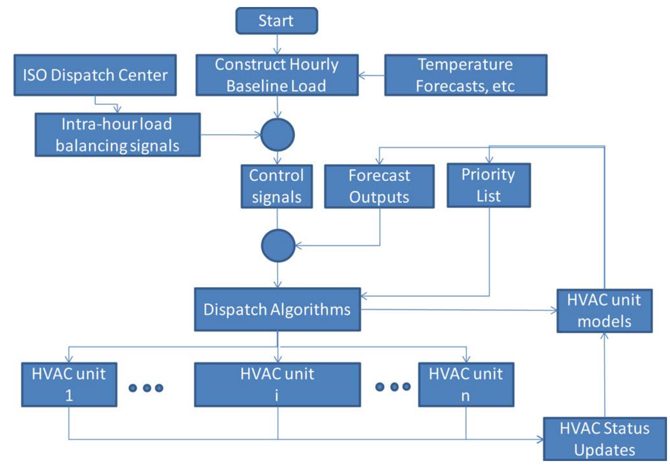

Fig. 10. Flow chart of HVAC control logic.

III. Control Algorithms

A flow chart of the direct load control logic is provided in Fig. 10.

HVAC units are divided into two groups based on their on/off status. Because space heating units are used in this paper for demonstration purposes, the units in the "on" group are prioritized in descending order based on their room temperatures, i.e., if the room temperature is closer to the upper thermostat setting T^+, the unit is at the top of the queue to be turned off. The units in the "off" group are prioritized in ascending order based on their room temperatures, i.e., if the roomtemperature is closer to the lower thermostat setting T^-, the unit is at the top of the queue to be turned on. The HVAC units that are "on" under direct load control will switch off immediately when they receive an "off" signal from the central controller, and *vice versa*.

The central controller is equipped with a forecaster to estimate the room temperature for the next time step, determine the on/off status of the HVAC units, and create two priority (turn-on and turn-off) lists for the two groups of HVAC units. The forecasting, T_f^{HVAC},can be tuned based on actual measurement, T_a^{HVAC}, collected from HVAC units every 10 minutes or every few hours to correct T_f^{HVAC}.

This forecast-and-update process will reduce the amount of data traffic from each controlled HVAC unit to the central controller. Note that the impact of the update-by-measurement process will be presented in our follow-on paper; this paper presents the simulation results assuming that the central controller receives perfect room temperature forecasts. This assumption is made to obtain the maximum capacity and quality of the HVAC load when the central controller has precise information and control of each HVAC unit. A number of factors can limit the capacity or reduce the quality of the balancing capabilities provided by the HVAC load. For example, to avoid stalling, when an HVAC unit is turned off, a minimum turn-off time, t_{off}, needs to be considered in the HVAC unit model so that during the minimum turn-off period, the HVAC unit is locked out for the "turn-on" service, reducing the balancing capacity. In addition, the impact of random communication delays and turn-on and turn-off delays may influence how well the HVAC load can follow the control signal. Because of the

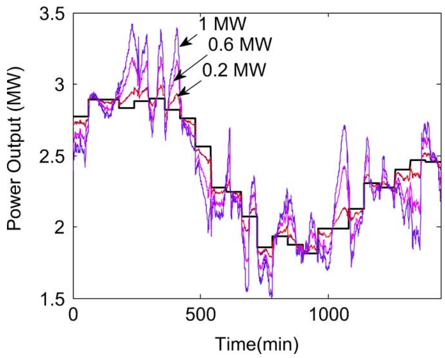

Fig. 11. Different load following signals.

space limitations, those factors will be discussed in a follow-on paper.

IV. Modeling Results

Two sets of control signals are studied: load following and ACE signals.

A. Response to Load Following Signals

The load following signal was normalized to 0.2, 0.6, and 1 MW, as shown in Fig. 11.

1000 HVAC units (rated at 6 kW) were used; thermostat high limit, T^{+}, is 23 °C with a deadband of 2 or 4 °C. Therefore, thermostat low limits are 21 °C or 19 °C. Outdoor temperature profile is picked from $T_{\text{ave}} = -10$, 0, and 15 °C.

The following observations are made from simulation results:

- The HVAC load follows the control signals very well for a deadband of 4 °C.
- The number of cycles of a heater unit ($T_{\text{ave}} = 0$ °C; deadband is 4 °C) is around 14–20 (see blue line in Fig. 12). To provide the 0.2–1 MW load following service, there will be two more cycles on average for each HVAC unit, with deadbands set at 4 °C.
- When the deadband is narrower, the capability of the HVAC load to follow the load following signal is reduced because tracking the control signals will partially synchronize diversified HVAC loads, as shown in Figs. 13, 14, and 17. When T_{room} of all households is close to T^{+} or T^{-}, the continuing "on" or "off" status of the HVAC units will cause T_{room} to exceed T^{+} or T^{-}, as shown at 420 minutes in Subplot 3, Fig. 14 ($T_{\text{room}} > T^{+}$). The occurrence of the violation can be minimized by increasing the number of HVAC units, increasing T^{+}, or decreasing T^{-}.
- If the deadband is 2 °C, the HVAC unit cycles two to four times more often to follow the control signals (see Fig. 15), shortening the life of the unit.
- When outdoor temperatures are high, the HVAC unit may be unable to provide enough load following capacity because its base load may be lower than the required load following down capacity (see the 15 °C case in Fig. 16). Note that the indoor temperatures in all cases (see Fig. 17) are always kept within their high and low limits; the centralized-dispatch algorithm simply changes the cycle length of each HVAC unit to obtain an aggregated load profile that matches the control signal.

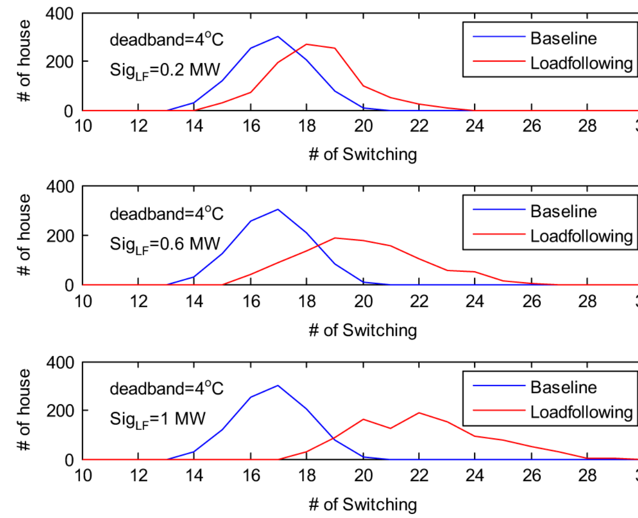

Fig. 12. Impact of different control signal magnitudes on HVAC daily cycles.

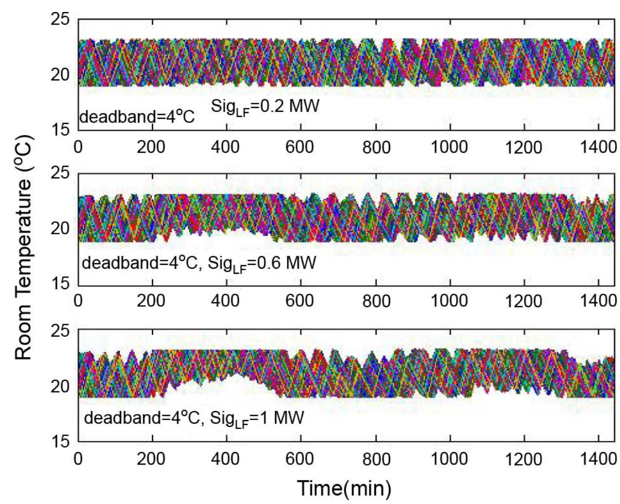

Fig. 13. Impact of different control signal magnitudes on room temperature profiles.

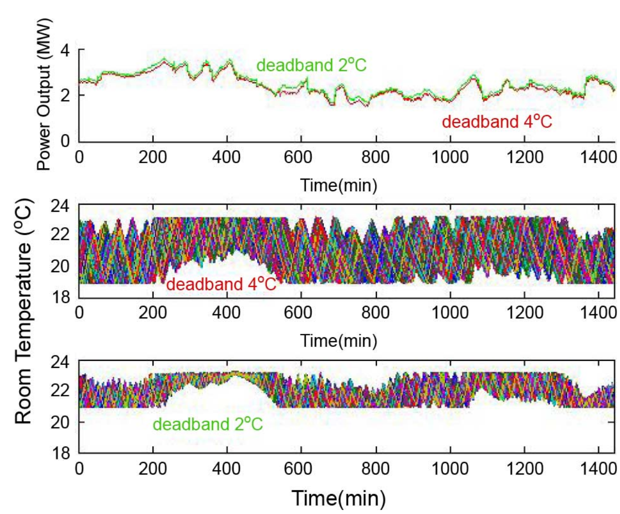

Fig. 14. Impact of different deadbands on room temperature profiles.

B. Response to ACE Signals

ACE signals were downloaded from the PJM website [17]. Note that ACE signals vary much faster than load following signals, as shown in Fig. 9. To make the ACE cases comparable

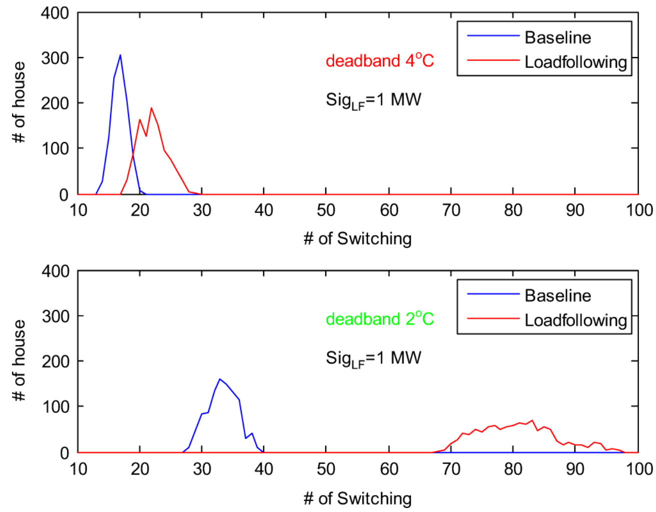

Fig. 15. Impact of deadbands on HVAC daily cycles.

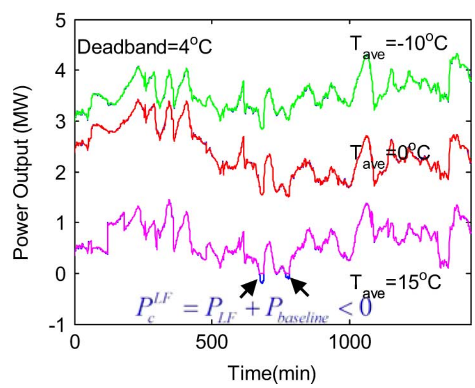

Fig. 16. Impact of outdoor temperatures on control signal following capabilities.

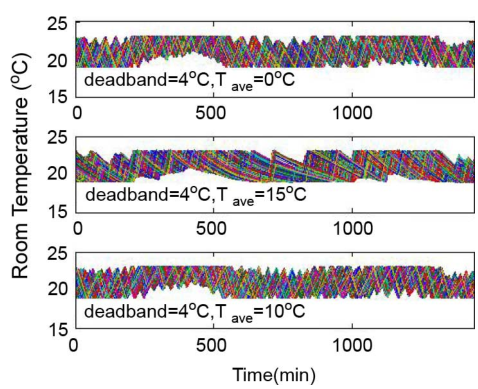

Fig. 17. Impact of outdoor temperatures on room temperature profiles.

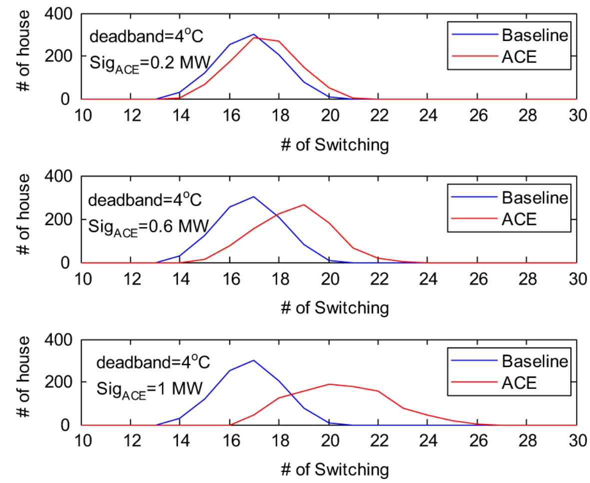

Fig. 18. Impact of different control signal magnitudes on HVAC daily cycles.

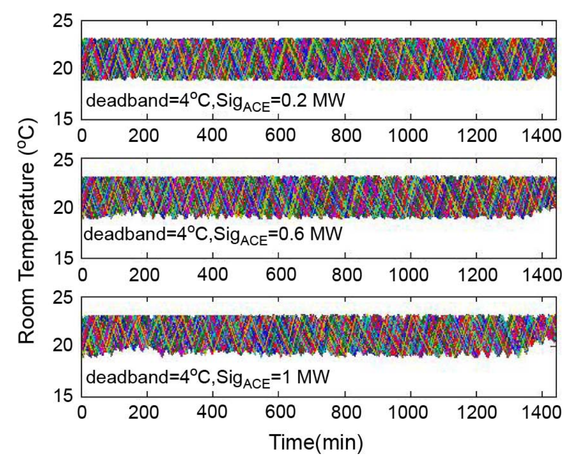

Fig. 19. Impact of different control signal magnitudes on room temperature profiles.

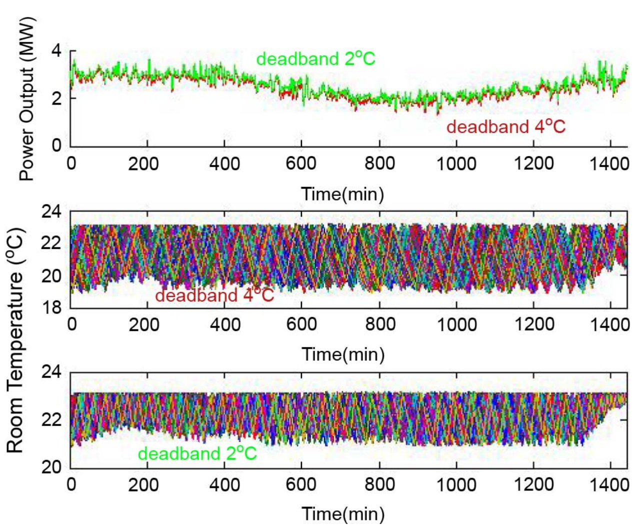

Fig. 20. Impact of different deadbands on room temperature profiles.

to the load following cases, the ACE signal was also normalized to 0.2, 0.6, and 1 MW, respectively; 1000 HVAC units were used; T^{+} is 23 °C with a deadband of 2 °C or 4 °C. Outdoor temperature profile is picked from $T_{\text{ave}} = -10$, 0, and 15 °C.

The following observations are made from simulation results:

- Following fast varying signals would be problematic for bulk regulating units such as hydro power plants and bulk energy storage devices because of ramping constraints. However, because the basic control unit of an aggregated TCA load is a 4- to 6-kW unit, the increases in daily cycles in the ACE following cases are similar to those of the load following cases. This is because each HVAC unit would have switched on/off at its own rhythm if not controlled; rearranging the HVAC units' on/off time slots will not significantly impact their total number of cycles and room temperature profiles if the signal magnitude is close to the magnitude and frequency of the normal HVAC load variations, as shown in Figs. 18 and 19.

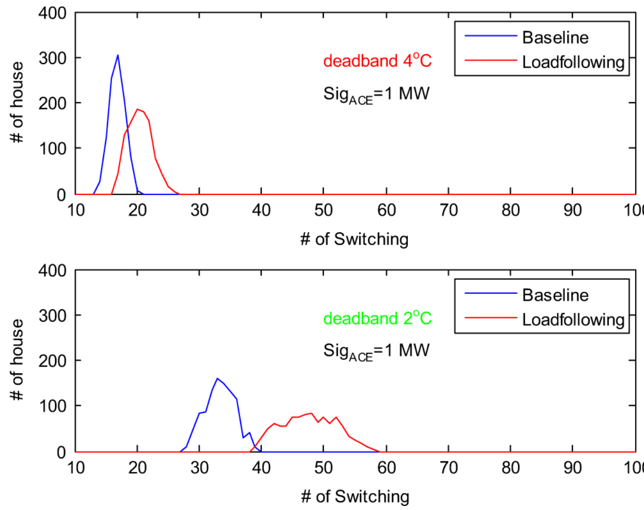

Fig. 21. Impact of deadband on HVAC daily cycles.

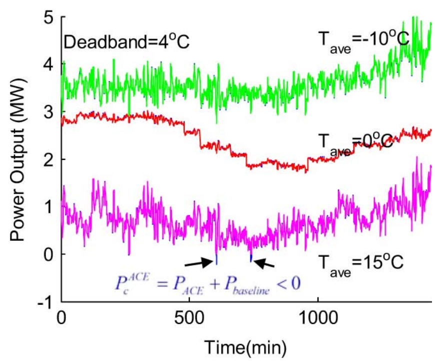

Fig. 22. Impact of outdoor temperatures on control signal following capabilities.

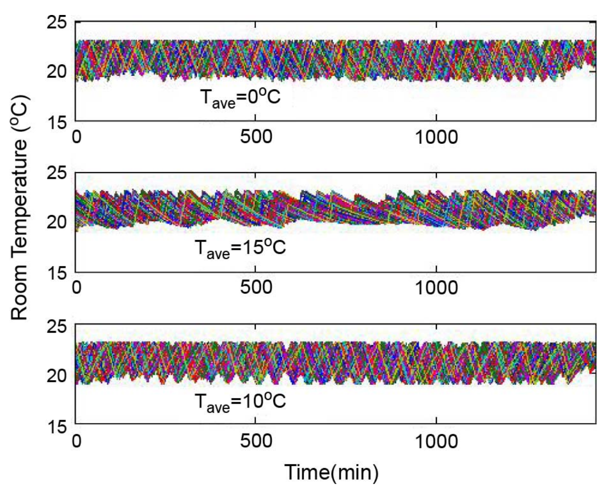

Fig. 23. Impact of different outdoor temperature profileson room temperatures (deadband: 4 °C).

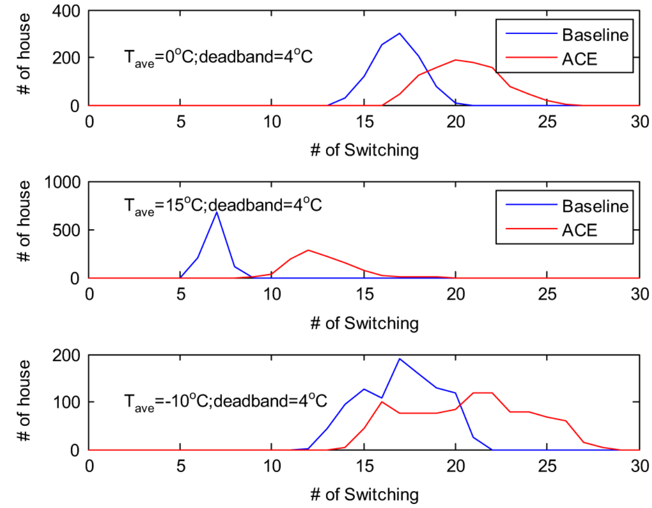

Fig. 24. Impact of different outdoor temperature profiles on the HVAC daily operation.

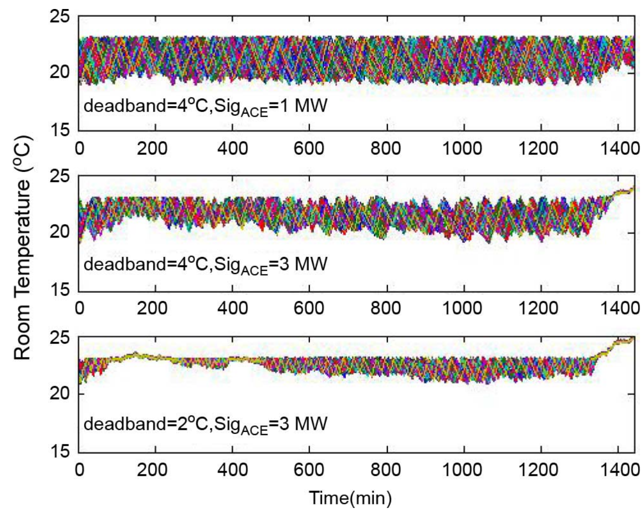

Fig. 25. Examples of out-of-capacity cases.

- As shown in Figs. 20 and 21, similar to the load following cases, a narrower room temperature deadband limits the capability of the HVAC unit to follow the ACE signal, causing higher increases in daily cycles.
- At higher outdoor temperatures, the HVAC unit cycles less. When the minimum power consumption of the aggregated HVAC baseline load is lower than the required ACE downward signals, all HVAC units will be forced off in the 15 °C case, as shown in Fig. 22 through Fig. 24. Therefore, the upward and downward load balancing capacity of the HVAC load is limited by the baseline settings that are determined by outdoor temperature profiles and customer room temperature deadband preference. It is then critical to predict the two factors accurately when considering the design of such direct load control schemes.
- As shown in Figs. 25 and 26, for a higher control signal magnitude of ±3 MW, the HVAC regulating capability is soon depleted. All HVAC units are quickly synchronized and frequently turned on and off to follow the control signal. The on/off plot of an HVAC unit is shown in Fig. 27. This behavior damages the HVAC unit lifetime and is undesirable. In addition, the room temperatures can no longer be held within the desired range. This result shows that the number of controlled HVAC units in response to a certain magnitude of load balancing signal needs to be carefully selected to leave a safe margin to prevent such synchronized switching phenomena. A randomization period may be needed periodically to regain the load diversity.

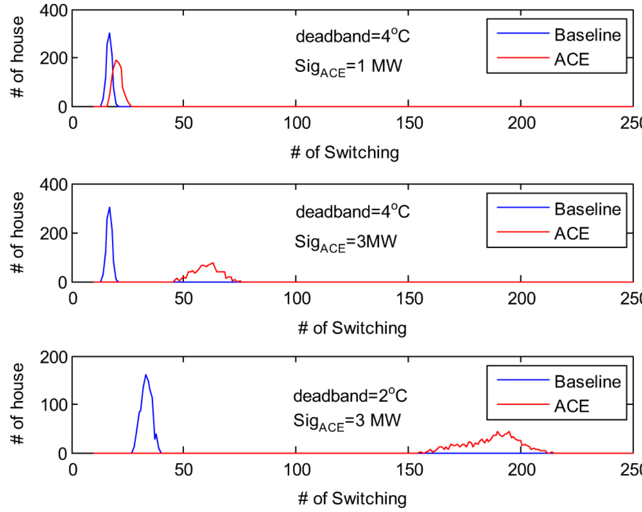

Fig. 26. Cycling status of HVAC units when following ± 3 MW ACE signals.

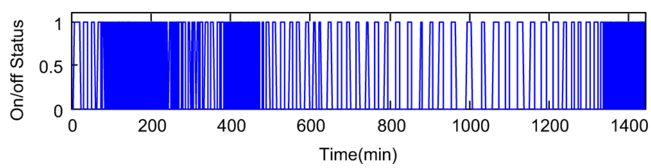

Fig. 27. Cycling status of an HVAC unit when following ± 3 MW ACE signals (deadband: $2\ ^{\circ}\mathrm{C}$).

V. Conclusions

This paper presents the direct control of HVAC units to adjust their power consumption to follow intrahour load balancing signals. First, a simplified model of a space heating unit was developed while considering the thermal energy balance. Then, the baseline aggregated HVAC power output was estimated from the modeled average load profile based on outdoor temperature forecast. Next, the control method of HVAC units for intrahour load balancing was proposed. Finally, operations of HVAC units were numerically simulated, and their capability to provide load following and regulation services was evaluated. The results indicated that approximately 1000 HVAC units (rated at 6 kW with $4\ ^{\circ}\mathrm{C}$ deadband) can provide 24 hours of load following or regulation services (1-MW bi-directional signals) by the proposed control scheme. The modeling results suggest that with a smart grid in place, load service providers can extend the control to TCAs and collect additional revenue from the ancillary service market to recover the cost invested in the two-way communication and control network. Customers can receive additional revenue by offering their appliances for high value load balancing services and help integrate more renewable resources into the power grid.

Our future work will focus on development of direct control algorithms of different kinds of TCA loads and improving the control and forecast accuracy using smart meter measurements to reduce the need for communication between the TCAs and the central controller.

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