Virtual Power Plant Control for Large Residential Communities Using HVAC Systems for Energy Storage

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Virtual Power Plant Control for Large Residential Communities using HVAC Systems for Energy Storage

Huangjie Gong, Student Member, IEEE, Evan S. Jones, Student Member, IEEE, Rosemary E. Alden, Student Member, IEEE, Andrew G. Frye, Donald Colliver, and Dan M. Ionel, Fellow, IEEE

Abstract—Heating, ventilation, and air-conditioning (HVAC) systems use the most electricity of any household appliance in residential communities. HVAC system modeling facilitates the study of demand response (DR) at both the residential and power system levels. In this paper, the equivalent thermal model of a reference house is proposed. Parameters for the reference house were determined based on the systematic study of experimental data obtained from fully instrumented field demonstrators. Energy storage capacity of HVAC systems is calculated and an equivalent state-of-charge (SOC) is defined. The uniformity between HVAC systems and battery energy storage systems (BESS) is demonstrated by DR control. The aggregated HVAC load model is based on the reference house and considers a realistic distribution of HVAC parameters derived from one of the largest smart grid field demonstrators in rural America. A sequential DR scheme as part of a Virtual Power Plant (VPP) control is proposed to reduce both ramping rate and peak power at the aggregated level, while maintaining human comfort according to ASHRAE standards.

Index Terms—Heating, Ventilation, and Air-conditioning (HVAC), Battery Energy Storage System (BESS), Home Energy Management (HEM), Demand Response (DR), Equivalent Thermal Model, Aggregated, Grey Box, Virtual Power Plant (VPP), Smart Home, Smart Grids, Equivalent Energy Storage, American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE).

I. INTRODUCTION

Heating, ventilation, and air-conditioning (HVAC) systems use the highest percentage of energy within typical residences [1]. They dominate the house energy usage and contribute the most to the peak power demand at the aggregated level. To accommodate large fluctuations in demand over the course of a day, expensive infrastructure must be installed to meet the maximum demand. This leads to extra cost and a need for optimized control to reduce the peak power.

Utilizing HVAC systems as demand response (DR) devices has great opportunity to yield significant energy savings, especially at an aggregated level. To properly study the simulated implementation of HVAC DR schemes, a valid model of HVAC energy use is required. A grey-box resistance-capacitance (RC) model provides accurate results for the indoor temperature with proper values for R and C [2], [3]. Aggregated modeling for a community of air conditioning loads has been proven effective for the study of large-scale DR implementation [4]. Commercial HVAC system modeling employs statistical methods that are also highly accurate [5].

The DR studies with residential-level HVAC models, however, are more recent and have yet to reach this degree of confidence due to the strong link among HVAC energy use, random user behavior, and external weather conditions. The effect of weather induces more variation in energy and is more difficult to capture at the residential level. Current research proposes various methods to develop residential HVAC energy models, such as power-temperature modeling through disaggregation of smart meter data [6], or employing whole building energy simulators like EnergyPlus [7], or eQUEST [8].

Studies have provided multiple demonstrations for the effectiveness of HVAC systems as DR devices through control or price-based schemes [9]. A study in which indoor temperature of an individual simulated building was controlled based on electricity retail prices found that heating and cooling energy use was reduced by 12% and 21% for the coldest and hottest months, respectively [10]. A bonus-based DR approach that employs Stackelberg game theory to reduce mismatch between residential energy use and renewable generation also yielded significant results with a reduced deviation ranging from about 32% to 43% [11]. A bi-level optimal control study including residential HVAC systems resulted in as much as 22% in energy savings [12].

To ensure adequate thermal comfort, the HVAC control follows Standard 55 of the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), in terms of external and internal temperature, relative humidity, individual metabolic rate, etc. [13]. The ASHRAE Standards quantify the comfort of the space using a numerical scale called the Predicted Mean Vote (PMV) that was derived from survey results where participants ranked their comfort from -3, very cold, to 3, very hot. This allows for an association between a range of environmental conditions to a comfortable status within a home that can be calculated as a PMV between -0.5 and 0.5, which may be used to control heating and cooling systems without affecting thermal comfort.

HVAC systems are widely perceived as solely energy-
The arrangement of the paper is as follows. The experimental results and the derivation of the parameters for the house thermal model are introduced in Section II. The HVAC as equivalent energy storage is analyzed in Section III. In Section IV, the aggregated HVAC load is modeled. The proposed sequential DR control and the simulation results are presented and discussed in Sections V and VI, respectively. The conclusions are drawn in Section VII.

II. EXPERIMENTAL RESULTS AND DERIVATION OF HOUSE THERMAL MODEL PARAMETERS

Beginning in 2008, TVA funded and managed a robotic house project with technical support from the ORNL. The robotic houses were constructed in a suburb of Knox County, TN in which the habitation of a family was physically emulated (Fig. 1). This project developed an analytical base for energy optimization and new technology implementation at the individual house level. A different initiative, the SET project based in Glasgow, KY, provided a testbed for the optimization of power flow at the community level. In the TVA robotic house, energy usage for different components, including the HVAC, was measured on an hourly basis. The experimental data from SET had a 15-minute resolution.

The equivalent model that represents a typical residence, which was defined by parameters such as thermal envelope area, thermal resistance, thermal capacitance, and heat transfer rate was derived from the TVA robotic house experimental data. The thermal envelope area is the only independent variable for the equivalent model. Other parameters for the equivalent thermal model were calculated using the thermal envelope area and coefficients, as follows:
The heat transfer function of the residential thermal model is described as follows:

\[
\frac{d\theta_t(t)}{dt} = \frac{1}{R} \left( \theta_O(t) - \theta_t(t) \right) - S(t) \cdot P_H, \tag{2}
\]

where \(\theta_t\) is the indoor temperature; \(\theta_O\), the outdoor temperature; \(S\), the ON/OFF status of HVAC, defined as:

\[
S(t) = \begin{cases} 
0, & \text{if } S(t-1) = 1 \& \theta_t(t) \leq \theta_L(t) \\
1, & \text{if } S(t-1) = 0 \& \theta_t(t) \geq \theta_H(t) \\
S(t-1), & \text{otherwise}
\end{cases} \tag{3}
\]

where \(\theta_L\) and \(\theta_H\) are the lower and upper band of the thermostat set point, of 70°F and 74°F, respectively for the TVA robotic house.

The HVAC system for the reference house was modeled with fixed parameters (Table I). The envelope area was calculated according to the floor plan. The coefficient of thermal resistance \(c_R\) was selected according to its relationship to outdoor temperature and justified with a confidence interval (Fig. 2). The \(c_C\) and \(c_P\) were adjusted based on the envelope area and recommended values [26]. With a cooling capacity of 4 tons and a Seasonal Energy Efficiency Ratio (SEER) of 13.5, the HVAC system had a constant input electrical power of approximately 3.6kW when it was ON (Fig. 3).

The experimental data from July, 2010, which was retrieved from the robotic house project supported by TVA and ORNL, was used for the validation of the residential thermal model. For most of the days in Fig. 4, the outdoor temperature was high in the afternoon. The daily HVAC electricity usage for the experimental and simulated data are compared and presented in Fig. 5. Apart from the first few days and the last day when the outside temperature was relatively low, the simulation had highly satisfactory results.

Further study found that the proposed residential thermal model resulted in lower electricity daily usage for the HVAC when the outdoor temperature was both low and measured on an hourly basis. This occurred due to the cessation of HVAC operation during higher temperatures that were artificially reduced by the hourly temperature measurements. For example, if the thermostat set point was 75°F and the outdoor temperature was 70°F for half the hour and 80°F for the other half, the experimental data would have the HVAC ON for only the half hour. However, the averaged hourly based temperature data

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**TABLE I**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal envelope area (A_r)</td>
<td>354 (m^2)</td>
</tr>
<tr>
<td>Coefficient of thermal resistance (c_R)</td>
<td>350 (^\circ)C \cdot m^2/kW</td>
</tr>
<tr>
<td>Coefficient of thermal capacitance (c_C)</td>
<td>0.011 (kWh/(^\circ)C \cdot m^2)</td>
</tr>
<tr>
<td>Coefficient of heat transfer rate (c_P)</td>
<td>0.040 kW/m²</td>
</tr>
</tbody>
</table>

---

**Fig. 2.** Analysis of the \(c_R\) equivalent thermal resistance coefficient for the reference house. Data corresponds to 5 hours during the time interval of direct interest for DR studies of each day in July 2010. Data was fitted with a 90% confidence interval, and only 2 points were outside the bounds.

**Fig. 3.** The daily simulation example of the HVAC system for the reference house. With a cooling capacity of 4 tons and a SEER of 13.5, the HVAC has approximately 3.6kW of constant electric power during operation.
would be 75°F, under which case the modeled HVAC would be OFF the entire hour.

III. HVAC SYSTEM AS EQUIVALENT ENERGY STORAGE

The HVAC system is described as equivalent energy storage, and its equivalent SOC is defined as:

$$SOC(t) = \frac{\theta_{\text{max}} - \theta_I(t)}{\theta_{\text{max}} - \theta_{\text{min}}},$$

where the $\theta_{\text{max}}$ and $\theta_{\text{min}}$ are the maximum and minimum room temperature, respectively. In this study, the lower thermostat set point always has the same value as the minimum room temperature. The upper thermostat set point varies for different user preferences, and is set to the maximum room temperature only under the DR control.

The concept of equivalent SOC of the HVAC system is illustrated in Fig. 6. When the HVAC system is operating in the cooling mode, the maximum and minimum room temperature correspond to the equivalent SOC of 0% and 100%, respectively. The room temperature increases due to the higher outside temperature when the HVAC is OFF, and this is the equivalent procedure of discharging the energy storage. When the HVAC is ON, the room temperature decreases in most of the normal cases and correspondingly, the equivalent SOC increases.

The energy capacity of a HVAC system is defined as the input electricity needed to change the room temperature from the maximum to the minimum with a fixed outside temperature. The pseudocode for the calculation is shown in Algorithm 1. The energy capacity of the HVAC system for each house is calculated with its own set of parameters.

In this study, the outside temperature $\theta_{O,F}$ for the calculation of the HVAC energy capacity is fixed to 86°F, as this is the average outdoor temperature in Glasgow, KY during the month of July when this DR study takes place [27]. The lower thermostat set point is fixed to 70°F for all the HVAC systems.

The maximum room temperature $\theta_{\text{max}}$, was selected to be 81°F as this is the highest indoor temperature that results in a comfortable PMV rating under typical conditions for July as calculated by the online CBE Thermal Comfort Tool that follows ASHRAE Standard 55 [28]. A typical relative humidity of 54%, clothing level of 0.5 clo representing common indoor summer wear, an air speed of 0.1 m/s, and metabolic rate corresponding to sitting were used to verify that 81°F results in
a PMV rating of 0.46 PMV. This is classified as acceptable as it is less than 0.5 PMV, meaning that 90% of people on average would be comfortable according to the ASHRAE Standards. The operative temperature was assumed equal to the indoor temperature or slightly lower, indicating the occupant would either be by a neutral or cool surface such as an interior wall out of sunlight or piece of furniture.

First in the equivalent energy storage study, the initial room temperature is set to the maximum and the HVAC is kept ON until the room temperature reaches the minimum. The required number of steps is recorded and used together with the heat transfer rate and the simulation resolution to calculate the energy capacity of the HVAC system. It is worth noting that the energy capacity is defined as the required electricity, therefore, the HVAC electric power, which is calculated as $P_H/COP$, is used for the calculation. The coefficient of performance (COP) and SEER are interchangeable.

The equivalent SOC of the HVAC system in the daily simulation example (Fig. 3) is shown in Fig. 7. In the morning, the HVAC was OFF and the room temperature increased until around 8:00, and the equivalent SOC decreased accordingly. When the HVAC was ON, the room temperature was decreased until it reached the lower thermostat set point. As a result, the equivalent SOC increased to 100%. The equivalent SOC did not drop below 60% in this example, indicating the potential to deepen “discharge” of the HVAC system through a control scheme.

The upper thermostat set point was set to the maximum room temperature during 11:00–16:00 for the DR control and the results are shown in Fig. 8. The equivalent SOC reached 0% as the room temperature became the maximum. The house could shed the HVAC power for a longer period of time by “discharging” the equivalent SOC to 0%.

### Table II

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value (distribution)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient of thermal capacitance $c_C$</td>
<td>0.011 kW·h/(°C·m²)</td>
</tr>
<tr>
<td>Coefficient of heat transfer rate $c_P$</td>
<td>0.040 kW/m²</td>
</tr>
<tr>
<td>Lower limit set point $\theta_L$</td>
<td>70°F</td>
</tr>
<tr>
<td>Upper limit set point $\theta_H$</td>
<td>$\mathcal{U}(74°F, 78°F)$</td>
</tr>
<tr>
<td>Initial indoor temperature $\theta_i(0)$</td>
<td>$\mathcal{U}(70°F, 74°F)$</td>
</tr>
<tr>
<td>Thermal envelope area $A_R$</td>
<td>$N'(354, 200^2)$</td>
</tr>
<tr>
<td>Coefficient of thermal resistance $c_R$</td>
<td>$N'(350, 280^2)$</td>
</tr>
</tbody>
</table>

IV. MODELING OF AGGREGATED HVAC LOAD

Every single residence in this study was modeled separately based on (2) and (3) with distinct sets of parameters. Each residential thermal model updates the indoor temperature dynamically considering the outside temperature, thermostat set points, and the DR signals. The aggregated HVAC power was calculated as:

$$P_A(t) = \frac{1}{SEER} \sum_{i=1}^{N} S^i(t)P^i_H,$$

where $N$ is the total number of studied HVAC systems; $P^i_H$ the heat transfer rate of house $i$ in Btu/h.

The parameters of the thermal models across the community of residences were selected to be either a specific constant value, normally distributed, or uniformly distributed (Table II). The values for some parameters of the residential thermal models were the same for all considered houses, i.e., the coefficients $c_C$ and $c_P$, and the lower limit set point $\theta_L$. The upper limit set points $\theta_H$ of all the houses without DR control were randomly generated to represent different user preference, noted as uniform distribution $\mathcal{U}(74°F, 78°F)$. The initial indoor temperatures were randomly generated within the lower limit of thermostat set point, 70°F, and the lowest of the upper limit set points, 74°F, noted as uniform distribution $\mathcal{U}(70°F, 74°F)$. Therefore, the initial temperature for all residences were bounded to the lower and upper set points.
Fig. 9. The distribution of daily HVAC electricity usage on a typical summer day for 10,000 houses in a large community case study. The experimental probability density function (PDF) is estimated based on daily residential electricity usage from the SET project on the same day. The average electricity usage is approximately 21kWh based on the simulation.

The distribution types and parameters related to the house construction, $A_R$ and $c_R$, were selected so that the simulation results matched the experimental data from the SET project. The $A_R$ and $c_R$ for the considered HVAC system models were subject to normal distributions and noted as $A_R \sim \mathcal{N}(354, 200^2)$ and $c_R \sim \mathcal{N}(350, 280^2)$. The daily electricity usages for each of the 10,000 HVAC systems in the example case were calculated and summarized into a histogram with a box size of 1kWh (Fig. 9). Both the experimental data and the simulation results were fitted to a nonparametric kernel-smoothing distribution and their probability density function (PDF) curves are presented in Fig. 9 as well. The comparison between the PDF curves of the simulated data and that of the experimental data demonstrates satisfactory results.

The energy storage capacity for each of the 10,000 HVAC systems was decided by their distinct sets of thermal model parameters, as described previously, and was calculated separately using the methods introduced in Algorithm 1. The results were summarized into a histogram (Fig. 10) to represent the community. The average energy storage capacity for the 10,000 HVAC systems is approximately 11kWh. Given that the typical energy consumption for HVAC systems is calculated at around 21kWh, the HVAC system as an energy storage device was charged/discharged approximately two rounds on the typical summer day in this study.

The simulated working status for the 10,000 participating HVAC systems without DR are shown in Fig. 11. In the early morning, even though the outdoor temperature was higher than the set point, not every HVAC turned ON due to the thermal inertia of the house. At approximately 9:00, many HVACs started to turn ON as the outdoor temperature increased quickly and the homes installation and shading could not prevent or slow heat transfer any longer.

Fig. 10. The distribution of the energy storage capacities of the HVAC systems for 10,000 houses in a large community case study. The energy storage capacity of each residence was calculated separately according to its own set of parameters. The average equivalent energy capacity of the HVAC systems is approximately 11kWh.

Fig. 11. The working status for the simulation of 10,000 participating HVAC systems without DR. Most of the HVAC systems started turning on around 9:00 due to the increase in outdoor temperature.

V. OPTIMAL CONTROL OF THE HVAC SYSTEMS

Two objectives were considered for VPP controls. The first is to reduce the peak power in the afternoon during 12:00 to 16:00:

$$\text{Minimize } P_{\text{max}} = \max \left( P_A(t) \right), \ t \in [12 : 00, 16 : 00].$$

The second is to reduce the ramping rate of the aggregated HVAC power for the entire day:

$$\text{Minimize } \Delta P_{\text{max}} = \max \left( \frac{P_A(t + \Delta t) - P_A(t)}{\Delta t} \right), \ t \in [0 : 00, 24 : 00].$$

The objectives are realized by the central control system operated by the utility, which generates the DR signals for each residence according to one-day ahead weather forecasting data.
The DR control signals for each house include the upper limit thermostat set point, \( \theta_{H,DR} \). When the DR event occurs in this study, the upper limit thermostat set point of the committed residence was changed to \( \theta_{H,DR} = 73\text{F} \) for precooling and 81F for peak reduction.

In this paper, residences committed to the DR control will not overwrite the signals from the utility, for three reasons. First, residences committed to DR control enjoy financial rewards and are bounded by contract [29]. Second, under the DR control, the room temperature would still be kept comfortable for most of the users according to ASHRAE standards as described in previous section. Third, the DR signals from the utility will only be implemented at each house for short durations of time.

Houses are divided into multiple groups, and each group has its own scheduled time to apply the DR control by changing the upper limit thermostat set point. The HVAC systems in the same group apply the DR control for the same period of time. The next group of HVAC systems apply the DR control after a fixed time gap. The behavior of HVAC systems during a DR event is described as follows:

\[
\begin{align*}
\theta_H^1(t_1) &= \theta_{H,DR}, \quad t_1 \in [T_S, T_E] \\
\theta_H^2(t_2) &= \theta_{H,DR}, \quad t_2 \in [T_S + \Delta T_S, T_E + \Delta T_E] \\
&\vdots \\
\theta_H^{n+1}(t_{n+1}) &= \theta_{H,DR}, \quad t_n \in [T_S + n\Delta T_S, T_E + n\Delta T_E],
\end{align*}
\]

(8)

where \( n \) is the group number; \( \theta_H^n \), the upper limit thermostat set points for all houses in group \( n \); \( T_S \) and \( T_E \) are the times when the 1st group starts and ends the DR, respectively; \( \Delta T_S \), \( \Delta T_E \) are the time gap between two groups to start and end DR, respectively.

In the example case, the 10,000 houses committed to DR control were divided into 100 groups, and each of their upper limit thermostat set points are shown in Fig. 12. The horizontal stripes indicate different customer preferences for indoor temperature. Two DR events were applied by changing the upper limit thermostat set points as shown by the blue and red vertical lines. The first DR event occurred in the morning as the upper limit thermostat set points of the first group were reduced to 73F from 7:00 to 8:00. Other groups followed sequentially by reducing their set points after a fixed time gap of 3 minutes between control adjustments, i.e., group two 7:03–8:03, group three 7:06–8:06, etc. Since there are 100 groups, the last batch of residences were precooled from 12:00–13:00.

The second DR event occurred in the afternoon for peak reduction between 12:00 and 16:00 (Fig. 12). Starting from 11:00, the first group of the HVAC systems increased the upper limit thermostat set point to 81F. Other groups increased their set points at a fixed time gap of 3 minutes, in a sequential way. The first group reverted to the original set points at 16:00 and other groups followed with a fixed time gap of 2 minutes, in the proposed staggered pattern. The time gaps to implement the DR control and to resume the original set point of the user are intentionally different to demonstrate the flexibility of the proposed sequential control.

It is worth noting that the DR signal for precooling and peak reduction in this case overlapped between 11:00 and 13:00, for three reasons. First, the precooling was for the reduction of ramping rate. Therefore, if the duration of precooling DR is short, the ramping rate would be large as many HVAC systems are turned ON in a short period of time. Second, if the precooling starts very early, the natural process of heat transferring from outside to the residence will start before the temperature outside has risen to an uncomfortable level, leading to unnecessary additional electricity usage. Third, the overlapping structure provides a buffer time to avoid sudden drops in the aggregated HVAC power.

\[
\text{VI. CONTROL RESULTS AND ANALYSIS}
\]

The time step for the simulations in this section is 1-minute. The simulation results were integrated to 15-minute resolution, which is the conventional time interval used by utilities in metering, to calculate the ramping rate. When 100% of the 10,000 residences participated in the DR control, the working status of the HVAC systems are shown in Fig. 13. The proposed sequential DR control resulted in three clear stripes of HVAC state changes, namely, the one starting at 7:00, the one at around noon, and the one starting at 16:00. The HVAC systems were turned ON and OFF in a sequential way in order to avoid sudden changes of the aggregated power when the thermostat set points were changed by the DR control.

The same 10,000 HVAC systems were simulated using the same outdoor temperature both with and without DR control. The outdoor temperature and average indoor temperatures for both cases are shown in Fig. 14. Also shown are the simulated indoor temperatures of individual houses with the DR control. In the study, the lower limit thermostat set point was fixed to 70F for all the houses. The upper limit thermostat set points for
all the 10,000 houses were uniformly distributed in the range of [74F, 78F] in order to represent various user preferences.

When the DR signal arrived in the afternoon, the upper limit thermostat set points for the batch of houses under control were set to 81F. In Fig. 14, only the highest value of the upper limit thermostat set point from all the residences at each time step was plotted. For example, when there was no DR signals, the upper limit thermostat set point for all the residences was between 74F and 78F (θ_H ∈ [74F, 78F]). When there was DR signal for precooling in the morning, θ_H ∈ [73F, 78F], and where the DR signal was for peak reduction, θ_H ∈ [74F, 81F]. The θ_H in the plot was 81F when there was DR control for peak reduction in the afternoon, and 78F for other durations.

The selection of the maximum allowed indoor temperature, which is 81F for the illustrated example, is based on a combination of human comfort regulations, as per ASHRAE Standard 55-2017, and user behavior preferences, as expressed through enrollment in different DR schemes that trade comfort controls versus unitary electricity cost [13]. It should be noted that the average temperature for all homes does not exceed 75F at any time and that only very few homes, which selected a minimum electricity cost DR program option, reach the 81F maximum temperature after 17:00, and even then, only for a very short duration of time.

The indoor temperature of all 10,000 residences were presented with a sampling frequency of 30-minute in boxplot (Fig. 15). When the residences were precooled (bottom), their indoor temperatures were lower at around 9:00, which allowed more HVAC systems to stay OFF and reduced the ramping rate. In the afternoon, the maximum indoor temperature of some residences reached 81F under the DR control, which was the highest temperature still acceptable for most users under the conditions explained in the previous section. Even so, given any time point, the indoor temperature for 75% of the residences was no more than 78F, which appeared at 16:00.

The equivalent SOC for the houses without DR is shown in Fig. 16. The HVAC systems operated as energy storage devices were “discharged” at different levels due to the various upper limit thermostat set points. None of the houses were “discharged” thoroughly to 0% without DR control.

Some of the HVAC systems were thoroughly “discharged” to 0% at the critical hours due to the DR control, as shown in Fig. 17. The sequential control implemented in this study avoided “discharging” all the HVAC systems to 0% at the same time, in order to avoid the large rebound ramping rate afterwards. The aggregated SOC started to decrease from 12:00, indicating the equivalent “discharging” process as use of stored energy. This demonstrates that the HVAC systems could operate comparably with the batteries.

The proposed sequential DR control strategy is exemplified by this study that successfully results in a very large reduction of the peak power from 12:00 to 16:00 through temporarily allowing higher temperatures inside the participating homes. The indoor temperatures in Fig. 14 were the results for 100% participation of 10,000 residences on an example summer day.
Fig. 16. Simulation results of the equivalent SOC for the 10,000 HVAC systems studied without DR control. None of the houses were “discharged” thoroughly during the peak hour.

Fig. 17. Simulation results of the equivalent SOC for the 10,000 HVAC systems studied with DR control. Houses were fully “discharged” as the equivalent SOC reached 0% at different period of time. The aggregated equivalent SOC did not reach 0% because not all the houses were fully “discharged” at the same time. The sequential DR control was implemented to avoid the large rebound ramping rate afterwards.

The corresponding aggregated HVAC power and equivalent SOC are shown in Figs. 18 and 19 with different residence participation for the same day. The simulation results for different residence participation levels are summarized in Table III where it can be seen that the ramping rate and total daily electricity usage are decreased with more participation. The residences participating in the simulated DR program were selected based on their house ID in ascending sequence in this study.

The aggregated HVAC power from Fig. 18 shows that, under normal operation without DR controls, the ramping rate around 8:00 was large due to many HVAC systems starting around the same time, and the peak power from 12:00 to 16:00 was high due to high outdoor temperature. The ramping rate, peak power in the afternoon, and the total daily HVAC electricity were reduced under the proposed sequential control, even with low residence participation. When the participation rate is high, e.g., 100%, the peak power period for the DR case was shifted to a later time as a consequence of indoor temperature recovery, and in addition, the ramping rate was greatly reduced.

The aggregated equivalent SOC of the 10,000 HVAC systems shown in Fig. 19 demonstrates the effectiveness of the proposed sequential DR control scheme, which provided benefit to the utility as described while still resulting in a near 65% aggregated equivalent SOC as was the same as on

<table>
<thead>
<tr>
<th>Participation [%]</th>
<th>$P_{max}$ [MW]</th>
<th>$\Delta P_{max}$ [MW/15-min]</th>
<th>Daily Elec. [MWh]</th>
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</thead>
<tbody>
<tr>
<td>0 (w/o DR)</td>
<td>21.3</td>
<td>36.2</td>
<td>213</td>
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<td>25</td>
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<td>100</td>
<td>16.8</td>
<td>23.4</td>
<td>203</td>
</tr>
</tbody>
</table>
the day before DR was applied. Another important note is that the total energy storage capacity for the 10,000 residences was fixed because the energy capacity of each HVAC system was fixed, as explained in Section III. The equivalent precharging process, which started from 7:00, avoided significant power draw at 12:00 and large ramping rate starting from 9:00. The peak power in the afternoon from 12:00 to 16:00 was reduced by the equivalent discharging process. The proposed sequential DR control managed to postpone the equivalent charging process to 18:00.

The outside temperature is stochastic and therefore, the DR control scheme for the simulation of aggregated HVAC power as an energy storage resource was repeated on two additional different hot days in the summer (Fig. 20). In this paper, the proposed sequential control was demonstrated in the hot days because the fuel for space cooling is 100% electricity, and the peak reduction is only needed when the HVAC systems have high power. The proposed sequential control was not shown for cold days as some of the residences might use fuels other than electricity for heating [30]. Therefore, the results of the sequential control for cooling are directly related to the number of residences participating in the DR control, while for heating, the portion of electricity-heating houses must be considered.

The simulation results for different summer days are presented in Fig. 21 and summarized in Table IV. In this comparison, the DR control participation was considered 100%. The case study for w/o DR and 100% participation in Fig. 18 and Table III is referred as “Day: 7/14” (middle).

The case “Day: 7/7” (top) represents a slightly cooler summer day. The proposed sequential control reduced the already low ramping rate by precooling and peak power by turning ON the HVAC systems in batches during a longer time span. The total daily electricity usage was increased by 2% under the proposed DR control due to the precooling. This happened because lower temperature in the morning resulted in more heat transferring into the houses.

The case “Day: 7/22” (bottom) represents a very hot day when the ramping rate and peak power of the aggregated HVAC power without DR control were high. The proposed sequential control reduced the maximum ramping rate by 35% and the peak power during 12:00 to 16:00 by 16% while the total daily electricity maintained nearly the same.

The aggregated equivalent SOC of the 10,000 residences for the three different days are shown in Fig. 22. For the 7/7 case (top), the equivalent SOC was maintained higher starting from 9:00 because of the precooling to avoid high ramping rate for “charging” starting from around 10:30. For the 7/14 case (middle), the precooling started from around 7:30, avoiding high ramping rate starting from around 9:00. For the 7/22 case (bottom), the precooling moved the equivalent “charging” process from 6:00 to early morning, reducing the ramping rate. For all the cases, the lower equivalent SOCs in the afternoon demonstrate the HVAC system can “discharge” as energy storage to reduce the peak power.

VII. CONCLUSION

This paper proposes an aggregation technique for the modeling of HVAC systems in large communities that is based on the robotic house managed by the Tennessee Valley Authority (TVA). This house is considered typical by their analysis and emulates human behavior with the operation schedules for the appliances inside. The proposed aggregation technique
employs a realistic distribution of parameters and loads, which were derived with data from the SET Project, one of the largest smart grid field demonstrators in rural America. The example building model and its equivalent circuit parameter values provide a useful reference that is suitable for Virtual Power Plant (VPP) and demand response (DR) studies of HVAC systems in large residential distribution systems.

Also proposed is a VPP sequential control scheme that temporarily allows higher indoor temperatures up to values that are still considered acceptable for typical preferences and standard regulations of human comfort. The results based on 10,000 HVAC systems show that, on a very hot summer day, when the DR participation was 100%, the peak power in the afternoon and the ramping rate were reduced by approximately 16% and 35%, respectively while the daily energy usage was almost the same. This paper also develops an equivalent energy storage model for HVAC systems and demonstrates that HV AC systems can be controlled in a charging/discharging procedure almost the same. This paper also develops an equivalent energy storage model for HV AC systems and demonstrates that HV AC systems show that, on a very hot summer day, when the DR participation was 100%, the peak power in the afternoon under DR control and reduced the peak power.

Fig. 22. Simulation results of the aggregated equivalent SOC for the 10,000 HVAC systems on different hot days (top to bottom: 7/7, 7/14, 7/22). With the DR control, the equivalent precharging process in the morning reduced the ramping rate. The HVAC systems as energy storage discharged deeper in the afternoon under DR control and reduced the peak power.

VIII. ACKNOWLEDGMENT

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REFERENCES


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