Smart Home HVAC Digital Twin ML Meta-model for Electric Power Distribution Systems with Solar PV and CTA-2045 Controls

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***Abstract*—Building modeling, specifically heating, ventilation, and air conditioning (HVAC) load and equivalent energy storage calculations, represent a key focus for decarbonization of buildings and smart grid controls. In this paper, an ultra-fast one-minute resolution Hybrid Machine Learning Model (HMLM) is proposed as part of a novel contribution in the field of residential physics-based smart home surrogate modeling. Emulation of white box models, or digital twins, with editable parameters through machine learning (ML) meta-modeling serves as an alternative to wide-spread experimental big data collection. The HMLM employs combined k-means clustering with multiple linear regression (MLR) to emulate minutely HVAC power timestep-to-timestep with satisfactory nRMSE error of less than 10% across an entire year test set. An approach is also described to characterize HVAC systems as generalized storage (GES) devices to unify household appliance and virtual power plant (VPP) controls in accordance with industry Communication Technology Association (CTA) 2045 protocol and Energy Star metrics. Synthetic output data from experimentally calibrated EnergyPlus models for three existing smart homes managed by the Tennessee Valley Authority (TVA) is employed in residential case studies and a discussion provided for the large-scale application to hundreds of homes.**

***Index Terms*—Heating Ventilation and Air Conditioning (HVAC), Machine Learning (ML), Surrogate Model, General Energy Storage (GES), ANSI/CTA-2045-B, Energy Star, Energy Take, Home Energy Management (HEM), Demand Response (DR), Smart Homes, Smart Grid**

I. Introduction

The heating, ventilation, and air conditioning (*HVAC*) system should be considered an important component for building decarbonization because of the current large proportion of residential load and the projected growth of 59% by 2050 [1]. Single family consumption was the majority of the forecasted increase, indicating a need for improvements in adaptability of HVAC system power and energy modeling for future looking models with changes to energy efficiency. To evaluate the HVAC energy performance, there are three different methods to developing digital twins for simulations: a physics-based model known as a "white box", a statistical or data driven model called a "black box", and a hybrid model that combines both white and black box known as a "gray box" model.

For white box modeling, there are many detailed characteristics required, such as the type of HVAC system, seasonal energy efficiency ratio (SEER) rating, and building characteristics e.g., insulation, air flow rate, ventilation, indoor/outdoor climatic conditions, door and window types, size/area, etc. Due to the number of parameters, which may be difficult to obtain, and the multi-physics equations involved, these models are time consuming to develop and simulate [2]. Though, the physics-based complexity provides the benefit of adjustable parameters, which includes the SEER and energy efficiency ratings of appliances.

Black box models may overcome some of the drawbacks of other models because of experimental or synthetic data training and quick operation with lower memory resources. The integration of black box, machine learning (ML) models into co-simulation platforms and model-in-the-loop calculations enables faster building model analysis such as the real-time optimization of energy storage (ES) in [3]. Development of new ML algorithms may improve the accuracy and capability of residential load component and energy modeling specifically for HVAC systems, which have been identified in low numbers and in need of further development [4].

Furthermore, the long-standing field of surrogate models, specifically meta-models in which ML models train on the output of another model, has been applied to building energy modeling (BEM). Within the past decade, 2010-present, this topic in academic research has expanded significantly. The recently developed workflow emulates computationally heavy white box digital twins such as EnergyPlus [5] with lighter black box models. This approach was found to be most common in office or commercial buildings focusing around input parametric studies for outputs of HVAC power or energy as well as indoor temperature [6]–[12].

Within these works, general trends included emphasis on generic models for building configurations, the benefits of meta-modeling or ML surrogate models for real-time and model predictive control (MPC), and improved memory usage and computational time. In a directly relevant example, multiple EnergyPlus models for a school, an office, and a

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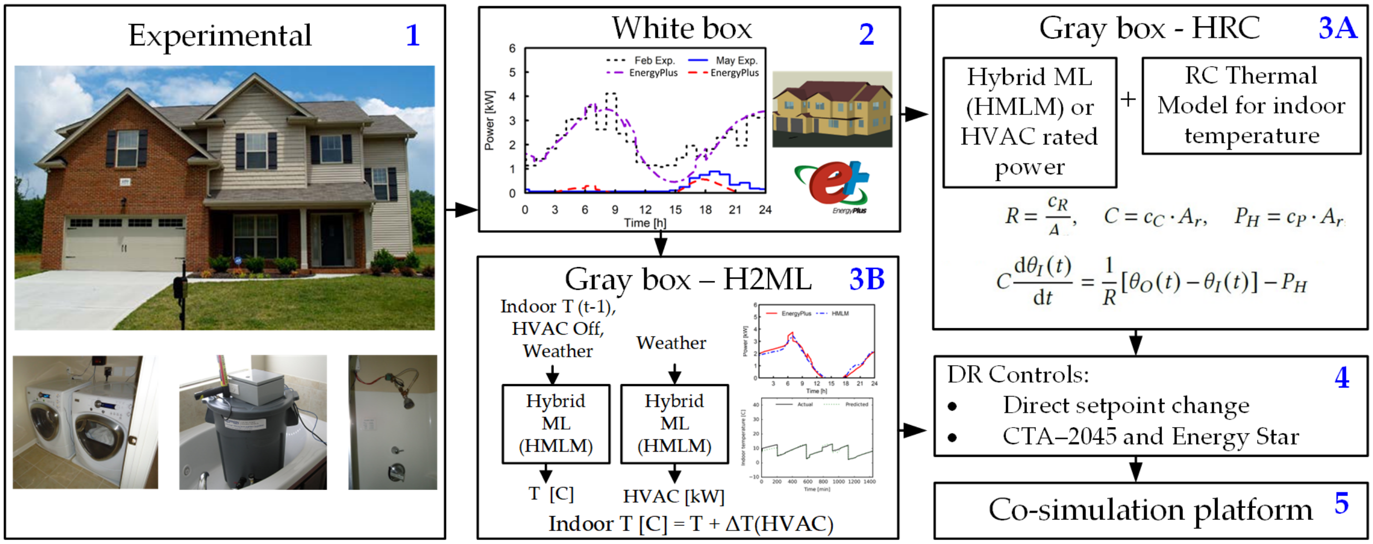


Fig. 1. The three step meta-modeling procedure for ultra-fasted ML digital twins of HVAC power and indoor temperature with steps 4 and 5 for the applications of controls and co-simulation platforms. Experimental data and building characteristics (1) were employed to calibrate a white box model, EnergyPlus-based digital twin (2). Then, the resulting synthetic output data was utilized in training a black box ML model. This procedure produces two gray box modeling approaches (3A and 3B) that are suitable for co-simulation platforms to greatly reduce simulation time compared with the original white box model.

hospital were emulated with ML models. The annual runtime was reduced from 10 minutes to 10 seconds, and a call issued for meta-model digital twins in network wide simulations [7]. Additional works with different building types that exemplify the versatility of the approach include [13], [14].

Residential building meta-modeling case studies were found to be sparse, which can be partially explained by limited data availability to researchers. A very recent residential meta-modeling effort in 2023 employed the ResStock large public dataset of census and survey residential data with EnergyPlus to train a single meta-model on hundreds of houses to output the total building end-use load (kWh) [15]. Inputs include weather and building parameters traditionally employed by physics-based simulators. The ML surrogate model was able to predict with low residual error for homes in new climate regions without having to first train a physics-based digital-twins in EnergyPlus. Other residential meta-modeling examples also considered applications of building design and controls in different locations, utilization of the meta-models with occupant comfort, setpoint inputs, and usefulness of this approach toward responses to climate change [16]–[18].

Over 50 meta-modeling references, which include design optimization, model calibration, and energy forecasting in building and district levels, have been summarized [17]. Research on residential meta-modeling or surrogate models of physics-based digital twins were identified as a gap in the literature. Additionally, all prediction horizons and time steps were 15min, hourly, monthly, or annually. Higher resolution models with adaptable HVAC SEER levels would be beneficial in co-simulation frameworks for residential distributed energy resources (DERs) and virtual power plant (VPP) control impact assessments, a gap addressed in this paper.

The main contribution of this paper is the development of residential meta-modeling with hybrid ML models (HMLMs) at high, minutely resolution to emulate building HVAC system operation from calibrated EnergyPlus digital twins. The proposed five step procedure employs meta-modeling to learn the output of the white-box models with faster and more interoperable black and grey box models that may be connected to co-simulation frameworks to receive control signals (Fig. 1). This paper is an expansion of conference proceedings paper [19] with further details of the ML modeling and additional contributions including high resolution HVAC case studies employing CTA-2045 industry protocol for VPP operation, and Energy Star metrics for general energy storage (GES) quantification of HVAC systems. A case study and discussion of the application of the ML meta-modeling procedure for the development of large synthetic communities of realistic houses suitable for co-simulation studies with distributed energy resource management systems (DERMs) is also provided.

II. Meta-Learning Method for Residential Smart Homes

Within this paper, two options for gray box meta-modeling are described toward computationally light and scalable building digital twins for co-simulation frameworks and VPP studies with highly variable DERs. In step 3A, a HMLM for the HVAC power and a thermal equivalent RC circuit for the indoor temperature change during controls is referred to as *HRC* standing for HVAC and RC circuit. In step 3B, both the HVAC power and indoor temperature change were modeled with HMLMs and are referred to as *H2ML* standing for HVAC through 2 ML models.

The EnergyPlus output HVAC system data was a synthetic dataset at the minute resolution based on experimental data with original resolutions of 15 minutes for both improvement

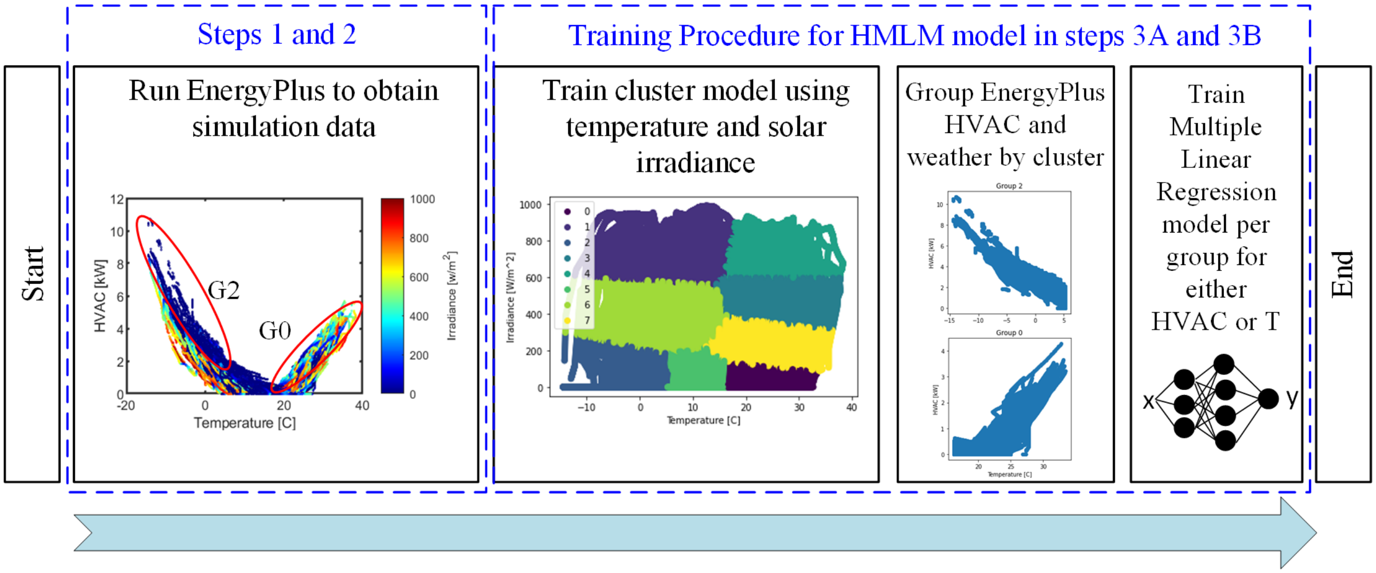


Fig. 2. The architecture of the training procedure for the hybrid ML model (HMLM) with k-means clustering and MLR using EnergyPlus simulation output data as employed in steps 3A and 3B from Fig. 1. The approximately linear trends of the HVAC system and outdoor temperature over the course of the year are isolated to improve performance of HVAC models across seasons and different types of days.

in the timestep length and computational requirements. The homes were treated as representative based on its building characteristics and experimentally based calibration process. For both minute-to-minute calculations and control, the smart home model for HVAC includes two sub-modes of operation: normal and transition for DR controls.

The proposed H2ML and HRC meta-modeling methodologies for VPP studies require significant time and data processing commitment to first construct calibrated EnergyPlus homes, scale them, and then create surrogate ML models of each. For this reason, the benchmark ML procedure with multiple linear regression (MLR) is demonstrated as highly satisfactory because it substantially passes building modeling standards as discussed further in Section III. Deep learning neural network models are considered the state-of-the-art artificial intelligence models and have been demonstrated as highly capable in experimental HVAC forecasting, such as in a novel method for separation from total load [20]. The use of deep learning may be applied to further improve the results in future studies. Special consideration to the selection of neural network configuration parameters such as the number of layers, batches, epochs, neuron nodes, and training and validation set size would be required per cluster grouping. Such tuning requires an increase in time to properly train the synthetic HMLM models in comparison to MLR as a benchmark.

A. Hybrid ML Model Training for Step 3A

In the proposed HRC methodology (step 3A), the HMLM was utilized for “normal” power operation and a thermal equivalent RC model was employed for transition between setpoint changes. In normal operation without controls, the indoor temperature was assumed equal to setpoint because this was the state of the training set from EnergyPlus. To train a HMLM for use as normal operation as part of a smart home digital twin, a two-part procedure to classify weather conditions and model the HVAC power was employed as visualized in Fig. 2.

First, k-means clustering was performed on input weather parameters that have the most influence over the HVAC load linearity, i.e. outdoor temperature and solar irradiance over an entire year. Different subsets of the inputs were labelled to isolate circumstances under which the HVAC system of a home would operate similarly, such as hot bright days in the summer, mild days in the shoulder months, and colder dark days in the winter. In Fig. 2, the V-curve of HVAC power by temperature visualizes example approximately linear HVAC groupings caused by different weather conditions.

Second, an MLR model was trained for each of the subsets differentiated by the group labels, and these are saved for use with their respective clusters in minute-to-minute calculations. After training, for each timestep the weather conditions are first classified into a subset representing both season and time of day, and then, a distinct MLR equation was employed to calculate the HVAC power more accurately. A k-value of eight was determined through numerical experimentation as a sufficient group size for separating approximately linear HVAC patterns with outdoor temperature.

For use in the transition periods, a gray box model was proposed that employed the rated HVAC power and equivalent RC thermal model for temperature. The heat transfer function used in the RC thermal model is described as follows:

$$R = \frac{c_R}{A_r}, \quad C = c_C \cdot A_r, \tag{1}$$

$$C\frac{\mathrm{d}\theta_I(t)}{\mathrm{d}t} = \frac{1}{R}[\theta_O(t) - \theta_I(t)] \pm P_H * COP, \quad (2)$$

where R, is the thermal resistance; C, the thermal capacitance; P_H, the HVAC system rated power; COP, the HVAC system coefficient of performance (COP) to transfer from electrical to thermal energy; θ_I, is the indoor temperature; and θ_o, the outdoor temperature. The RC model uses the thermal envelope and resistance of the home to calculate the change in indoor temperature during a transition period in which the HVAC system is turned off or at full rated power.

B. Hybrid ML Model Training for Step 3B

The H2ML gray box (step 3B) approach has been proposed in which the EnergyPlus model was simulated with the HVAC system forced to "off" for the entire year. This output file may then be employed to repeat the HMLM two-part procedure for the indoor temperature, $\theta_I(t)$ in place of the RC equivalent circuit. This was done specifically to capture the effect of weather on the indoor temperature through the walls, roof, insulation, etc. of the home separately to the effect of the HVAC system, which may be modeled through thermodynamic conversions from electrical energy to thermal energy. To improve the performance of the HMLM, the indoor temperature at the previous timestep was included as an input along with the outdoor temperature, relative humidity, and solar irradiance.

Using a modified version of the specific heat formula [21], the temperature within the home during normal operation and transition periods may be calculated as:

$$\Delta T = P_{HVAC}(t-1) * (t_s) * \eta, \quad \eta = \frac{COP * 3.6x10^6}{m * c}, \quad (3)$$

$$\theta_I(t) = \theta_I(t-1) + \Delta T, \quad (4)$$

where ΔT is the change in temperature resulting from the HVAC system; $P_{HVAC}(t-1)$, the power for the HVAC system (kW) in the previous time step; $t_s = 1/60$ as it is the duration of the timestep (min.) and conversion to match energy units in this case hours; η, the conversion from electricity energy units (kWh) to temperature (°C); m, is the air mass constant calculated based on the volume of the home; c, the air specific heat capacity.

The gray box models may serve as a model-in-the-loop inside co-simulation platforms (Fig. 1) such as those proposed in [19], [22]. Either modeling type, H2ML or HRC, may be more advantageous depending on the available physics parameters for the smart homes. For example, depending on known information for the homes, it may be more appropriate to approximate either the RC parameters for expected reasonable heat and cooling time duration in the HRC method or the air mass constant for the home volume in the H2ML method. The benefits on the meta-modeling approaches as they apply to scalability for hundreds of homes in co-simulation frameworks are discussed further in Section V.

Table I
COMPARISON OF K-MEANS CLUSTER NUMBER, k, IMPACT ON HVAC POWER FORECASTS FOR THE CONVENTIONAL HOUSE. INPUTS TO THE K-MEANS AND MLR MODELS INCLUDE θ_o, θ_d, G, R.

Groups	MAE [kW]	RMSE [kW]	CV(RMSE) [%]	nRMSE [%]	R^2 [-]
3	0.478	0.642	64.8	8.39	0.686
4	0.404	0.548	55.3	7.15	0.772
5	0.417	0.556	56.0	7.25	0.765
6	0.377	0.518	52.3	6.76	0.796
7	0.357	0.495	49.9	6.46	0.814
8	0.359	0.497	50.1	6.49	0.812
9	0.359	0.496	50.1	6.48	0.813
10	0.352	0.489	49.3	6.38	0.819
11	0.352	0.489	49.3	6.38	0.821
12	0.344	0.483	48.8	6.31	0.822

θ_o = Outdoor temperature, θ_I = Indoor temperature, G = Irradiance, R = Relative Humidity, $\theta_d = \theta_o - \theta_I$, $\theta_p = \theta_o$ input at $t - 15$

III. MODEL VALIDATION AND ANALYSIS WITH EXPERIMENTAL SYNTHETIC DATA

The data used in this study was from experimentally validated EnergyPlus models of Tennessee Valley Authority (TVA) robotic field demonstration homes in Knoxville, TN [23]. Included in the study are three homes of conventional, retrofit, and near net zero energy (NNZE) type. The net annual energy use of the three homes is approximately 20, 12, and 6MWh respectively as there are significant differences in the construction and heat pump HVAC systems, i.e., in SEER rating, operational speed, and insulation type. In this case study, the EnergyPlus models were simulated twice following the meta-learning procedure, step 2, as described in Fig. 1 to create the training and test sets across two years. Typical meteorological year (TMY) and 2013 .epw weather files for Knoxville, TN were employed to capture trends of historical performance in training and testing, respectively.

The HMLM training procedure is proposed to be used with TMY3 weather data through epw files in EnergyPlus as developed by NREL. These TMY3 files are an industry benchmark for energy building modeling and represents the average climate, not extremes, across the entire year for a region [24]. Through the meta-model training based on the EnergyPlus output data, the HMLM capture the average behavior across a year for use in VPP studies to study controls and impact estimates. The accuracy of the weather grouping may be updated with newer data sets, such as f-TMY, and uncertainty calculations to improve future estimates of weather considering climate change such as developed in [25], [26].

Furthermore, one of the benefits of the proposed structure of the hybrid ML method with k-means is that it isolates the seasonal variance which may remove the need to update HVAC models. For example in [27], a time-series LSTM model saw improved results when updated with new data every 7 weeks, i.e. approximately 8 updates a year. This matches

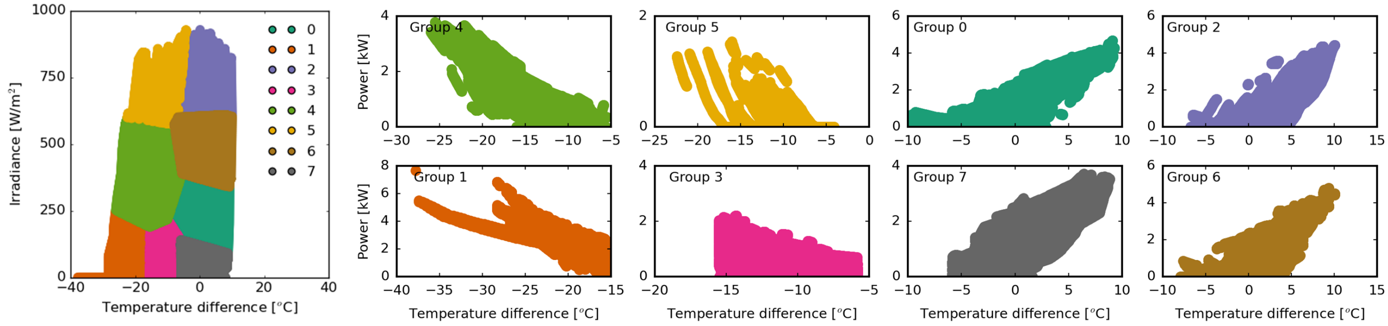


Fig. 3. Visualization of the minutely 2013 test data as partitioned into groups by k-means forecasting of the irradiance and temperature difference, i.e. $\theta_d = \theta_o - \theta_I$. The unsupervised labeling isolates approximately linear trends, and the HMLM MLR performance per group were satisfactory (Table II).

Table II
ERROR METRICS FOR CLUSTER GROUPINGS CORRESPONDING TO DIFFERENT SEASONS AND TIMES OF DAY.

Group	MAE [kW]	RMSE [kW]	CV(RMSE) [%]	nRMSE [%]	R^2 [-]
0	0.447	0.620	61.3	13.3	0.72
1	0.478	0.580	22.8	7.5	0.608
2	0.562	0.714	62.8	16.1	0.584
3*	0.309	0.390	81.9	17.7	0.430
4	0.360	0.477	57.6	12.6	0.669
5*	0.196	0.312	170.7	20.3	0.182
6	0.509	0.659	49.6	13.8	0.820
7	0.224	0.375	100.4	10.1	0.374

* Seasonal transition period where lower peak power partially explains reduced accuracy.

the determined group size selection of 8 distinct models per weather and daytime conditions as discussed in Section III-A.

A. Parameter Evaluation for Annual Weather Clustering

An elbow curve evaluation of k values was conducted to determine the number of clusters used in step 3A and 3B. The k-means cluster size, k, evaluation shows a plateau in improvements of MAE and nRMSE starting at six groups (Table I). With a k value of eight, the groups segment with natural seasons in the region and result in approximately linear trends between HVAC power and outdoor temperature difference within each group. For this reason and that little significant difference in overall HVAC power forecasting error metrics was seen between k-values greater than six, this group size was selected for further study. Further parametric studies for the best k value in the hybrid procedure with various ML types to forecast each group may be conducted in the future.

The clustering results for the k value of eight from the test year for this model are visualized in Fig. 3. The approximately linear HVAC power trends against the temperature difference, θ_d, were isolated through the k-means clustering in the hybrid ML model. The performance of the MLR in each group as part of the HMLM for step 3 from Fig. 1 was tabulated in Table II. Within each group, the MLR performance varies as typical behavior of HVAC systems varies by season and time of day. Automatic partitioning into winter, shoulder, and summer night and day subsets is a benefit of the k-means clustering. As expected, the performance of the very low power shoulder months in spring and fall have reduced model accuracy.

B. Parametric Studies for HVAC Power Models

An input parameter study was completed on the conventional home to determine the best inputs in step 3A and 3B, i.e. the MLR portion of the model (Table III). Outdoor temperature [°C], setpoint temperature assumed equal to indoor temperature [°C], the difference between the outdoor temperature and the indoor temperature, the relative humidity [%], and solar irradiance [W/m^2] were considered. All combinations at the minute resolution surpass ASHRAE building modeling guidelines for hourly R^2 values higher than 0.75. The gathered academic consensus for specific HVAC modeling accuracy at the daily resolution was a CV(RMSE) of less than 30% [28]. Because minutely power was significantly more volatile than hourly and daily resolutions, approximately 50% CV(RMSE) for all models has been considered highly satisfactory.

Comparable performance of all combinations was found with less than 10% nRMSE. The thermal inertia from previous time steps for outdoor temperature as an additional input to the model provided only slight improvement at minutely resolution as compared to lower resolutions such as hourly. This may be partially explained by the possibility that outdoor temperature variation over time is not as significant in a minute as it is in an hour. For this reason, the HMLM selected from the parametric study included the inputs at time t of outdoor temperature, difference between outdoor and indoor temperature, relative humidity, and irradiance as θ_o, θ_d, RH, and G, respectively.

The minutely HVAC power for each home type was trained and tested following the two-part HMLM procedure (Table. IV). The retrofit home with the most efficient HVAC system was modeled with the highest accuracy of the three homes with an R^2 of 0.88 and a nRMSE of 3.5%. The residual error distributions for the homes in Fig. 5 are strongly clustered around zero, with up to 80% of all errors in the test year within ±0.25kW. Example days in the summer visualize the

Table III
CASE STUDY FOR A CONVENTIONAL HOME LOCATED IN KNOXVILLE, TN WITH A MINUTELY MAXIMUM HVAC POWER OF 4.7 AND 7.7KW IN THE SUMMER AND WINTER, RESPECTIVELY.

Inputs	MAE [kW]	RMSE [kW]	CV(RMSE) [%]	nRMSE [%]	R^2 [-]
θ_o, G, R	0.348	0.486	49.1	6.3	0.820
θ_o, θ_d, G, R	0.359	0.498	50.2	6.5	0.812
θ_o, θ_I, G, R, θ_p	0.321	0.452	45.6	5.9	0.844
θ_d, G, R, θ_p	0.336	0.469	47.4	6.1	0.832

θ_o = Outdoor temperature, θ_I = Indoor temperature, G = Irradiance, R = Relative Humidity, $\theta_d = \theta_o - \theta_I$, $\theta_p = \theta_o$ input at $t - 15$

Table IV
ERROR METRICS FOR THE HVAC META-MODELS OF ENERGYPLUS SYNTHETIC DATA FOR THREE BUILDING TYPES. THE INPUTS WERE θ_o, θ_d, G, AND R FOR EACH MODEL.

Home type	MAE [kW]	RMSE [kW]	CV(RMSE) [%]	nRMSE [%]	R^2 [-]
Conventional	0.359	0.498	50.2	6.5	0.81
Retrofit	0.125	0.173	44.7	3.5	0.88
NNZE	0.194	0.286	71.4	7.7	0.68

HMLM capturing the minutely trends of the HVAC power for each home (Fig. 4).

Additionally, to test the HMLM procedure for the indoor temperature, the white box EnergyPlus model for the conventional home was successfully replicated for indoor temperature with a high R^2 value of 0.99 and an MAPE of 0.4%. This is expected as the central indoor temperature does not change significantly in a minute from natural heat transfer through insulated walls. The indoor temperature was also calculated originally by the EnergyPlus model and, therefore, it lacks experimental randomness and was a desirable training data set for ML techniques. This model was considered a viable alternative to the RC equivalent model as part of step 3B for the development of hundreds of smart home models for a co-simulation framework.

IV. SMART HOME STUDIES WITH THE NEW MODEL AND CTA-2045 PROTOCOL

In power system modeling, data of varying resolution is needed based on the equipment used for controls and simulations (Fig. 6). Black box ML models are applicable in many power system simulation scenarios as they can be trained at various resolutions. They are commonly used for stationary load flow forecasts and complement the range of tools used from the micro-second to minute resolution with home energy management (HEM) system operations.

To implement HVAC controls in HEM systems, unification of GES modeling with industry standard communication protocol, such as from the Consumer Technology Association (CTA) and Energy Star, is beneficial so that batteries, water heaters, appliances, and now HVAC systems may receive the same signals [29]. Industry communications protocol

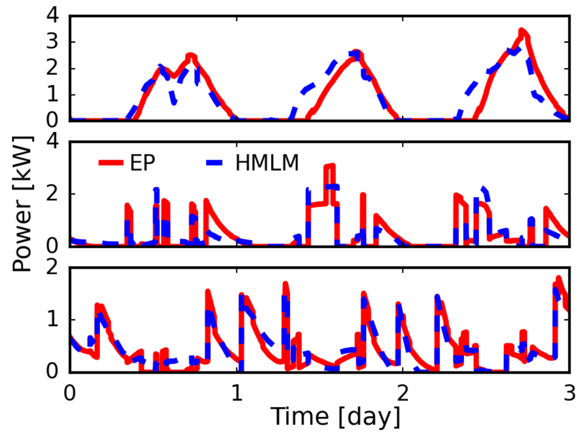


Fig. 4. Summer example HVAC calculations from the HMLM of EnergyPlus (EP) synthetic data for three days in June of the conventional (a), retrofit (b), and NNZE (c) homes.

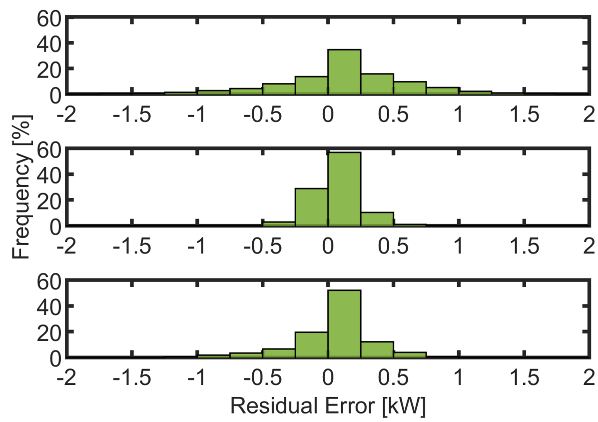


Fig. 5. Residual error distribution strongly clustered around zero error for conventional (a) retrofit (b), and NNZE (c) homes based on EnergyPlus synthetic data, which was separately validated against experimental data.

CTA-2045 defines "load-up" and "shed" commands that may be paired with "energy take" and equivalent state-of-charge (SOC) calculations for GES controls of the HVAC system [30].

A report by the Electric Power Research Institute (EPRI) conducted at the National Renewable Energy Lab (NREL) investigates a CTA-2045 shed event with a thermostat, and it assumes the response of the HVAC system to be a change of 4°F [31]. Proposed in this paper is a process to select new setpoints to match desired energy take levels during CTA-2045 DR events (Fig. 7). This format of controls unifies BEM behind the Energy Star metric of energy take and matches operation of other thermal ESS types such as the EWH demonstrated in [32], [33].

A. Formulation of Residential HVAC System as GES

To calculate the new setpoints for load-up and shed events while considering limitations of thermal comfort for the occupant, minimum, θ_{min}, and maximum, θ_{max}, allowed temperatures were considered. The equivalent HVAC energy

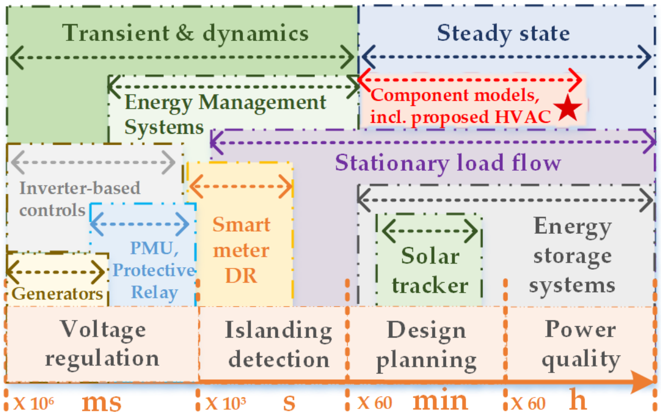


Fig. 6. Time scale comparison for electric power systems operation and control. The proposed HVAC model fills in the gap of ultra-fast multi-physics simulations with one minute time resolution, as marked by the red star [19].

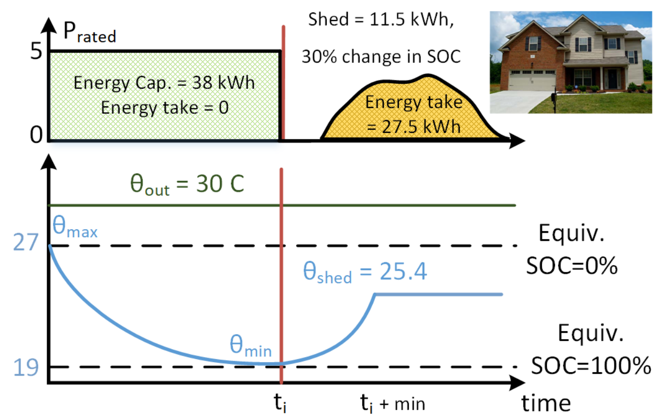


Fig. 7. Proposed application of CTA-2045 for the thermal energy shed command in HVAC systems. Energy capacity for an example experimental conventional home is shown for a variable speed, 13.5 SEER system.

capacity, $\overline{E_{H,C}}$, during the summer was defined as the energy required to change the indoor temperature from its allowed maximum to its minimum:

$$\overline{E_{H,C}} = \sum_{\theta_I=\theta_{max}}^{\theta_{min}} P_H * t_s, \tag{5}$$

in which the bounds would flip from θ_{min} to θ_{max} during winter. It is important to note that the outdoor temperature influences the energy capacity of the home due to the increased energy required to cool the home on hotter days. Within this work, a single energy capacity on a mid-summer day with a peak temperature of 30^{o}F was calculated.

The energy take, $E_T(t)$ (kWh), was defined as the amount of energy the system could absorb or take from the grid. In this case, the HVAC system electrical energy required before the current indoor temperature would reach the T_{min}. The energy take was calculated based on the equivalent state-of-charge (SOC) as in [32] and as follows:

$$SOC(t) = \frac{\theta_{max}(t) - \theta_I(t)}{\theta_{max}(t) - \theta_{min}(t)}, \tag{6}$$

$$E_T(t) = (1 - SOC(t)) * \overline{E_{H,C}}, \tag{7}$$

in which $\theta_I(t)$ was calculated utilizing gray box models described in Section II. During times of DR, CTA-2045 protocol applies changes to the HVAC system's $E_T(t)$ to reduce or increase the energy stored. For HVAC systems that typically operate according to temperature setpoint within a tolerance dead band, a new setpoint, $T_s(t_{DR})$, may be formulated as:

$$T_s(t_{DR}) = \theta_{max} - \frac{\overbrace{E_T(t_i) + \delta E_T}^{E_{T,lim}}}{\overline{E_{H,C}}} * (\theta_{max} - \theta_{min}), \tag{8}$$

where t_i is the initial time the DR signal was received, δE_T, the change in energy take (electrical kWh), and $E_{T,lim}$, the new target energy take.

For an EWH, a common CTA-2045 compatible device, the temperature of the water may be considered more independent of direct change from the occupant, and, thus, status of the heating element may be determined directly from the $E_{T,lim}$. As occupants interact more commonly with the temperature of their HVAC systems, the CTA-2045 interface for control has been formulated to indicate a setpoint for the load-up and shed periods in ^{o}C. This was intentional to improve consideration of thermal comfort with occupant understanding and interactions.

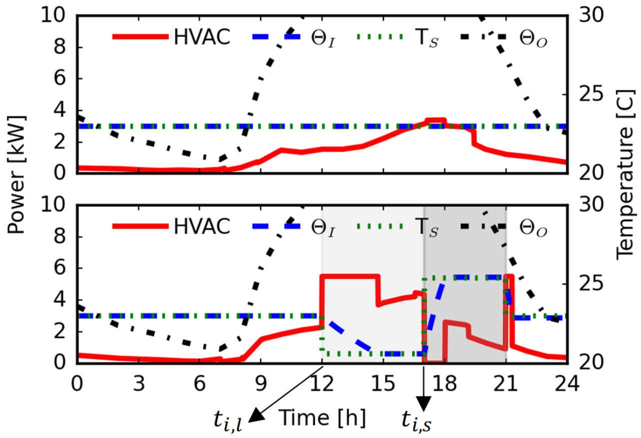
B. Case Study with CTA-2045 Controls for HVAC System

As an example, the conventional house was simulated with the HRC method described as Step 3A on June 18, 2020, which was a very hot day with peak temperature of 33.4^o (Fig. 8a). The RC parameters were selected of the type described in [32] for the transition periods during the shed period to cool the home and the load-up period when the HVAC system is off. The energy capacity of this home was calculated as 38kWh with a T_{max} of 27^{o}C and T_{min} of 19^{o}C.

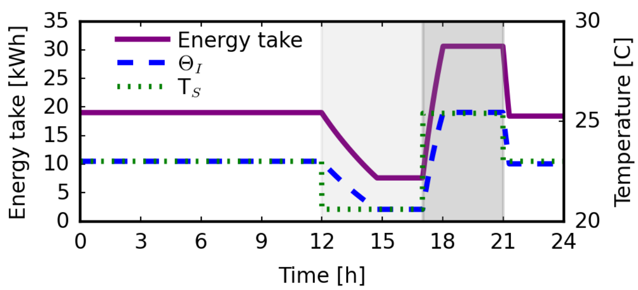
Load-up and shed periods were from 12:00 to 17:00 and 17:00 to 21:00, respectively, and the δE_T was set to 11.5kWh, approximately one-third the energy capacity of the home to represent a moderate VPP scenario with mild impact on the occupant. The change in energy take and indoor temperature are visualized in Fig. 8b. The HVAC load is shifted in time with increased power during the load-up period and removed load from 17:00-18:00, a common peak time for the utility as occupants return from work.

V. Discussion for Application to Large-scale Electric Power Distribution Studies

Efforts from national laboratories have been made to provide public EnergyPlus models for 120+ million buildings from satellite imagery and to develop future weather .epw input files for the entire U.S. [26], [34]. These examples showcase the growing field of residential distribution system simulation for smart grid planning. The size of such endeavors limit



(a)



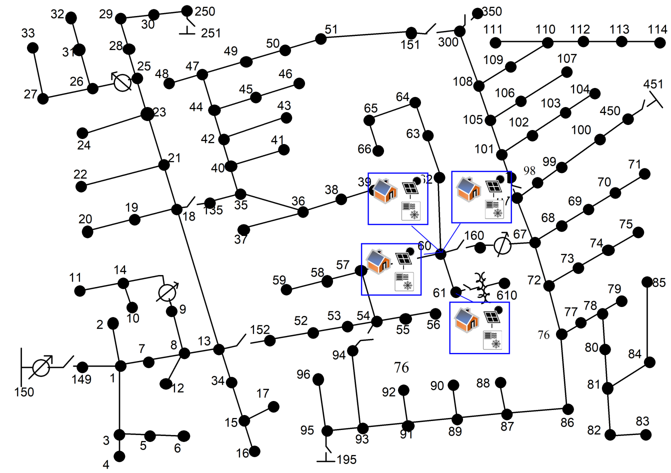
(b)

Fig. 8. Conventional home baseline on a hot summer day with peak temperature of 33.4^{o}C as simulated by the HRC method (top a) and with "load-up" and "shed" commands visualized with gray shading (bottom a). CTA-2045 signals are received at $t_{i,l}$ and $t_{i,s}$, and energy take changes gradually (b).

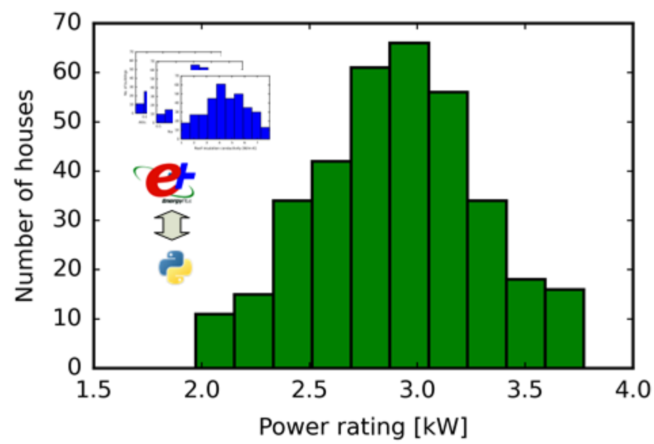
calibration of EnergyPlus models before VPP simulation, and many assumptions for the building characteristics, including insulation, roof, and window area, were necessary. While smart meter data has become more available to utilities at the 15 minute resolution, specifically in 2022 for 73% of residencies in the U.S. [35], minute-to-minute resolution data may be more beneficial for VPP coordination of DERs and EV charging. The expense and immense effort involved in the collection, transmission, preparation, and utilization of so much measured data from AMI as well as the assumptions required for direct physical modeling highlight a significant need for alternative transitional methods, such as those proposed in this paper.

The proposed meta-modeling method with validated initial EnergyPlus models of a few representative smart homes has the advantage of accurate building parameters based on experimental data. Ranges of varied construction from conventional to near net zero energy may be used for neighborhood VPP simulations of hundreds and thousands of homes (Fig. 9). The synthetic data sets may then provide estimates to local utilities for load growth forecasting with varied appliances or EV smart charging as well as infrastructure planning and DER controls.

The high interoperability and scalability of this approach with the HMLM modeling has also been applied with co-simulation frameworks, specifically as conducted in another



(a)



(b)

Fig. 9. The proposed ML meta-modeling procedure based on EnergyPlus may be repeated in Python to generate digital twins for hundreds of realistic synthetic homes for distribution systems such as the IEEE 123 node system (a). Distributions for distinct building characteristics were generated for HVAC power rating, air flow rates, COPs, insulation, roof materials, etc. based on the range between the conventional home to the NNZE home to provide realistic randomness (b).

paper by our group of authors [36]. An additional case study with 50% hosting capacity of distributed rooftop solar on the IEEE 123 node test feeder has been visualized in this section. The rated power of the solar generation was randomly assigned between 3-7.5kW.

The two paths proposed enable co-simulation of electric power distribution systems with 351 distinct gray box smart home models equipped for CTA-2045 protocol controls of the type described in Fig. 1. An example synthetic load profile for a smart home within the case study is visualized in Fig. 10. The HMLM was used for the HVAC load, and the baseload and water heater daily load data were publicly available from the DOE SHINES smart home project in Florida [37]. The solar photovoltaic (PV) generation in the houses with DER was calculated according to the weather following [38].

The many house types with various energy capacities de-

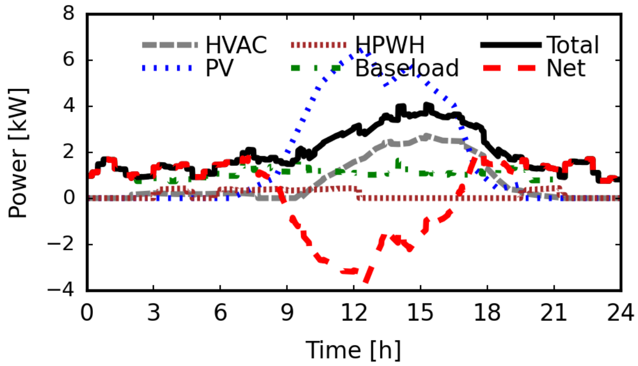


Fig. 10. Total synthetic load for a home based on the proposed HMLM of a conventional HVAC system with high load, typical experimental baseload, and a high efficiency heat pump water heater (HPWH).

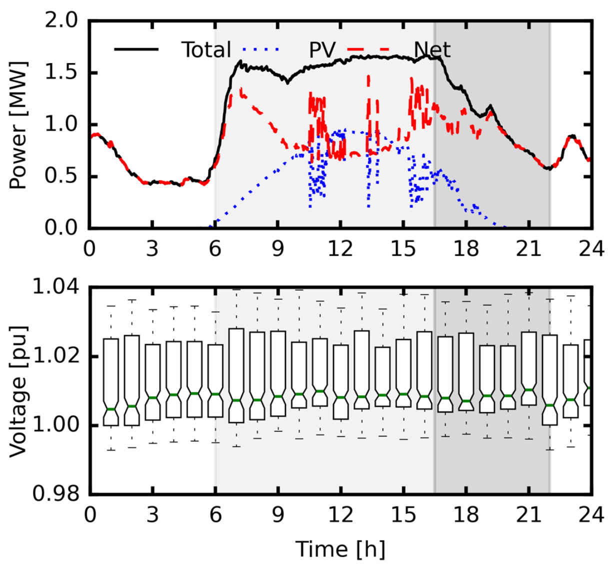


Fig. 11. Example large-scale simulation of the IEEE 123 node test feeder as a benchmark distribution system with VPP controls of HVAC systems through CTA-2045 protocol for load-up (light gray) and shed (dark gray) commands. The increased utilization of solar PV and impact of controls on voltage across the system may be assessed.

pending on HVAC system and home construction for community wide energy management systems were co-simulated at the minute resolution with load-up and shed periods (Fig. 11 and Table V). The co-simulation platform and interoperable, computationally light models enables individual assessment of the CTA-2045 controls and system wide power system effect evaluation, including voltage and asset impact. Successful pre-cooling across the community was achieved as illustrated in Fig. 12. There was an increase in energy during peak solar PV hours with a load-up to pre-cool the homes and a decrease of energy during the shed period without an increase in indoor temperatures on a summer day.

The VPP control of residential appliances including water heaters and HVAC systems as GES could be expanded to

Table V

EXAMPLE VPP SIMULATION RESULTS INCLUDING CHANGES IN TOTAL AND HVAC ENERGY COMPONENT, AND PV GENERATION EACH REPORTED AT THE MAIN SUBSTATION OF THE MODIFIED IEEE 123 NODE SYSTEM.

Time [h]	VPP [kW]	Power [kWh]	Δ Main [kWh]	Δ HVAC [kWh]	PV [kWh]
0	None	868.88	0.00	0.00	0.00
1	None	836.19	0.00	0.00	0.00
2	None	522.11	0.00	0.00	0.00
3	None	442.32	0.00	0.00	0.00
4	None	434.86	0.00	0.00	0.00
5	None	461.00	0.00	0.00	16.39
6	L	619.39	96.57	94.78	134.09
7	L	1339.31	144.85	142.02	314.50
8	L	1143.98	184.13	181.62	488.28
9	L	908.12	181.56	178.32	645.93
10	L	787.72	210.83	206.81	634.99
11	L	1246.51	212.71	209.48	741.24
12	L	888.62	198.73	195.34	924.73
13	L	722.74	232.04	228.12	843.29
14	L	755.99	239.07	235.05	827.19
15	L	874.20	245.46	241.28	524.28
16	L & S*	1003.30	214.28	211.04	536.13
17	S	1047.91	−75.67	−74.59	358.00
18	S	1118.26	−116.24	−114.51	156.21
19	S	1061.54	−217.35	−214.18	37.04
20	S	877.30	−272.06	−266.73	0.43
21	S	732.49	−250.21	−246.52	0.00
22	None	568.71	−126.42	−124.41	0.00
23	None	881.37	24.02	23.92	0.00

* Load-up (L) issued at 16h and Shed (S) command at 16.5h, explaining the increase in energy allotted for this hour.

include residential battery energy storage systems (BESS). For example, the methods developed to smooth the net load with DERs and maintain the distribution system voltages with BESS may be applied to further benefit the grid performance [39], [40]. The HVAC synthetic modeling approach may be applied with GES controls including BESS to optimize the economics, voltages, and load tap settings through the methods demonstrated in [41].

VI. CONCLUSION

The residential meta-modeling of three calibrated EnergyPlus models at one minute resolution, the first in its field, was highly satisfactory for HVAC power [kW] with nRMSE values lower than 10%. The proposed algorithms set the basis for high resolution meta-models in BEM and future improvements may be made with the application of more advanced deep learning algorithms in the HMLM structure in place of MLR. Two paths toward large scale co-simulation, HRC and H2ML, with both HVAC power and indoor temperature were formulated for GES evaluation. Smart controls following industry protocols, CTA-2045 and Energy Star provided the capability to shift residential load to align with solar PV and avoid peak demand times. Single home and community VPP operation on the IEEE 123 node test feeder for HVAC systems were demonstrated with “load-up” and “shed” commands for energy take and setpoint changes. Utilization of ultra-fast high

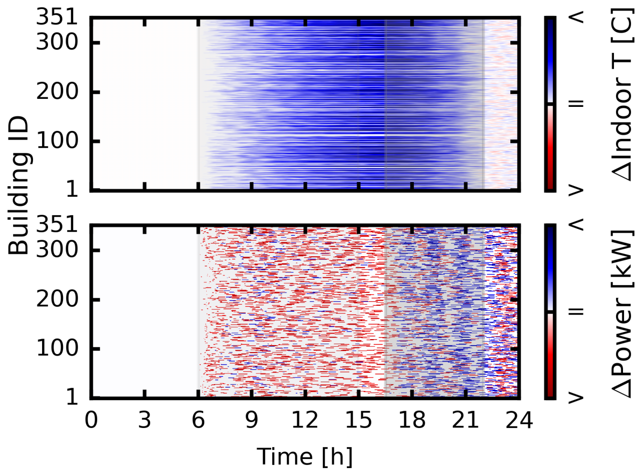


Fig. 12. The difference between the base operation and with controls during load-up and shed in the summer (-5 to 5 kW,C^{o}). During load-up, the power increases and the homes were pre-cooled, while the power decreases during shed without large differences in indoor temperature.

resolution surrogate models as simulated in this work enable transitional estimates of representative communities and the impacts of VPP operation without the expense of wide-spread component monitoring.

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