Improving power quality efficient in demand response: aggregated heating, ventilation and air-conditioning systems

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ABSTRACT

This study aims to identify the role of aggregated heating, ventilation, and air conditioning (HVAC) loads based on system characteristics using the lazy state switching control mode focusing on the overall power consumption rather individual response speed. This study is attempted to provide secondary frequency regulation using aggregated HVAC loads with more stable operation with the lazy state switching control mode based on conditional switching of the HVAC unit's working state. The stability of power consumption improves power quality in smart grid design and operation. The aggregated HVAC must reach a stable condition before tracking the automatic generation control signal and fully developed smart grids complex structure. Still, HVAC slowed responses make inappropriate for faster demand response services. Unsuitable control algorithm leads to system instability and HVAC unit overuse. An extended command processing on the client side is proposed to deal with the adjusting command. The unique advantages of the proposed algorithm are three folds. (1) the control algorithm preserves its working state and has nothing conflicting with the lockout constraints for individual system units; (2) the control algorithm shows promising performance in smoothing the overall power consumption for the aggregated population; and (3) the control logic is fully compatible with other control algorithms. The proposed modeling and control strategy are validated against simulations of thousands of units, and the simulation result indicates that the proposed approach has promising performance in smoothing the power consumption of aggregate units' population.

Keywords: Renewable energy; Smart Grid; Demand response; Power quality; Heating, ventilation and air conditioning (HVAC); Lazy state switching.

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Nomenclature

Abbreviations

AGC	automatic generation control
DR	demand response
ETP	equivalent thermal parameter
HEMS	home energy management system
HVAC	Heating, ventilation, and air conditioning
LSS	lazy state switching
TCL	thermostatically controlled loads
PEV	plug-in electric vehicles

Indices

i	index of state-space
t	index of time

Variables and parameters

x_a	inner air temperature (°F) of HVAC unit
x_m	inner mass temperature (°F) of HVAC unit
T_o	outside air temperature (°F)
U_a	thermal conductance (Btu/hr.°F) of the building envelope
H_m	thermal conductance (Btu/hr.°F) between the inner air and inner solid mass
Q_a	the heat flux (Btu/hr) into the inner air mass
Q_m	heat flux (Btu/hr) to the inner solid mass
C_a	thermal mass (Btu/°F) of the internal air
C_m	thermal mass (Btu/°F) of the building materials and furniture
U_{set}	HVAC temperature (°F) setpoint
δ	HVAC unit's temperature (°F) deadband
$T_{a,\min}$	minimal air temperature (°F) for a population of HVAC loads
$T_{a,\max}$	maximum air temperature (°F) for a population of HVAC loads
$T_{sp,i}$	temperature setpoint (°F) of HVAC unit i
ΔT_{sp}	the amount of temperature setpoint change
S	the working state of an HVAC unit
ε_t	an infinitesimal time delay
f_i^*	the probability for an HVAC unit to reside in a certain temperature segment
$\Delta m_i^{on/off}$	the number of HVAC units in state i at a given moment
n	the total number of HVAC units in the simulation tests
P	power consumption (W) of single HVAC unit
P_{HVAC}	total power consumption (W) of the aggregated loads
η	power system's transmission efficiency
ΔP	instantaneous power increase
$U_c(\mu_*, \delta_*)$	represents a uniform distribution centered by μ_*, and spans the distance δ_*
δ_m	parameters deadband vector
Uniform(*,*)	Uniform distribution between two values
Uc(*,*)	uniform distribution center by the first value with deadband of the second value
μ_{Af}	center value of floor area (ft²)
μ_{Ia}	center value of air exchange (1/hr)
μ_{Rc}	center value of roof R-value (°F.ft².hr/Btu)
μ_{Rw}	center value of wall R-value (°F.ft².hr/Btu)
μ_{Rf}	center value of floor R-value (°F.ft².hr/Btu)
μ_{Rd}	center value of door R-value (°F.ft².hr/Btu)
δ_{Af}	deadband of floor area distribution
δ_{Ia}	deadband of air exchange distribution
δ_{Rc}	deadband of roof R-Value distribution
δ_{Rw}	deadband of wall R-Value distribution
δ_{Rf}	deadband of floor R-Value distribution
δ_{Rd}	deadband of door R-Value distribution
R_{on}	ratio of "on" units in aggregated HVAC loads

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1. Introduction

Future smart grid, power quality has gained particular importance due to increase number of sensitive loads and faces new challenges (Bidram and Davoudi 2012). Especially, variable renewable energy generation and unstable load demand are both sources of uncertainties in the grid (Eksin et al. 2015). At the supply side, renewables, such as solar and wind energy, are established as mainstream sources of energy (Ismail et al. 2019). Renewables have undergone rapid growth globally and supply 40% of the world's energy. They are expected to play a major role in the future power generation by 2040 (Cai and Braun 2019; Sedady and Beheshtinia, 2019). However, the integration of large-scale renewable energy affects the power system in many ways. The intermittent nature of renewable energy presents significant challenges on system security and operation, when a larger proportion of renewable energy sources are integrated in, e.g., more than 20% (Pourmousavi et al., 2014; Zhu et al., 2015). If the penetration of renewables is around 50% or more, the traditional automatic generation control (AGC) is incapable to maintain the frequency within acceptable limits (Malik and Ravishankar 2018). The power grid needs new resources for frequency reserves to provide high quality power supply.

As a cost-effective balancing resource, demand response (DR) is supposed to provide balancing service, which used to be provided by conventional generation units (Jin et al., 2018; Müller and Jansen 2019). Prior studies presented various types of candidate loads for DR, including thermostatically controlled loads (TCL) and plug-in electric vehicles (Antti et al., 2019; Hamidreza et al., 2019). Among these, heating, ventilation, and air conditioning (HVAC) account for 50% of total building energy consumption (Ma et al. 2019). The HVAC systems are becoming more and more popular, driven by economic growth and the desire for a better life. It is estimated that power consumption of HVAC systems will increase 33 times by the end of this century (Ma et al., 2019). The systems have larger heat capacity and longer cyclic time, and they are more susceptible to outer climatic conditions (Giwa et al., 2019; Vakiloroaya, 2014). The heat capacity of buildings act as a battery; the energy increases when the HVAC unit is on (charging) and decreases when the unit is off (discharging). The elasticity of HVAC power consumption is utilized to reduce the user's energy cost and provides DR services such as peak shaving and ancillary services (Ji et al., 2014; Lu, 2012; Nguyen and Le, 2014). The HVAC systems potential for DR needs to be evaluated.

Several methods for modeling and control of aggregated HVAC systems have been proposed, including direct load control and indirect load control. For instance, Wang et al. (2014) developed highly accurate modeling and control strategies based on the control center for large population of HVAC loads, wherein the HVAC loads execute commands from the control center unconditionally. These control modes act quickly, but some limitations exist: (1) The lockout constraint has little effect on normal operations but drastically affects the collective response for a large number of HVAC aggregated together because it needs to interrupt their normal operations frequently; (2) Most control algorithms have to choose between computing accuracy and system performance. The models with first-order equivalent thermal parameter (ETP) model show better performance but larger computing error. Models based on the second-order ETP have been extensively studied nowadays; they show relatively high computing accuracy but put a heavy calculation burden on the control center with lower performance (Bashash and Fathy, 2013; Zhang et al., 2013); (3) The control algorithms may face serious power flickers and fluctuations due to synchronized state switching of multiple HVAC units when adjusting their thermostat setpoints, with the peak power when all units are "on" and the minimum power when all units are "off". To suppress the power variation, the algorithm becomes more complex. (4) The control algorithms increase the frequency of unit's on/off switching.

Zheng and Cai (2014) found that the number of on/off cycles was about 0–3 cycles per hour without DR control and increased to about 1–20 cycles per hour using various DR control algorithms. These issues considerably increased the operation cost of DR control algorithms. Li et al. (2017) proposed the lazy state switching (LSS) control concept for aggregated HVAC loads. This study aims to improve the control algorithm and provide secondary frequency regulation services in a fully developed smart grid environment by controlling a large number of HVAC loads. The main contributions are summarized as follows.

1. This study ensures safe and stable operations of users' HVAC systems, to protect users' load, and to preserve system stability, reducing the frequency of unit's on/off switching. This works well with the lockout effect and to minimize users' electricity bills as well as to smoothen the total demand curve, and make the DR control more acceptable to users.
2. This study proposes the idea of homogeneity control to realize controlling the parameters' distribution interval. One can test the aggregated system performance of different homogeneities to verify the adaptability of the control methods.
3. The proposed control algorithm is fully compatible with other control algorithms, and integrates into the same DR systems with other control algorithms, which enables a DR system to have multiple control modes at the same time.
4. The proposed modeling and control method is validated using GridLAB-D, which is capable of simultaneously simulating thousands of unique buildings using the second order ETP model (GridLAB-D 2012). Simulation results show that the proposed control algorithm effectively eliminate power flicker and power fluctuation and quickly restore the system to a steady state after the control center broadcasts commands to adjust the HVAC setpoint.

The rest of this study is organized as follows. Section 2 briefly reviews related literatures. Section 3 discusses the characteristics of HVAC units. Section 4 develops the temperature distribution model for aggregated populations of HVAC units. The improved LSS control mode is developed in Section 5. The experiment results and discussions are explained in Section 6. Finally, conclusions and future studies are presented in Section 7.

2. Literature Review

The structure of a smart grid is highly complicated with high penetration of renewable generation, contains lots of nonlinear or sensitive loads, and requires power supply with higher quality and stability (Pourmousavi et al., 2014; Sedady and Beheshtinia, 2019). Although numerous studies have focused on aggregate HVAC to smoothen the fluctuations of renewable generation, the power quality problems caused by the DR system itself have been overlooked. The system voltage and frequency seriously affected by the variation in load demand (Kabache et al. 2014). The switching of high-power loads imposes a considerable impact on the power grid and produces the same effect when switching large amount of loads at the same time (Zhang et al., 2013). Power fluctuations may cause various problems, including voltage flicker and frequency deviation, incurring poor power supply for consumers, which causes lights to flicker and may damage useful electronic equipment (Abdul et al., 2014). This is a potential problem in aggregated DR systems, especially in HVAC load-based systems.

Prior studies have focused on DR systems to provide ancillary service, which is an important electric service, and the system is used by residential, commercial, or industrial users (Cui and Zhou 2018; Ma et al. 2017). The system realizes the communication between grid utilities and customers, guides users to schedule power consumption to save energy, reduces costs, and helps grid operation (Muhammad et al., 2019; Ma et al., 2017). As a representative TCL, HVAC units are studied extensively in the literature. Some studies have regulated HVAC units by turning them on or off directly at the customer premises. Lu et al. (2005) presented a state-queuing model and a temperature priority list strategy to control on/off states of HVAC units. Vanouni and Lu (2015) presented a centralized control method to provide continuous regulation services. Zhou et al. (2017) proposed a novel two-level scheduling method to minimize the power imbalance cost. Hao et al. (2015) modeled the aggregated HVAC as a stochastic energy storage battery and proposed a priority-stack-based control to control the power consumption to follow AGC signals and reduce the tracking errors by the on/off states directly. However, direct HVAC regulation does not consider the temperature setpoint and the deadband, and the tracking error is very large when large number of loads toggle their working state simultaneously (Ma et al. 2017).

Adjusting the HVAC setpoint is a control method for the regulation of HVAC units (Yin et al., 2016). It is the key to study the load temperature dynamics for aggregated systems of thousands of HVAC units (Adhikari et al., 2018). Lu and Chassin (2004) proposed a state-queuing mode of setpoint adjusting based on price response and analyzed the degeneracy of states followed by a damping process. The control center or the operator needs to adjust the system on a timely basis, so it is hard for the system to reach a stable state. It was concluded that the aggregated system cannot respond to AGC signals before achieving a stable condition (Bashash and Fathy, 2013). To improve stability, Bashash and Fathy (2013) developed Lyapunov-stable sliding mode controller based on a Monte Carlo model for real-time management of thermostatic air conditioning loads, assuming that communication is accessible and loads quickly respond, without considering the synchronized operation of multiple loads and their impacts on the power system. However, sliding mode control is well known for its chattering effect.

Zhang et al. (2013) analyzed the inner air and mass temperature and proposed a 2D temperature evolution model. They then developed a highly accurate aggregated model. At the same time, the increased communication data require high-speed communication equipment and quick response HVAC units. Tindemans et al. (2015) developed a heuristic algorithm based on setpoint adjusting for decentralized implementation. Setpoint adjustment enlarges the energy storage capacity, but it often causes large chattering effects and tracking errors (Ma et al., 2017; Gowa et al., 2019). The reason is that all HVAC units change their setpoint instantaneously when they receive control signals, resulting in many loads changing their working state simultaneously.

Communication latency is another important part of the total response time. In future smart grids, each HVAC unit may be under the control of a different home energy management system (HEMS). The DR client does not communicate with the DR server directly, and the HEMS communicates with the DR server on behalf of the HVAC unit (Yan et al., 2017). The network traffic and transmission speed are limited. From the perspective of load characteristics, a typical residential HVAC system switches 0–3 times per hour without DR control (Zheng and Cai 2014). Its long working cycle, slow response, and potentially higher frequency on/off cycling make them inappropriate for fast DR service (Beil et al., 2016).

Achieving users' engagement for DR system is required from the viewpoint of system implementation (Parrish et al. 2019). The utility and system operator may expect customers to implement home automation, enroll in some DR systems, and respond predictably to DR signals (Ghanem and Mander 2014). However, consumer participation in DR may not follow these expectations. It is supposed that DR participation is voluntary rather than compulsory through regulation (Parrish et al., 2019). The potential uncertainties and risks require decision-making whether to engage or not to conduct a cost-benefit analysis to be considered (Jordehi, 2019). The cost of DR includes the initial investment involving the technology's cost and preparation of a response schedule. Possible risks include discomfort cost, rescheduling and on-site generation cost, and unexpected operations imposed on a load. At present, the DR penetration level is small; for example, it is only 6% in the U.S. (Wei et al., 2016). The users benefit more systematically when a DR system is designed to improve user engagement. It is important to protect their load from overuse in addition to the limited reduction in consumer bills. The risk of unexpected operations to the load is likely to dissuade many customers from DR participation.

In summary, advanced DR system designs maintain power quality and grid stability while properly taking advantage of the HVAC units' operation characteristics, completely considering the users' interests and the risks imposed on the loads. This study aims to provide secondary frequency control with a large number of HVAC units, which has fewer requirements on communication network, has higher stability of whole power consumption, and tends to protect user loads at the same time.

3. HVAC Unit Dynamic Model

The characteristics of a single HVAC unit form the basis to develop an aggregated load control model. Containing numerous variables and constraints, an HVAC system is a complex, nonlinear, and discrete system (Khasawneh 2014). HVAC systems have a large heat capacity and long cyclic time, and they are more susceptible to outer climatic conditions (Vakiloroaya 2014). The dynamics of inner air temperature is studied based on the second order ETP model (GridLAB-D 2012). The compressor time delay constraint is also discussed, which is important in aggregated load control modeling.

Residential HVAC units belong to different users and are controlled individually by simple hysteresis controllers. Prior studies described the thermodynamics of an HVAC unit (Zhang et al., 2013). This study adopted the popular ETP model to describe the dynamics of air and mass temperature using two coupled first-ordered ODE (GridLAB-D 2012).

$$\begin{cases} \dfrac{dx_a}{dt} = \dfrac{1}{C_a}\left[-(U_a + H_m)x_a + H_m x_M + U_a T_o + Q_a\right] \\ \dfrac{dx_m}{dt} = \dfrac{1}{C_m}\left[H_m x_a - H_m x_m + Q_m)\right] \end{cases} \tag{1}$$

For a given HVAC system with known initial conditions, the solution trajectory for x_a is uniquely determined. Figure 1 shows typical coupled air and mass temperature trajectories with setpoint $U_{set} = 75°\mathrm{F}$, deadband $\delta = 2°\mathrm{F}$, and initial outside air temperature $T_o = 90°\mathrm{F}$. t_1 indicates the time when the unit's setpoint is raised by 1 °F. The air temperature trajectory is different for each working cycle, especially when the thermostat setpoint is changed. The green dashed lines indicate the time period when the unit remains off, ignoring the switching on signals due to the lockout effect.

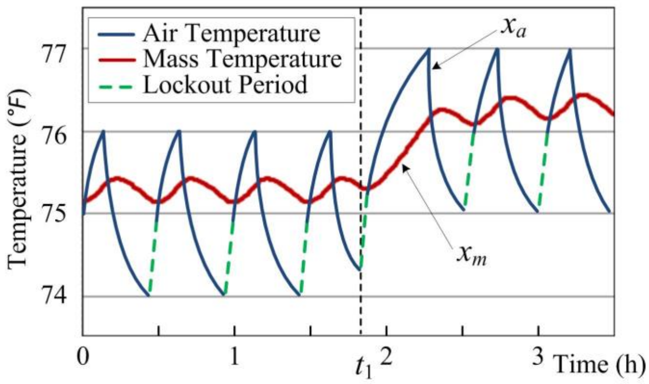


Figure 1 Characteristics of a single HVAC unit

The lockout effect is an important protection function to ensure the compressor remains off for certain amount of time, e.g. 5 min. During this period, the high pressure in the compressor chamber is released. It may cause physical damage if the compressor restarts early under pressure (Zhang et al., 2013). The lockout effect does not affect normal operations. However, it can seriously impact the aggregated load response during DR control. Zhang et al., 2013 introduced another state vector for the locked population, thus increasing the complexity of the algorithm. However, it is difficult to obtain the real-time status of all HVAC loads because of communication latency.

4. Temperature Distribution Model for Aggregate HVAC Units

The basic principle of aggregate system analysis is to study the time-course evolution of population instead of characterizing all individual HVAC units. Modeling and controlling of a large population of HVAC units is a challenging task for at least two reasons. First, it takes a long time, from minutes to hours, for the aggregated system to reach a sable state, but the outdoor temperature keeps changing, pushing the control center to send out control commands from time to time. The commands toggle some units' working state immediately. The aggregated system runs under an unstable state most of the time. Second, most of the control algorithms tend to change the HVAC unit's on/off state from time to time to result in reduction of the unit's lifetime and fluctuations of overall power consumption. Zheng and Cai (2014) evaluated this impact and found that the number of on/off cycles increased from approximately 0–3 times per hour at normal to approximately 5–20 times per hour under DR control. All these significantly increase the operating cost.

4.1 Temperature Distribution Based on State-space

Based on the physical model of individual load discussed in Section 3, this section first discusses the temperature distribution of HVAC loads for a large population (subsection 4.1). Based on the distribution model, we analyzed the aggregated dynamics when adjusting the population's setpoints (subsection 4.2) and the aggregated impact to the power system (subsection 4.3).

Let $[T_{a,\min}, T_{a,\max}]$ denote the inner air temperature range at a certain thermostat setpoint. One can discretize this temperature range evenly into n small segments of uniform width, resulting in a $2n$ state-space model in Figure 2. At each segment, the unit takes some time from entering to leaving; the difference in time at different temperature segments shows the characteristics of the dynamic process.

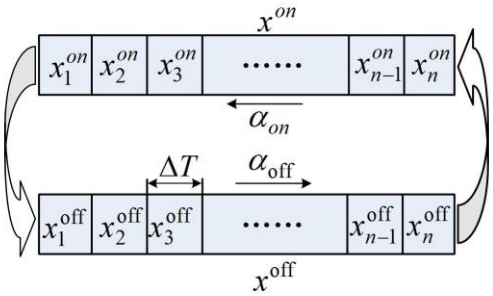


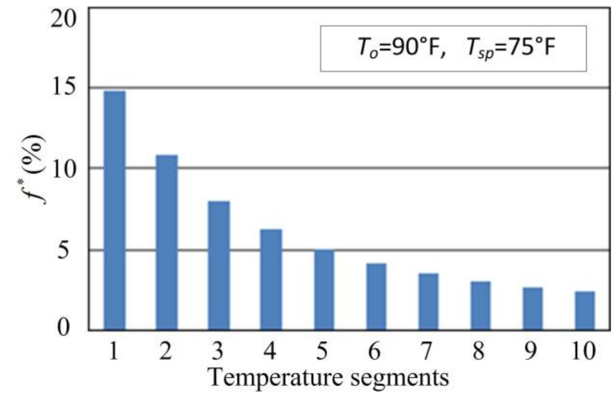
Figure 2 HVAC unit state-space transition model

The probabilities for an HVAC unit to reside in each of the $2n$ states form the basis to study the distribution of the aggregated loads. When an HVAC unit runs at a steady state scenario, the inner air temperature evolves across the states. Temperature distribution statistics were analyzed based on the simulation tests. A total of 2000 sets of physical parameters are generated, which are randomly distributed around their nominal values with a certain amount of variance, as described in Table 1. Each of them represents the real condition in one house.

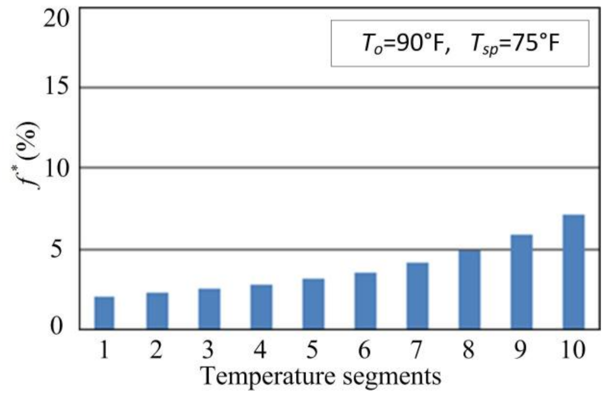
In this simulation test, this study sets the outdoor temperature T_o = 90 °F, which remained unchanged, and set all the units' cooling setpoint at T_{sp} = 75°F. When the population runs for enough time, the aggregated system reaches a steady state, and the power consumption becomes relatively stable. This study discredited the deadband into 10 segments uniformly and obtained 20 different states to study the temperature distribution within the temperature deadband. At any time, some of the loads reside in the ON states, moving toward the lower limit of the temperature, while some others reside in the OFF states, moving toward the upper limit. The objective of this subsection is to statistically analyze the number of units in each state and calculate the proportion of them in all units. The proportion of the units in segment i is calculated as follows.

$$f_i^* = \frac{\Delta m_i^{on/off}}{n} \tag{2}$$

where $\Delta m_i^{on/off}$ is the number of units of state on/off residing in the segment i at a given moment and n is the total number of HVAC units, which is 2000 in this test case. Figure 3 shows the units' temperature distribution over the states. It shows that the loads are not uniformly distributed. For the "on" group, it becomes more dense as the temperature reduces that means the speed of temperature evolution reduces near the lower limit, as shown in Figure 3 a). It is the reverse distribution for the "off" group, as presented in Figure 3 b).



a) Probability distribution of "ON" states



b) Probability distribution of "OFF" states

Figure 3 Probability Distribution of HVAC Units over ON/OFF states

The number of units staying in a specific state is estimated. The total power consumption is estimated by adding the number of units in all "on" states. We assume that all the units' power P and energy efficiency η are equal when their state is "on". The total power demand is then determined by the number of units in the "on" state at any time.

$$P_{HVAC}(t) = \frac{P}{\eta}\sum_{i=1}^{n}\Delta m_i \qquad (3)$$

4.2 System Evolution in Response to Control Commands

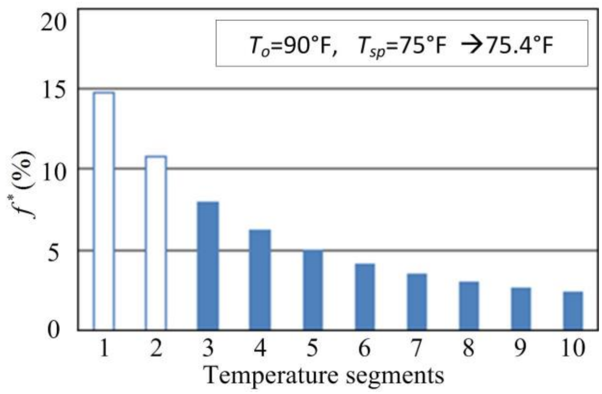
This study analyzed the dynamic process when adjusting units' setpoints using the temperature distribution model described in Section 4.1 and assumed that all HVAC units are working under the cooling mode. The basic principle of controlling the aggregate system is to adjust the population's thermostat setpoint, thus regulating the overall power consumption. The first case begins from the steady state described in subsection 4.1; the central controller sends a control command to raise the population thermostat setpoint by 0.4 °F; all HVAC units respond to control commands immediately. We redefine the states in the same pattern centered by the new setpoint, and then there are some "out-of-regime" states.

Figure 4 showed the system states in the temperature distribution model. The white block implies "out-of-regime" states. For the "off" state, the temperature of the "out-of-regime" states is lower than the new low limit. Therefore, the HVAC units take more time to increase their temperatures to the new upper limit. However, for the “on” states, the HVAC units in the “out-of-regime” states need to switch their state immediately. The instantaneous increase in power of the entire system is expressed as follows.

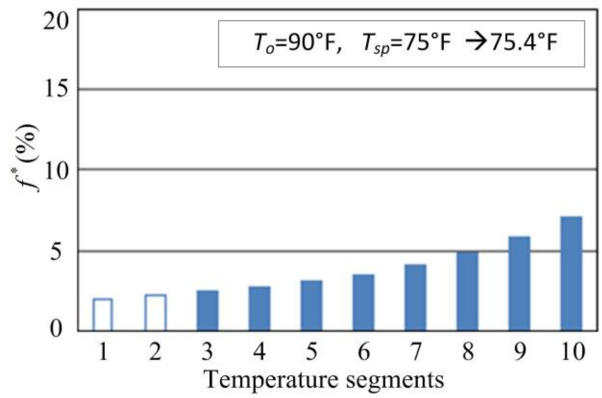
$$\Delta P = -\frac{P}{\eta}(m_1^{on} + m_2^{on}) \tag{4}$$

Figure 5 showed the instantaneous probability distribution when the central controller sends out a command to decrease the population’s thermostat setpoint by 0.4 °F. For the “on” states, the HVAC units of “out-of-regime” states need to work longer. The “off” states need to switch “on” immediately. The amount of instantaneous power increased is expressed as follows.

$$\Delta P = \frac{P}{\eta}(\Delta m_9^{off} + \Delta m_{10}^{off}) \tag{5}$$

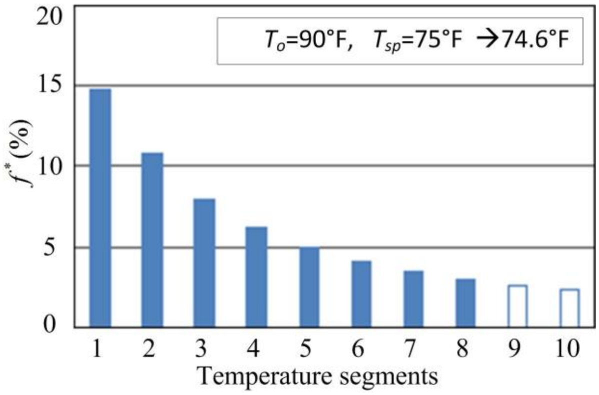


a) Instantaneous distribution of “ON” states

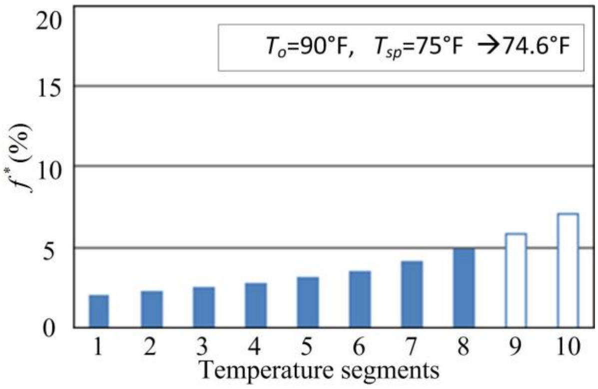


b) Instantaneous distribution of “OFF” states

Figure 4. Instantaneous probability distribution of the system after the thermostat setpoint is increased



a) Instantaneous distribution of “ON” states



b) Instantaneous distribution of “OFF” states

Figure 5. Instantaneous probability distribution of the system after decreases the thermostat setpoint

4.3 Power Fluctuation

The overall power consumption shows an immediate spike, followed by a damping oscillation process. A major contributor that affects the aggregate transient process is the diversity of the parameters of HVAC units. The highly homogeneous load populations often arouse strong oscillations, whereas a well-diversified load population undergoes a damping process with quick attenuation. In the literature, these observations are made mostly based on first-order thermostatically controlled load models; the second order ETP model of HVAC units also yields a similar behavior.

The oscillation process is validated against realistic simulations using GridLAB-D with thermostat setback programs, under different homogeneity of aggregate populations. In these two test cases, all the HVAC units participate in the same setback program where the set points are simultaneously shifted up from 75 °F to 76 °F at $t=1$(h) and released at $t=4$(h). The homogeneity of the population is controlled by reducing the parameters' distribution interval around their nominal values. The default distribution intervals are described in Table 1 (Adopted from Zhang et al. 2013). The quantified homogeneity of 0.2 δ_m is shown in Table 2. Detailed information about these parameters is provided in (GridLAB-D 2012).

Table 1. Default parameter values/distribution of the building used in GridLAB-D simulations (Adopted from Zhang et al. 2013)

Distribution	Value	Value
$U_c(\mu_{Af},\delta_{Af})$ Uniform distribution of floor area	$U_c(2250,1500)$	Uniform(1500,3000)
$U_c(\mu_{Ia},\delta_{Ia})$ Uniform distribution of air exchange	$U_c(0.625,0.75)$	Uniform(0.25,1)
$U_c(\mu_{Rc},\delta_{Rc})$ Uniform distribution of roof R-value	$U_c(30,20)$	Uniform(20, 40)
$U_c(\mu_{Rw},\delta_{Rw})$ Uniform distribution of wall R-value	$U_c(20,20)$	Uniform(10,30)
$U_c(\mu_{Rf},\delta_{Rf})$ Uniform distribution of floor R-value	$U_c(22.5,25)$	Uniform(10,35)
$U_c(\mu_{Rd},\delta_{Rd})$ Uniform distribution of door R-value	$U_c(3,4)$	Uniform(1,5)

Table 2. Parameters values/distribution of homogeneity 0.2 δ_m

Distribution	Value	Value
$U_c(\mu_{Af},0.2\delta_{Af})$ Uniform distribution of floor area	$U_c(2250,300)$	Uniform(2100,2400)
$U_c(\mu_{Ia},0.2\delta_{Ia})$ Uniform distribution of air exchange	$U_c(0.625,0.15)$	Uniform(0.55,0.7)
$U_c(\mu_{Rc},0.2\delta_{Rc})$ Uniform distribution of roof R-value	$U_c(30,4)$	Uniform(28, 32)
$U_c(\mu_{Rw},0.2\delta_{Rw})$ Uniform distribution of wall R-value	$U_c(20,4)$	Uniform(18,22)
$U_c(\mu_{Rf},0.2\delta_{Rf})$ Uniform distribution of floor R-value	$U_c(22.5,5)$	Uniform(20,25)
$U_c(\mu_{Rd},0.2\delta_{Rd})$ Uniform distribution of door R-value	$U_c(3,0.8)$	Uniform(2.6,3.4)

Here, $U_c(\mu_*,\delta_*)$ represents the uniform distribution centered by μ_* and spans the distance δ_*. For a uniform distribution in the range $[V_*^-,V_*^+]$:

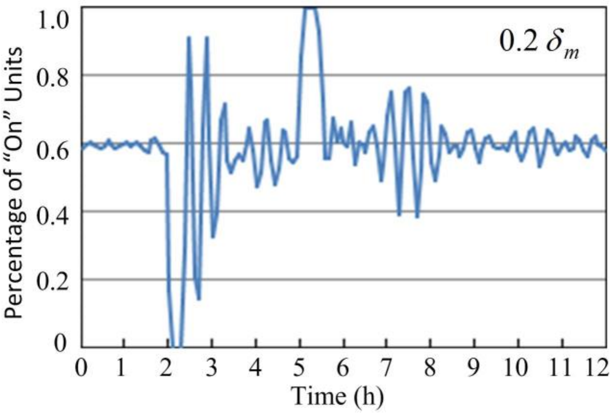
$$\begin{aligned} \mu_* &= (V_*^- + V_*^+)/2 \\ \delta_* &= V_*^+ - V_*^- \end{aligned} \tag{6}$$

To simplify the notation, we collect the parameters' distribution distance to form a parameter deadband vector as follows.

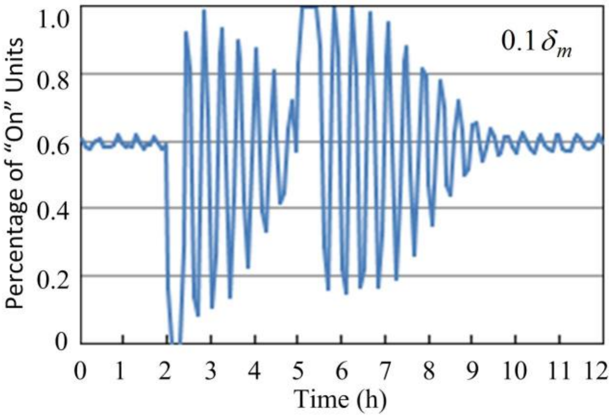
$$\delta_m = \left[\delta_{Af}, \delta_{Ia}, \delta_{Rc}, \delta_{Rw}, \delta_{Rv}, \delta_{Rd}\right]^T \tag{7}$$

For the uniformly distributed parameters, keeping their center values unchanged, the load homogeneity is controlled by adjusting the parameters' distribution interval.

Figure 6-a) shows the percentage of "On" units of the population whose parameter distribution interval is 0.2 δ_m. In another simulation test, the parameter distribution intervals are deceased to 0.1 δ_m. The percentage of "On" units is shown in Figure 6 b).



a) Parameter distribution interval is 0.2 δ_m



b) Parameter distribution interval is $0.1\delta_m$

Figure 6. Aggregated response of 1F setback program of different population homogeneities

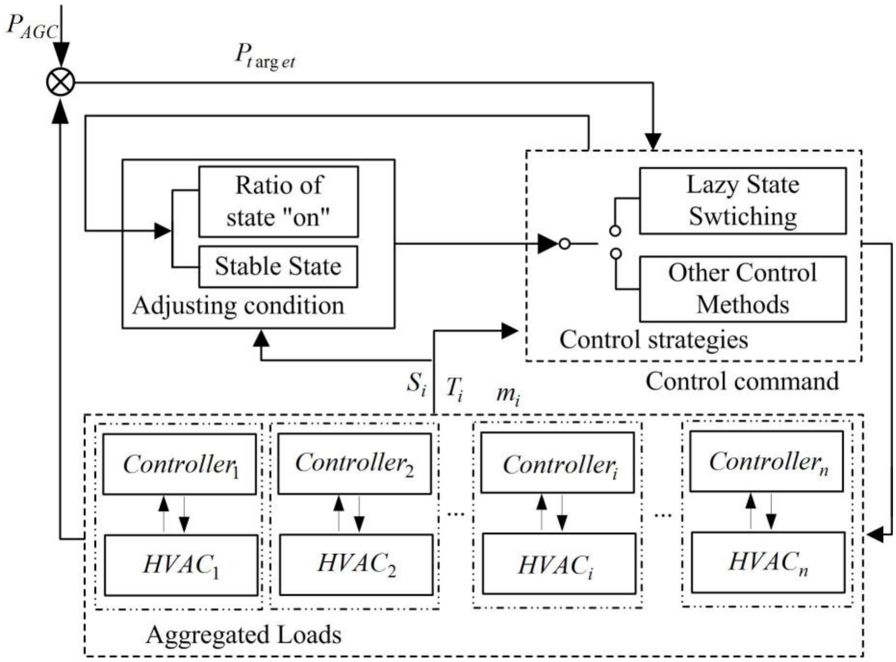
5. Improved LSS Model

This study aims to improve the LSS mode as a new control method (Li et al. 2017). The key idea to maintain stability of power consumption is to preserve the diversity of temperature distribution of the aggregate population. This involves changing the way that HVAC loads respond to control commands. In practice, the LSS control mode can not eliminate load oscillations completely after a control action to preserve the diversity in the temperature distribution and reach a new steady state quickly instead of oscillating. Another distinguishing characteristic is that the LSS mode reduces the frequency of the HVAC unit's on/off switching.

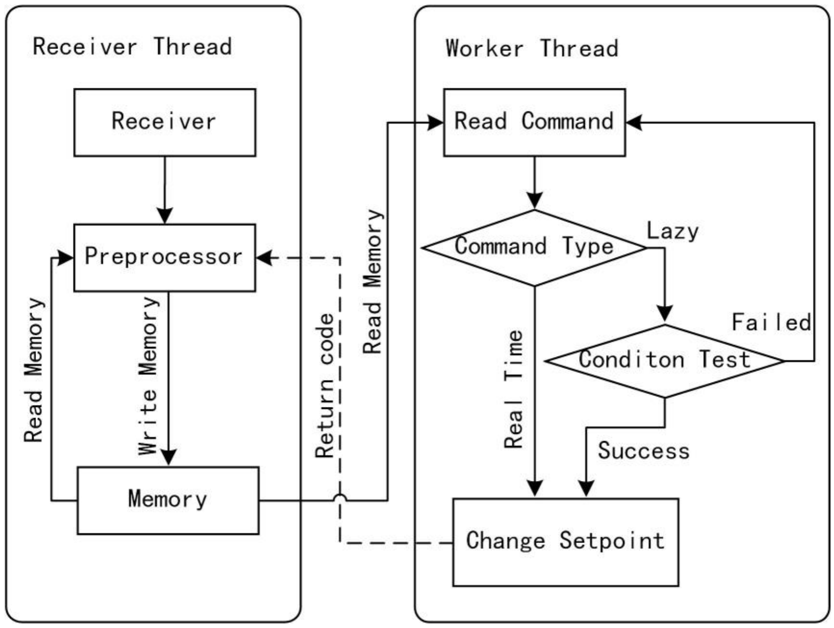
5.1 Designing of HVAC Units for Improved LSS Control

The units are not distributed uniformly among different temperature segments. There are more units in the segments near the limit where their working states are changed. This means that a small adjustment of the setpoint will cause many units to change their working states and cause serious power fluctuations.

The LSS method does not require any units to toggle any HVAC unit's working state immediately and tends to extend the units' working state as long as possible. Units of different working states act differently when the control center broadcasts a command to adjust the populations' thermostat setpoint. For example, when it needs to adjust load setpoint to a lower value, all "ON" state HVAC units execute the command immediately and maintain their "ON" state until the new lower limit T_{-}^{new}; but all the "OFF" units do not execute the command. They just keep the command till the temperature reaches the upper limit T_{+}^{old}, and they execute the command to change their setpoint only after they change their working state to "ON". The flowchart of the DR system with the LSS is shown in Figure 7.



a) Flowchart of DR system



b) Flowchart of smart controller

Figure 7. Flowchart of DR system with LSS control

Figure 7 a) shows the structure of the control center that uses the ratio of "on" units (R_{on}) and system stability condition as the switching indices to select the control strategy. R_{on} indicates the potential of system regulation. In the limit cases, if all units are "on", R_{on} is 1, which means the aggregated loads cannot increase system power anymore; if all units are "off", R_{on} is 0, which means there is no more power consumption to reduce. In contrast to other control methods, the LSS control requires each HVAC unit to be equipped with a smart controller embedded in the HVAC unit or HEMS. Figure 7 b) indicates the logic process of the smart controller handling the control command, which contains two working threads.

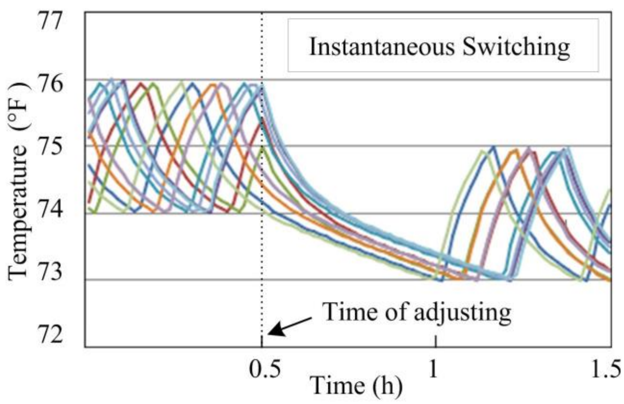
When a command is received, the receiver thread pass it to the preprocessor. The preprocessor reads the shared memory, searches whether there exists a saved command, and merges them together. For example, if there exists a command to increase the setpoint by 1 °F, and the new command is to decrease the setpoint by 0.4 °F; then the merged command is to increase the setpoint by 0.6 °F. Then, the preprocessor saves the merged command to the memory.

The worker thread reads the shared memory periodically to check the command type and executes it in different ways according to the command type. If the command is a lazy one, the thread will do a condition test. The worker thread executes the command after the conditions are met. It then transfers the return code to the preprocessor to handle the saved command. The command cannot be executed until the condition is satisfied. The HVAC unit condition switch is expressed as follows.

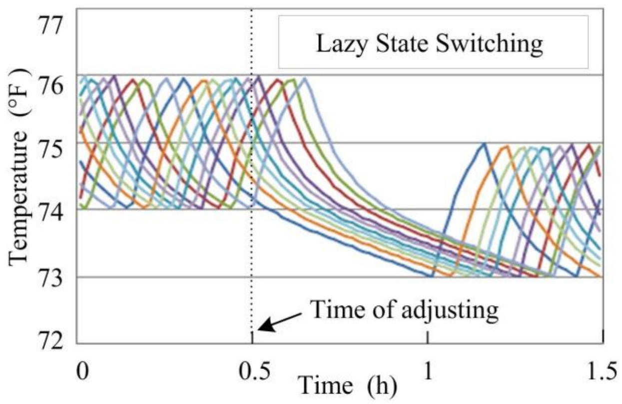
$$T_{sp,i}(t)=\begin{cases} T_{sp,i}(t-\varepsilon_t) & S(t-\varepsilon_t)=0 \\ & \&\,\Delta T_{sp}(t-\varepsilon_t)\cdot[T_{sp,i}(t-\varepsilon_t)-T_o]<0 \\ T_{sp,i}(t-\varepsilon_t)+\Delta T_{sp}(t-\varepsilon_t) & S(t-\varepsilon_t)=1 \\ & \&\,\Delta T_{sp}(t-\varepsilon_t)\cdot[T_{sp,i}(t-\varepsilon_t)-T_o]>0 \end{cases} \tag{8}$$

5.2 Improved Response Mode of Individual HVAC units

This study begins from the steady state with $U_{set}=75°\text{F}$, $\delta=2°\text{F}$, $T_o=90°\text{F}$ to examine the effects of the individual and aggregate dynamics of HVAC under LSS control mode when adjusting the setpoint. The setpoint is reduced by 1 °F. Figure 8 a) shows the inner air temperature trajectories of ten samples with instantaneous switching in other control modes. Figure 8 b) shows air temperature trajectories under the LSS mode of ten samples.



a) Ten samples with instantaneous switching



b) Ten samples with LSS control

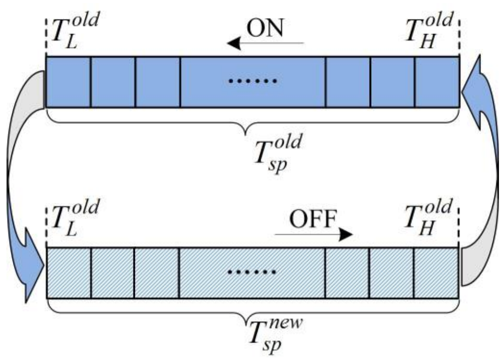
Figure 8. Temperature trajectories of ten samples

In the case of instantaneous switching, all the loads adjust their on/off states according to the new setpoint immediately after receiving the control command. There is a serious impact on the diversity of the aggregated loads after the control actions. However, under LSS control, some loads satisfying the switching condition execute the command and keep working till the new temperature limit is reached; others keep their working state until they reach the older temperature limits.

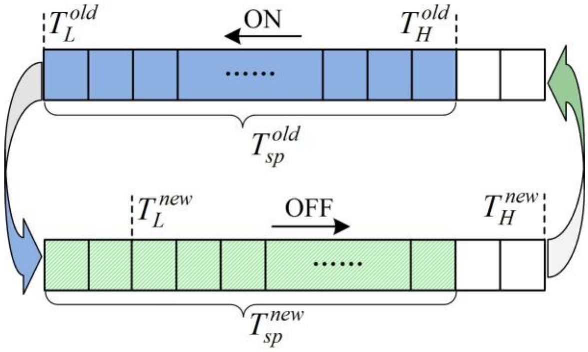
5.3 Preservation of Diversity in HVAC unit Air Temperature

This subsection discusses the load temperature distribution dynamics when adjusting the system thermostat setpoint. The key to maintain a stable power consumption is to maintain the diversity of the aggregate population of HVAC units. To illustrate the improvement of LSS control mode, we examine the load diversity changes when adjusting the system setpoint.

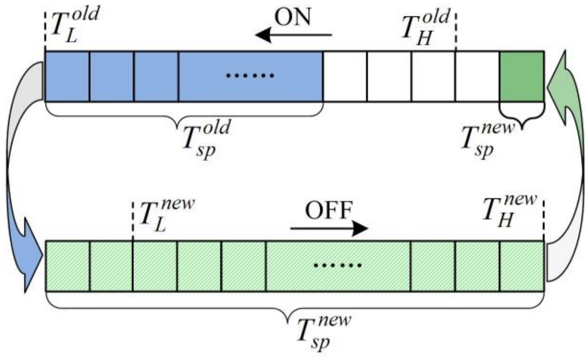
Previous studies have attempted to improve the aggregate control. Their main drawback is that they tried to control all units instantly and tried to avoid the lockout constraints based on a large operational cost. Figure 9 shows the system state evolution process when the system is controlled to increase the setpoint under the LSS control mode.



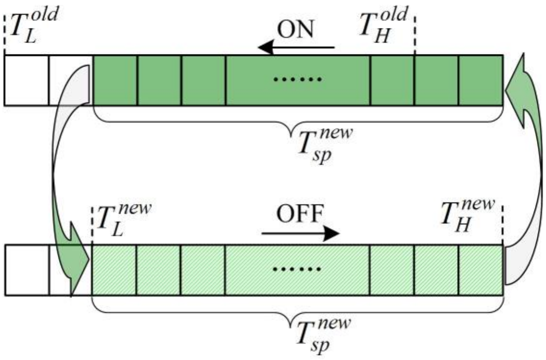
a) Temperature distribution under the initial setpoint



b) Temperature distribution after receiving the adjusting command



c) Temperature distribution in the middle of the transition process



d) Temperature distribution at the end of the transition process

Figure 9. Density evolution of the process when shifting up the population's setpoint

6. Discussions

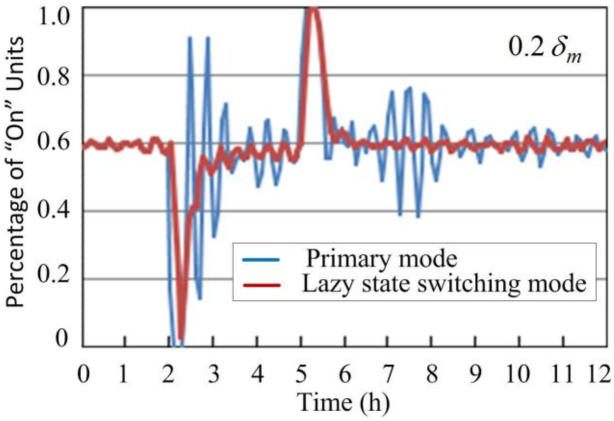
Two high homogeneity scenarios are studied to evaluate the proposed control method to illustrate the adaptability and performance of the proposed control method. The stability of the aggregated loads is illustrated by varying the percentage of "ON" units. The proposed aggregate model provides a robust control mechanism for large populations of HVAC units. We use the same setback program that shifts the population's thermostat setpoint by 1 °F higher at $t = 2$ h and changes it back at $t = 5$ h. Figure 10 shows the dynamic process of 2000 HVAC units of different homogeneities.

Under the LSS control mode, the aggregate HVAC system's response curve follows the red line in Figure 10. This study notes the following observations:

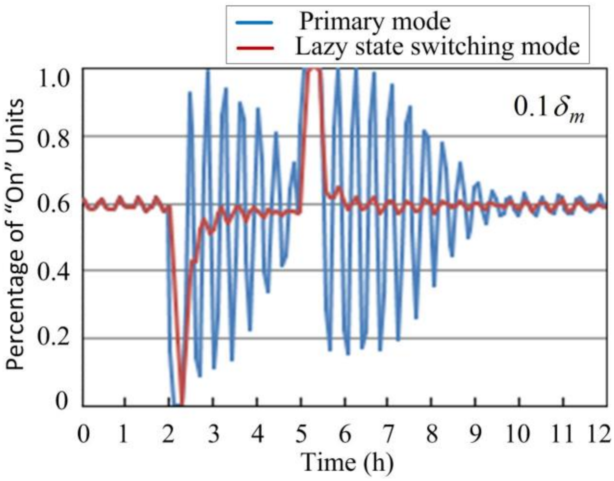
1. The initial spike is weaker and a little late, which comes with a climbing process. The

power flickers and fluctuations disappeared, which is inevitable under instantaneous switching control methods.

2. There was almost no succeeding fluctuation under the proposed control mode.
3. The proposed model tends to maintain the working states of the HVAC units and protects the unit from overuse.
4. The frequency of HVAC units' on/off switching would be lower than normal operation because HVAC units are controlled to prolong their work cycle from time to time.



a) Unit parameter distribution interval is 0.2 δ_m of the default intervals



b) Unit parameter distribution interval is 0.1 δ_m of the default intervals

Figure 10. Aggregate responses under setback program with different parameter distribution intervals

The stability of the aggregated system can not only improve power quality but also improve the ability to respond to signals. The aggregated loads cannot track AGC signals until the system achieves a stable condition. A good performance in the stability of power consumption shows the potential of the proposed model to improve power quality in the control of aggregate HVAC systems.

However, this study is subject to a number of uncertainties. (1) The weather conditions are associated with considerable uncertainties. Various parameters and evolution speeds have a direct impact on HVAC units in a complicated way. The time scale beneath which HVAC systems work are comparable significantly to weather conditions; therefore, to control and adjust the aggregate system, this study considers the trends of weather variations; and (2) the first spike with a large amplitude and long duration time still exists, and other resources are required to balance the power variation. The amplitude and interval of system regulation are limited by the compensation capability of other resources. Third, there are unavoidable uncertainties including users' preferences and unexpected operations.

7. Conclusion

This study improved the LSS control mode to provide secondary frequency regulation in a fully developed smart grid environment, which fully adapted to the slow response and operation constraints of HVAC systems. The LSS mode shows promising performance in maintaining the diversity of inner air temperature distribution of units in the aggregate system. It is essential for an aggregated system to restore stability after control actions and get ready quickly to track the next AGC signals. Traditional control methods tend to monitor the system status in real time, which is always accompanied by a high operation cost.

In contrast to traditional control methods, the LSS control mode has a minor requirement for real-time monitoring of HVAC' working states and does not require any unit to interrupt its working state. This study tends to extend some units' work cycles, which preserves the population's state diversity during the adjustment. For individual HVAC units, the LSS mode can reduce the frequency of the unit's on/off switching, which protects them from overuse. The power consumption is quickly restored to a stable state, thus making it easy for the utilities to improve DR applications based on HVAC systems. Integrated with other resources, the aggregate HVAC system adjusts the overall power consumption within limits and improves the efficiency and controllability of the whole system.

Future study is required to adapt the proposed control method to a changing ambient temperature and to develop adaptive control algorithms for the control center. Others should focus on integrating the LSS mode with other control algorithms to achieve better results. This study may provide valuable and useful ideas for researchers and industrialists working to develop better control methods. It is hoped that these novel methods will help improve the renewable usage and power quality in future smart grids.

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