Co-simulation of Smart Grids and Homes including Ultra-fast HVAC Models with CTA-2045 Control and Consideration of Thermal Comfort

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Abstract: A novel co-simulation framework was developed and demonstrated through virtual power plant (VPP) simulations that include hundreds of unique building models randomly populated into a modified IEEE 123-bus feeder system. The framework employs ultra-fast models for heating, ventilation, and air-conditioning (HVAC) systems as well as building thermal envelopes that are satisfactorily accurate for both electric power and indoor temperature. The approach circumvents generic control time limits typically in conventional implementations by enabling occupant thermal comfort monitoring. The HVAC and building models contain parameters by which they are characterized as generalized energy storage (GES) systems based on Energy Star definitions. This enables their compatibility with the Consumer Technology Association (CTA) 2045 standard control commands and event types. Example CTA-2045 "shed" events are illustrated to exemplify this feature and to analyze power distribution system effects in terms of power flow and voltages.

***Index Terms*—Building Energy Model, co-simulation, CTA-2045, Generalized Energy Storage (GES), HVAC, machine learning, OpenDSS, power distribution system, smart grid, smart home.**

I. Introduction

Residential communities use approximately 25% of total annual energy in the U.S., with heating, ventilation, and air-conditioning (HVAC) systems, accounting for the largest end use at about 50% [1]. The application of virtual power plant (VPP) control for HVAC systems, in aggregate, offers a significant opportunity for decreasing total energy use and the shift or reduction of load peaks [2]. Load control, especially for electric power distribution systems with highly variable distribution-side generators such as solar photovoltaic (PV) systems, is an invaluable tool for utilities in managing the emerging smart grid.

Simulation testbeds play an important role in both the development of such VPP control schemes and in the planning of distributed energy resource (DER) deployment [3]. Battery energy storage systems (BESSs) can be an effective, but costly, utility grid energy management solution and, therefore, are typically optimally planned through distribution system simulation [4]. Control strategies that coordinate multiple types of DERs, such as BESSs and solar PV, are an integral aspect of the smart grid which can be developed and tested through simulation [5].

This paper presents a novel co-simulation framework that acts as a testbed for control strategies that may employ various generalized energy storage systems (GES), particularly HVAC systems, and distributed energy resources (DER). The provided case study exemplifies simulated demand response (DR) control of ultra-fast HVAC system models in accordance with the Consumer Technology Association (CTA) 2045 standard [6] through characterization as GES based on Energy Star definitions.

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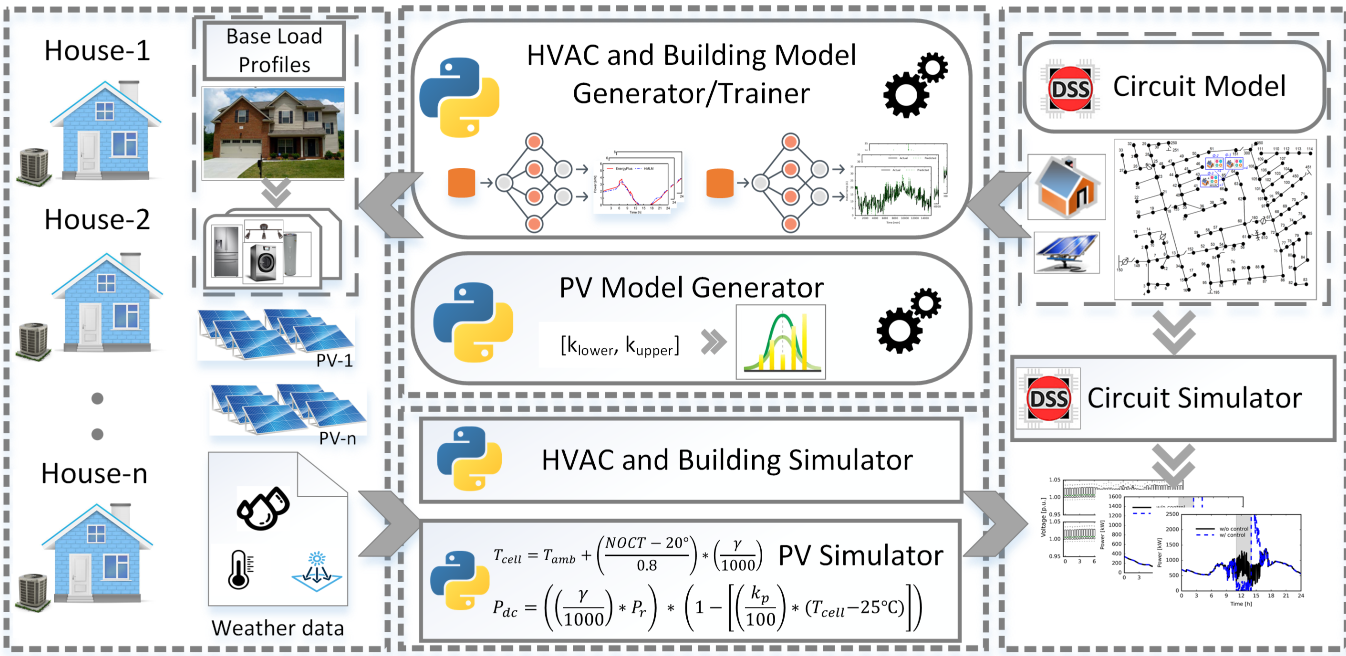

Figure 1. Schematic illustration of the newly developed co-simulation framework with multiple building models and HVAC CTA-2045 control implementation. The framework employs ultra-fast HVAC system and building thermal envelope models with distinct base load energy profiles for typically human behavior-based loads. Using OpenDSS software, a full representative community of individually unique building models for both electric power and indoor temperature is simulated. It is also capable of incorporating other DER types, such as solar PV and battery energy storage (BES) systems.

II. Co-simulation Framework and Generalized Energy Storage

A large novel co-simulation framework has been developed that employs many software features, including the Electric Power Research Institute (EPRI) open-source distribution system simulation software (OpenDSS) and ultra-fast hybrid machine learning models (HMLM) for HVAC system load and indoor temperature, to act as a test bed for control schemes, GES, and DER deployment (Fig. 1).

Considering occupant thermal comfort is a major challenge in conventional implementations, and, therefore, a generic time limit for HVAC control events are typically employed. Such limits can be inadequate in preventing violation of typical thermal comfort limits for occupants. Improved control methods through the CTA-2045 standard for DER control types and GES characterization based on Energy Star definitions are proposed in the following in order to address the issue [7].

HVAC systems, considering the thermal properties of the building in which they operate, may be defined as GES, which is made possible through analogies of equivalent state-of-charge (SOC) and energy storage capacity [8]. The equivalent SOC and "current available energy storage capacity" of an HVAC system may be respectively defined by:

$$SOC_H(t) = \frac{\theta_{max} - \theta_I(t)}{\theta_{max} - \theta_{min}}, \tag{1}$$

$$E_{C,H}(t) = \overline{E_{H,C}} \cdot (1 - SOC_H(t)), \tag{2}$$

where the θ_{max} and θ_{min} are the maximum and minimum room temperature, respectively; θ_I, the indoor temperature; $\overline{E_{H,C}}$, the input electric energy required to reduce house indoor temperature from its maximum to its minimum while experiencing indoor temperature change from external weather conditions as well.

During simulation, the HVAC system and building models, discussed further in Section III and generally illustrated in Fig. 2, determine their corresponding electric energy capacities internally upon initialization and for each timestep as outdoor temperature changes. This captures the system's dependency on weather for energy capacity, which is a phenomenon also experienced by conventional electric energy storage systems.

When a control event is issued, such as "shed", a change to the setpoint is determined by translating from SOC and the energy capacity of the particular model at the time of issuance. Calculating the setpoint change in this way considers the individual system characteristics, enabling more accurate prediction of the maximum energy which may be used from the demand-side without violation of indoor temperature limits.

III. Aggregate Building Modeling

The building models utilized in the co-simulation framework may be organized into four (4) components: HVAC system, thermal building envelope, residential solar PV system, and base load (i.e. other home appliance electric load). Three houses representative of a spectrum of energy efficiency, from conventional performance to near-net-zero energy (NNZE), were modeled and calibrated in EnergyPlus [9]. EnergyPlus

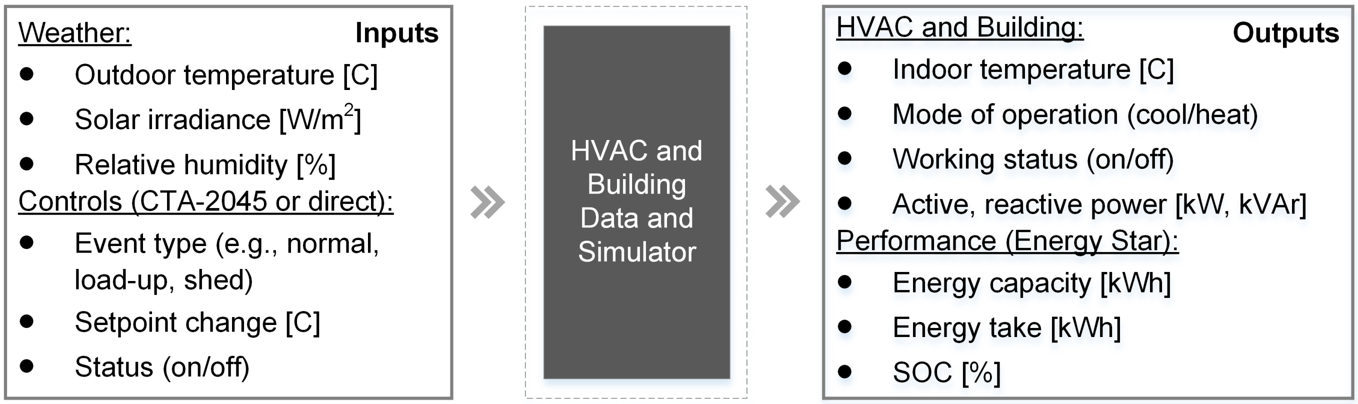

Figure 2. Schematic of HVAC building time dependent simulator capable of executing both explicit commands and CTA-2045 events, as well as providing Energy Star GES performance, such as electric energy capacity, energy take, and equivalent SOC.

is a well established simulator for whole-building simulation and considers physics-based principles related to building construction, including the thermal envelope, as well as weather characteristics for the calculation of HVAC system energy use.

A machine learning (ML) process was applied to train and develop new black and grey box versions of EnergyPlus models through methods including multi-linear regression (MLR), k-means clustering for weather grouping, and thermodynamic equations for specific heat conversions (Fig. 2) [10]. This process enables both ultra-fast simulation and straightforward integration with other software as incorporated in the co-simulation framework discussed in Section II and illustrated in Fig. 1.

The training produces multiple models, which are satisfactorily accurate in capturing both the heating and cooling thermal energy use of the HVAC system, as well as the indoor temperature behaviour of the building, while experiencing external weather effects. The inclusion of building indoor temperature enables the tracking and prediction of thermal comfort for occupants, which is a notable contribution and is integral for improved HVAC control.

Through the new EnergyPlus Python plugin, software was developed to generate many unique EnergyPlus building models by varying internal HVAC and building characteristics, while using the three models discussed previously as a basis (Fig. 3). HVAC system performance characteristics include the heating and cooling thermal energy capacities, coefficients of performance (COP), and air flow rates. The varied building thermal properties include conductivity, thickness, density, and specific heat of construction materials such as studs, insulation, and associated air cavities for walls and roofing as well as for attic trusses and additional ceiling insulation. Window U-factors and solar heat gain coefficients (SHGCs) were also considered.

Assuming a normal distribution between endpoints determined by the properties of the conventional and NNZE base models, 351 EnergyPlus building models were generated for the case study described in section IV. The building models correspond to electric distribution circuit nodes for power system analysis, which is further discussed in section V.

The generated EnergyPlus models are then simulated for an example location and time based on weather data to produce synthetic data of HVAC energy use and indoor building temperature for the ML training process. For the following example, a typical meteorological year (TMY) for Knoxville, TN was selected as it was the original location of the actual buildings by which the base models were calibrated. It should be noted that the ML versions of the models trained on this synthetic data are not limited to the location for which the EnergyPlus input weather data is representative. The ML models capture the thermal properties of the building and thermal energy characteristics of the HVAC system and their relationship with weather, regardless of the weather experienced.

Unique residential solar PV systems of typical power ratings within a range of 3kW to 7.5kW were also assigned to 52 (15%) of the building models and simulated based on weather data through physical equations (Fig. 1). Unlike HVAC and PV systems in the studies, other typical household appliances and devices are primarily human behaviour-based and not dominantly weather dependent. Therefore, each building was assigned a random day of energy use for other typical house loads. The schedules were based on minutely measured household energy use data sourced from the EPRI SHINES project [11].

IV. Case Study for HVAC Systems with CTA-2045 Control

With the building models prepared, two "shed" events were applied to the HVAC systems. The first event, in the morning from 6:00 to 8:00, reduces the peak that occurs due to many HVAC systems beginning operation at similar times as the cooler night transitions into a much hotter day with significant solar irradiance.

HVAC systems use more energy when experiencing a large change in temperature, such as when the sun rises, to prevent

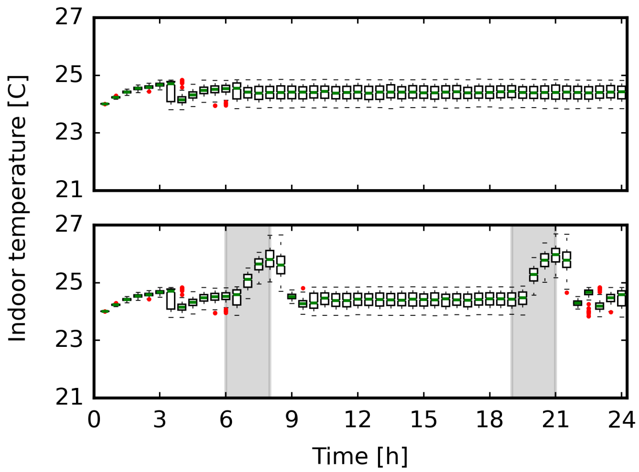

Figure 3. Indoor temperatures of the individual buildings for both the baseline and shed cases. The grey areas represent the periods during which the "shed" events were applied. Indoor temperatures deviate during the events and are reduced afterward at different rates due to the unique thermal characteristics of each building.

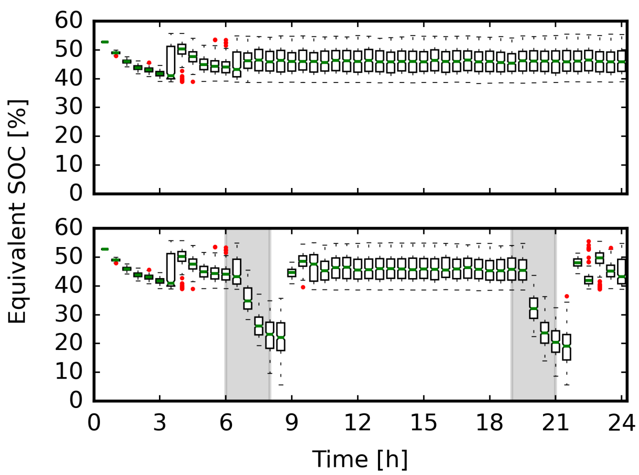

Figure 4. Equivalent SOC of the individual buildings as defined in terms of GES. Sampling was conducted every 30 minutes for both the baseline and shed cases.

indoor temperatures from rising quickly with the outdoor temperature. By noon, they settle into normal operation and maintain the indoor temperature with less energy use since outdoor temperature experiences relatively small change until sunset. The solar PV generation and lower base load from occupants leaving the house in the midday also contribute to this morning peak and create an additional peak in the evening (Fig. 5). The second "shed" event is issued from 19:00 to 21:00 to successfully reduce this peak.

During a control event, the HVAC systems respond individually by determining a new setpoint based upon their electric energy capacities and equivalent SOC as well as a set maximum temperature considered to be the limit to which

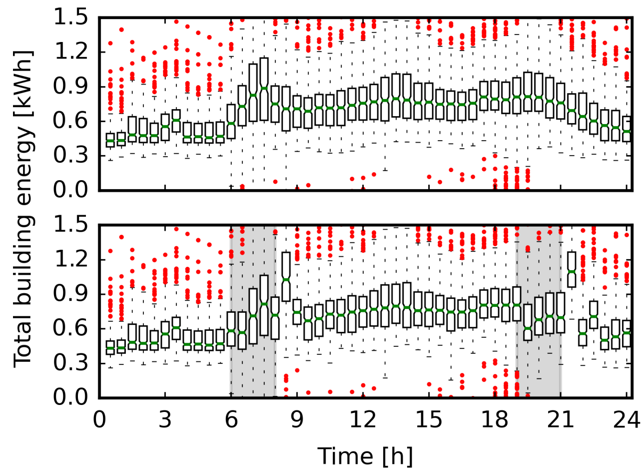

Figure 5. Total energy use of the individual buildings, including the HVAC system and base load, summed in increments of 30 minutes for both the baseline and shed cases.

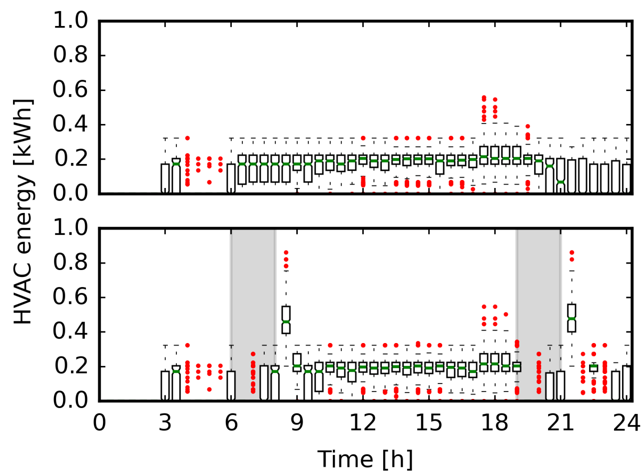

Figure 6. HVAC system energy use of the individual buildings summed in increments of 30 minutes for both the baseline and shed cases. Sharp increases in energy use are observed immediately after control periods to quickly reduce indoor temperature of many buildings to setpoint simultaneously. Some energy use occurs during the control windows for cases in which maximum setpoint (or minimum SOC) was reached early.

occupant comfort would be violated according to ASHRAE standards [8]. This causes indoor temperatures and "energy take" to rise during the control period at different rates as equivalent SOC depletes until minimum charge (corresponding to maximum indoor temperature) is reached (Figs. 3, 4).

The HVAC systems will not use energy until the new setpoint (or minimum SOC) is reached. It may be observed in Fig. 4 that some of the HVAC systems reach their minimum SOC before the event ends, causing more energy use toward the end of the control period than the beginning (Fig. 6). This novel control method ensures that occupant thermal comfort limits would not be violated.

HVAC systems that did not operate during the control period

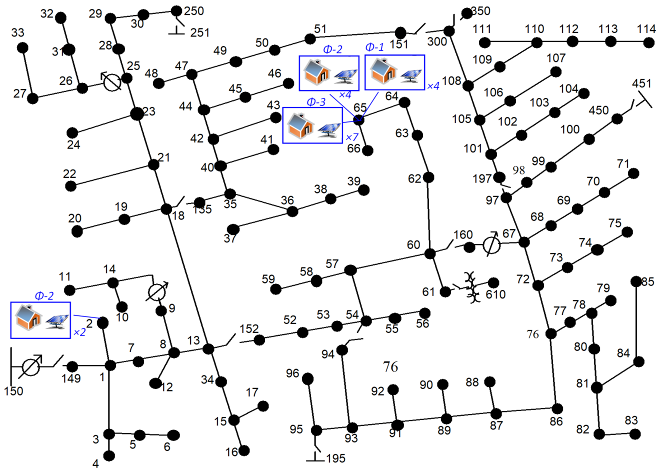

Figure 7. The circuit diagram for the modified IEEE 123 test system employed for the case study. The original circuit has a peak load of 3.6MW, 1.3MVAr and is to be representative of a very large residential subdivision in the U.S.

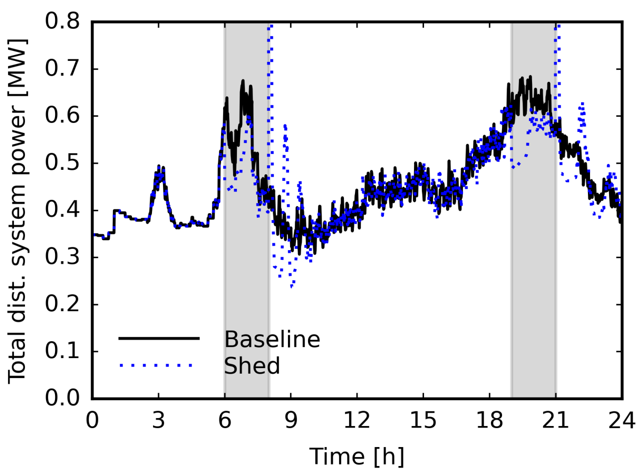

Figure 8. Total active power for the distribution system for both the baseline and "shed" event cases. Both morning and evening peaks are successfully reduced by about 53kW (9.4%) and 75kW (11.8%), respectively. Sequential control to phase in HVAC systems may be applied to alleviate the spikes in power of around 1.6MW and 1.8MW observed upon event completion [8].

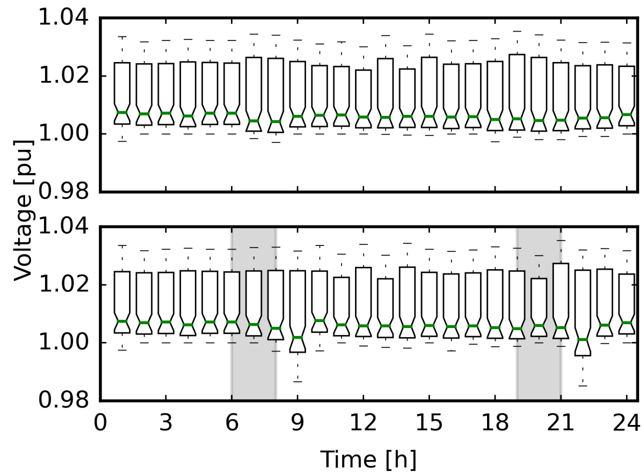

Figure 9. The voltage of all system buses for both the baseline and "shed" event cases sampled every hour. Notable voltage variation occurs during the power spikes illustrated in Fig. 8 while remaining within the acceptable 5% deviation.

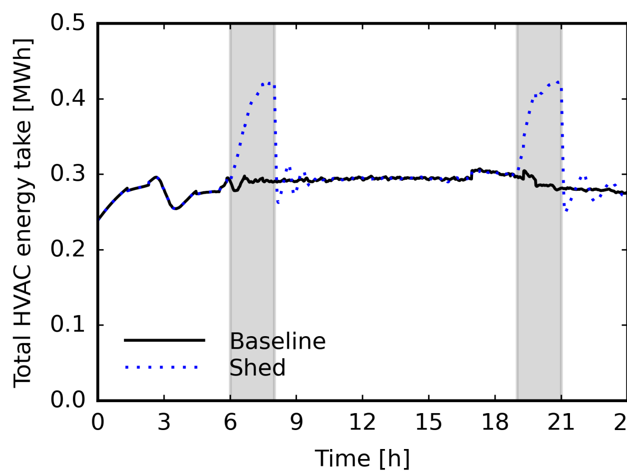

Figure 10. The total energy take of the HVAC systems for both the baseline and "shed" event cases. This illustrates the displaced energy due to the control events.

due to the superior insulation and higher thermal inertia of their associated building envelope will resume cooling simultaneously once the "shed" event is complete. This phenomenon is due to the HVAC systems' programming to reduce indoor temperature to the original temperature setpoint as fast as possible (Fig. 3).

V. Power Distribution System Analysis

The co-simulation framework was utilized to simulate a very large subdivision in the U.S. with the buildings randomly populated at appropriate connection nodes throughout a modified IEEE 123 bus test distribution system (Fig. 7). The initial load allocation of the test power system was considered by assuming 10kW at each of the original peak load settings corresponds to a single building. This method resulted in 351 uniquely generated building models within the example power distribution system for both baseline and "shed" event cases. Co-simulation with OpenDSS allows for analysis of the aggregate effects of the buildings at the distribution system system level.

The total system active power and bus voltages are observed with studies of power losses, reactive power, and voltage violations also possible. The "shed" events successfully reduce the morning and evening peaks by an average power of about 53kW (9.4%) and 75kW (11.8%), respectively. Anticipated spikes in total system power of about 1.6MW and 1.8MW occur after the control events due to many of the HVAC systems resuming operation collectively once the control period ends as discussed in section IV (Fig. 8). This phenomenon effectively displaces most of the energy that would have been used during the two-hour control periods to time windows of only a few moments that occur immediately afterward (Fig. 10).

It should also be noted that this sudden maximum cooling in many of the buildings induces a transient response in power caused by indoor temperatures overshooting their cooling setpoint due to thermal inertia. In turn, the HVAC systems cease operation to allow temperatures to increase. With the example day being very hot and with considerable solar irradiance, the houses heat up quickly, causing another much smaller spike in power. This behavior continues as a ripple effect until all of the HVAC systems settle into normal operation as illustrated in the baseline case.

Changes in bus voltages were minimal during the “shed” events when compared to baseline in Fig. 9, which provides voltages of each bus in the example power system sampled hourly. Increased voltage variation was detected for the hours in which the power spikes occur, but bus voltages remained well within the acceptable levels of 0.95 to 1.05p.u.

Additional control strategies may be applied to alleviate these anticipated spikes in power and associated system transients as well as to minimize variation in bus voltages. Sequential control of the HVAC systems is a method in which the systems are gradually phased in over time [8]. Allowing the HVACs to resume operation in a sequential order in this way expands the time window in which the displaced energy from the control may be used, effectively eliminating the power spike.

VI. Conclusion

A novel co-simulation framework was developed and presented with example simulation results at the component and full system level. The framework utilizes new ultra-fast HVAC and building thermal envelope models that are satisfactorily accurate for both electric power and indoor temperature, enabling monitoring of occupant thermal comfort. These models are also characterized as GES based on Energy Star definitions, such as electric energy capacity, energy take, and equivalent SOC. Considering the HVAC systems as GES enabled the development of novel advanced control mechanisms, which comply with the CTA-2045 standard, that prevents the violation of occupant thermal comfort according to ASHRAE standards.

A method of HVAC and building model generation and randomized allocation of 351 unique houses into the IEEE 123-bus feeder system was employed for power distribution system simulation. A case study with CTA-2045 “shed” control events to reduce load peaks experienced in an example residential power distribution system for a summer day in Knoxville, TN is provided. The morning peak is successfully reduced by an average power of about 53kW (9.4%) and the evening peak by 75kW (11.8%). Transient responses with power spikes are observed upon completion of the control events due to many of the HVAC systems resuming operation simultaneously to quickly reduce indoor temperature to the original setpoint. Additional control of the HVAC systems to gradually phase them back into operation in a sequential order is proposed to alleviate this response and may be included in future work.

VII. Acknowledgment

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