Multi-Physics and Artificial Intelligence Models for Digital Twin Implementations of Residential Electric Loads

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***Abstract*—Heating, ventilation, and air-conditioning (HVAC) and electric water heating (EWH) represent residential loads. Simulating these appliances for electric load forecasting, demand response (DR) studies, and human behavior analysis using physics-based models and artificial intelligence (AI) can further advance smart home technology. This paper explains the background of residential load modeling, starting with the concept of digital twin (DT) as well as the different types of methods. Two major types of appliance load monitoring (ALM) and their advantages/disadvantages are then discussed. This is followed by a review of multiple studies on residential load modeling, particularly for HVAC, EWH, and human behavior. Further examples of electric load forecasts and DR case studies using experimental smart homes are provided. The results and impact of these studies are discussed, as well as their contribution to the advancement of smart home technology and large-scale application.**

***Index Terms*—smart home, smart grid, heating ventilation and air conditioning (HVAC), electric water heater (EWH), machine learning (ML), residential, electric load forecasting, appliance load monitoring (ALM), artificial intelligence (AI)**

I. Introduction

Heating, ventilation, and air-conditioning (HVAC) and electric water heating (EWH) have great contribution to the annual energy use of residential loads, as found by the U.S. Energy Information Administration (EIA) [1] and shown in Fig. 1. These appliances account for the large spikes in net power usage in many smart homes such as the Honda Smart Home (HSH) [2] as illustrated in Fig. 2. Home and component modeling of appliances such as HVAC and EWH is necessary for future development of smart home technology. A method of modeling residential loads is to create a digital twin (DT). A DT is a digitally mirrored asset which models the asset and all sensor data, technical documents, and the capabilities to simulate its behavior [3]. A main contribution of this paper is to review studies on residential appliance modeling and highlight their applications.

Appliance load monitoring (ALM) includes a set of techniques for obtaining real-time power consumption feedback for appliances, which can inform consumers and allow them to make decisions that could conserve energy [4]. There are two major categories of ALM: intrusive load monitoring (ILM) and non-intrusive load monitoring (NILM). The first involves using a low-end measurement device close to the appliance, while NILM employs a smart meter typically placed at the electric panel [5]. An example of ILM is a "smart plug," a power outlet with remote control capabilities. A home energy management system (HEMS) may employ ILM such as a smart plug for appliance control shown in Fig. 3.

According to [6], there are three methods for modeling residential appliances, such as HVAC: "white box," a physics-based approach; "black box," a data-driven approach; and "grey box," a hybrid approach using a combination of physics and sensor data. Software like EnergyPlus can be used to create a white box model, but many parameters are needed to construct the model (type of HVAC system, insulation, ventillation, etc.).

Establishing these parameters may be very time consuming and in some cases parameters are unavailable. One advantage of a white box is the ability to create a model in the absence of a dataset. A black box model can be established from historical data of an existing system using artificial intelligence (AI) techniques of machine learning (ML) without the need for physical parameters, avoiding some of the difficulties of white box modeling. Grey box approaches such as thermal modeling are used to bypass some of the difficulties of white box modeling, while still maintaining physical meaning [7].

II. Residential HVAC Modeling

Within this section, examples of HVAC modeling with grey and black box models are provided. Studies for home-level HVAC load prediction have identified long short term memory (LSTM) and recurrent neural networks (RNN) as the most promising ML approaches. For example, an LSTM model to predict short-term daily energy consumption of air conditioning was introduced in [8]. An LSTM model was developed in [9] to perform short-term forecasts of HVAC power consumption in buildings. In [10] the authors combined LSTM with forward models to create a grey box model for real-time estimation of cooling loads.

Additionally, a previous work by our group created a grey box model for HVAC power and indoor temperature that is suitable for control studies as an equivalent energy storage system was proposed in [11]. This model was exemplified with experimental data and characteristics from three robotic houses operated by the Tennessee Valley Authority (TVA) [12], [13].

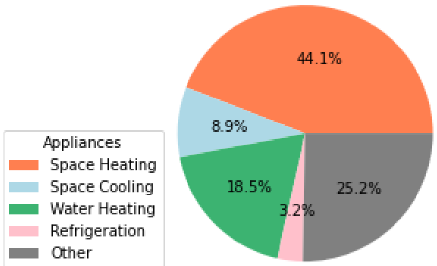

Figure 1. Distribution of residential load by appliance, based on the US Residential Energy Consumption Survey (RECS) from the EIA [1].

The TVA homes vary by physical construction and energy efficiency of the appliances into three types: conventional, retro-fit, and near-net-zero energy (NNZE).

A demand response (DR) case study of an HVAC system using this grey box model for the conventional home is exemplified in Fig. 4. The HVAC was turned off from 8:00 AM to 1:00 PM. This time was chosen as it is likely that the residents would be away at work during this time. The HVAC was turned on at full power at 1:00 PM and until the indoor temperature returned to a comfortable level, and then resumed normal operation. This status control approach could save energy and reduce peak load if applied during peak demand times. The model itself relied on physical parameters of the home which are difficult to obtain for many data sets, thus, black box, ML models are considered to create realistic models from minimal required data.

In other works by our group, an encoder-decoder LSTM ML model for day-ahead forecasting of residential HVAC energy usage based on previous load and future weather inputs was created in [14]. Further research has been performed to separate the HVAC system load from LSTM total power forecasts, effectively reducing data collection costs as smart meters would be the only required monitoring equipment [15]. These papers use the SHINES Smart Home field demonstration with rooftop solar PV, which is managed by the Electric Power Research Institute (EPRI) and funded by the Department of Energy (DOE) [16].

A comparison example is included in Fig. 5 between the LSTM day-ahead forecasting methods on a SHINES Smart Home from dedicated HVAC measuring devices and the discussed LSTM HVAC separation method from total load forecasts. In the figure, an example summer week demonstrates that both methods which capture the trends of measured power, and thus, the minimum data set approach are strengthened. Models based on LSTM can be further applied to estimate HEMs behavior to include renewable energy from residential PV installations based on day ahead forecasts (Fig. 5).

Another approach to HEMs modeling is to unify controls of HVAC systems, electric water heaters (EWHs), and batteries under industry standards CTA-2045 and Energy Star [18]. The HVAC system for this unification must be modeled as

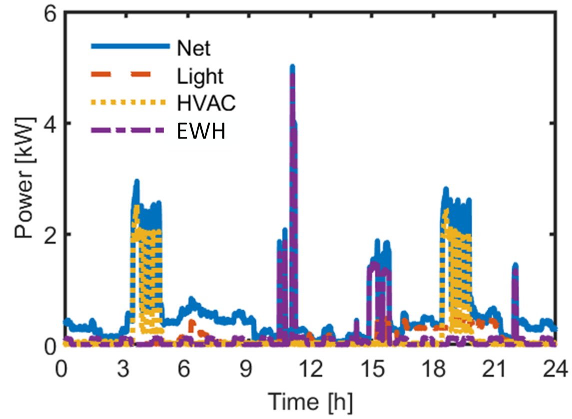

Figure 2. Example of rapidly changing power based on the data for the Honda Smart Home (HSH) [2], illustrating the very large power spikes and variations from appliances such as WH and HVAC.

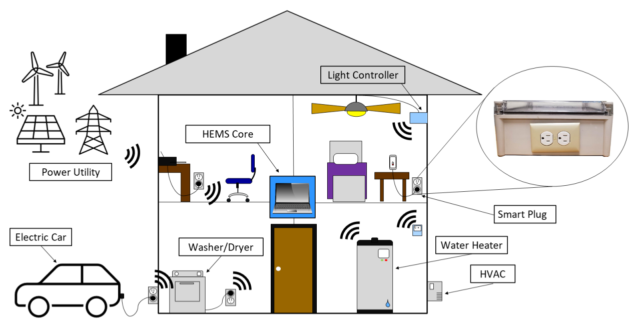

Figure 3. An HEMS controls manage smart appliances in the home to respond to user and utility controls. Intrusive load monitoring (ILM) devices, such as the illustrated smart plug [17], are monitoring equipment for advanced appliance level controls.

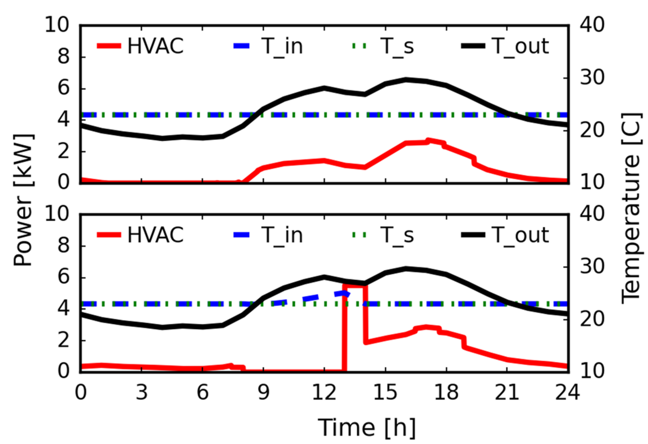

Figure 4. Simulation of HVAC using a grey-box equivalent RC circuit illustrating an uncontrolled operation (top) and a DR event implemented during the summer (bottom) with indoor temperature calculations.

an equivalent energy storage system. Through these efforts major appliances can be controlled through the same protocol in a single HEMs and optimizations can be applied to decide

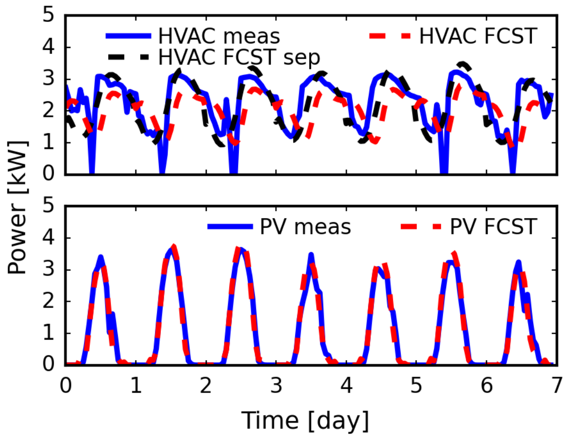

Figure 5. Example forecasts of day-ahead HVAC power through advanced ML techniques. Based on an LSTM model trained using dedicated measured data, forecast, and smart meter data for the total house power, HVAC FCST sep, (top). PV generation day-ahead forecasts during summer can be used to assess rooftop PV alignment with high HVAC load (bottom).

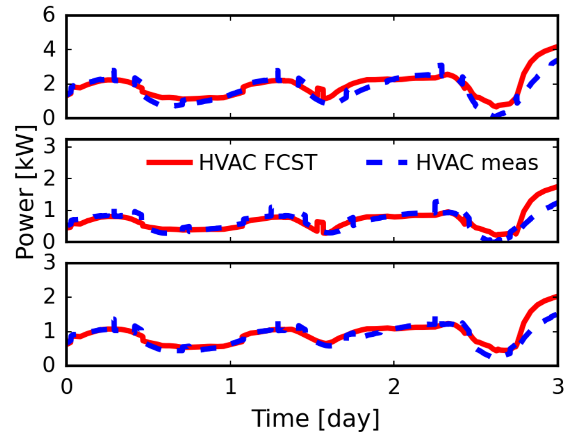

Figure 6. Three days of HVAC forecasts at the minute resolution based on a black box ML procedure for calibrated white-box model replication of three separate smart houses: conventional (top), NNZE (middle), and retro-fit (bottom).

which appliance should undergo DR commands in different scenarios.

Our group's previous research proposes use of black box models to replicate white box models for improved integration of detailed smart home modules, suitable for CTA-2045 controls, into co-simulation frameworks for large distribution systems and control studies [18]. HVAC calculated power from the proposed black box ML replication procedure for each of the three aforementioned TVA houses is shown in Fig. 6.

These calculations are completed at the minute resolution based only weather inputs into the computationally efficient trained model, and are thus suitable for large scale synthetic DR control studies, as described by our group in [19]. Community-wide DR control of HVAC systems could have significant impact on aggregated peak load seen by the utility. Thus, individual models with high granularity of resolution that are also computationally efficient and scalable, such as models reviewed in this paper, are of great interest.

III. Advanced EWH Simulation and Controls

Similarly to the HVAC system, EWH also has a substantial contribution to residential power profile. Illustrated in Fig. 7 is the simulated power profile and temperature of an EWH in a typical three bedroom house in California over the course of a day, as well as hot water draw (HWD) by appliance [20]. An energy management system was developed to analyze user habits to determine EWH control time periods to save energy and reduce user cost while ensuring occupant comfort [21].

According to [22], shifting controllable loads like EWH to run from battery energy storage systems (BESS) and solar PV can reduce the peak power demand for a residence. Two DT's were developed for both EWH and heat-pump electric water heater (HPEWH) using experimental data from large-scale projects [23]. These models were used in DR case studies, where it was found that approximately 14 % of daily energy usage for EWH could be shifted.

A simulated "shed event" for EWH under DR control following the CTA-2045 protocol is exemplified in Fig. 8. The simulation provides satisfactory results as compared with the experimental data published by the National Renewable Energy Laboratory (NREL) and EPRI [24]. This results in a shift/delay of the heating process to ideally correspond to a time during the day when hot water is not typically drawn.

Control of BESS together with EWH is proposed in [25] to operate a community of grid-connected net zero energy (NZE) homes as dispatchable generators. According to [26], NZE homes typically employ solar PV as their main source of energy. Solar PV can generate electricity during the day, returning the excess to the grid or storing it in batteries. Shifting EWH load into the high PV generation window through advanced modeling and controls in a HEMS can save energy and reduce peak load with smaller battery energy capacity being required.

IV. Residential Human-behavior tied appliance Modeling

As previously discussed by our group, appliance usage behavior is important to accurately represent load profile at the household level due to significantly larger load variability in smaller-sized networks [27]. Usage-behavior-driven models (also referred to as bottom-up models), are able to evaluate and predict impact of DR by gaining insight into the processes effecting the aggregated load profile. Bottom-up models are becoming increasingly important in smart grid technology.

As previously discussed by our group, a significant amount of energy in homes in the US is used by electric plug loads (see Fig 1). If these plug loads could be managed to respond to user behavior data, it may potentially save energy. A smart plug proposed by our group in [17] has electronic communication capabilities to be toggled ON/OFF. This design can be further

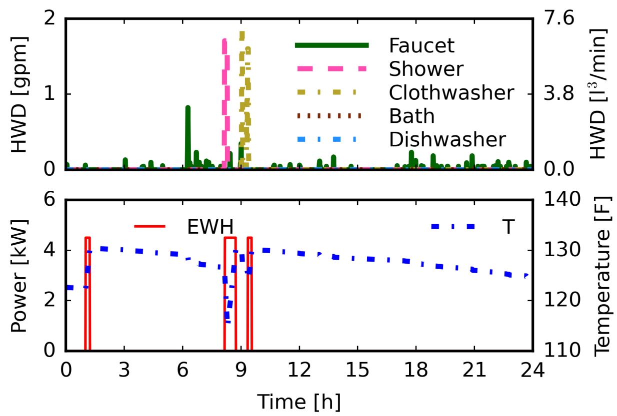

Figure 7. Hot water draw (HWD) for a three bedroom house based on the data from CBECC-Res [20] (top) and simulated the corresponding EWH temperature and power.

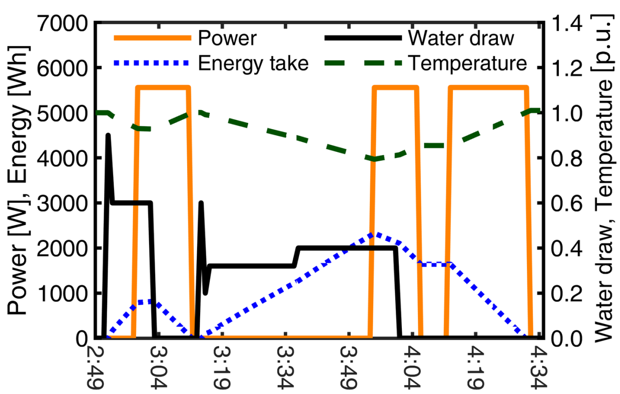

Figure 8. Simulated DR control for an EWH “shed event” [22] with temperature and water draw base values of 140 F and 1 gallon per minute (gpm). The simulation has satisfactory results as compared with experimental data published by NREL and EPRI [24]. Energy Star and CTA-2045 standards can potentially unify controls for all types of energy storage.

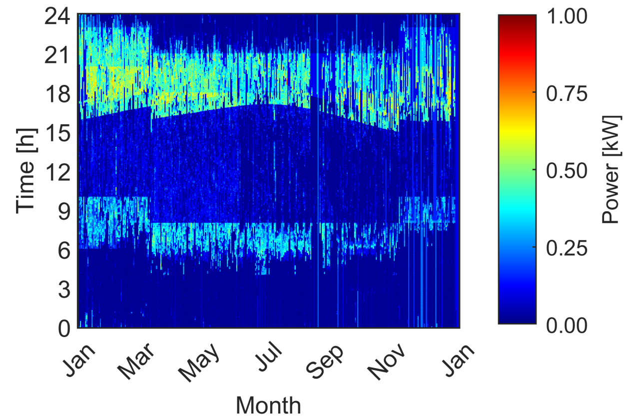

Figure 9. Based on data available from the HSH, regular patterns of usage tied to human behavior and daylight hours across seasons are identified, as expected, and daylight and time may be used to forecast lighting load.

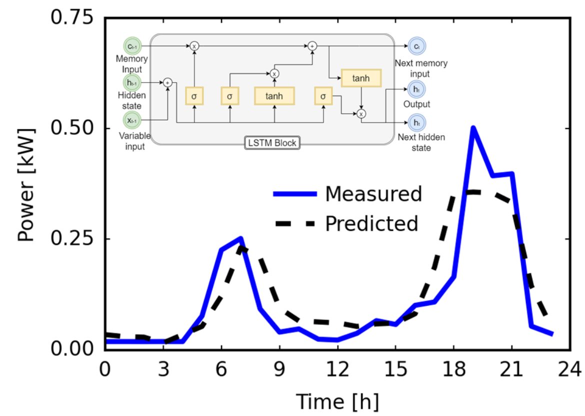

Figure 10. Day-ahead forecast for electric light power based on the HSH using a Vanilla LSTM machine learning model. Typical bimodal peaks caused by occupancy schedule are captured.

developed and connected to a HEMS for human behavior analysis. An example of human behavior tied appliances used in an HEMS is provided in [28], where an artificial neural network (ANN) algorithm was used to control a washing machine and refrigerator for DR along with the major appliances, EWH and HVAC.

The load for electric lights has strong correlation with human behavior and seasonal sunlight. A clear pattern between lighting load usage and daylight over the course of a year is visualized in Fig. 9. Due to this correlation, lighting load can be accurately predicted using ML models. A recent study by our group on the effectiveness of LSTM models to predict individual house power found that while prediction of net total power was poor, individual components like HVAC and lighting could be predicted with much higher accuracy [14]. A lighting day ahead forecast for the HSH using a Vanilla LSTM model is shown in Fig. 10.

If typical human behavior can be established both at the individual residence and at the aggregated community level, this would allow for the load to be shifted from peak hours, while also maximizing human comfort. Widespread adoption of DR is limited currently, and researchers are investigating how to best incentivize users [29]. Greater success in DR adoption and participation may be found through primarily weather-based loads such as HVAC that have limited effect on daily routines and habits.

Further developments of ultra-fast and representative smart home component models can be used to create modular DTs that are adaptable and scalable to multiple houses. Profiles of baseload demand from plug loads can be formed by identifying patterns in human behavior and used in these smart home DT along with black and grey-box models of major component loads such as HVAC and EWH (Fig. 11). Large-scale synthetic data can be used to apply DR controls to individual homes and community.

V. Conclusion

Due to their substantial contributions to residential loads, modeling of HVAC and EWH, and DT implementations are

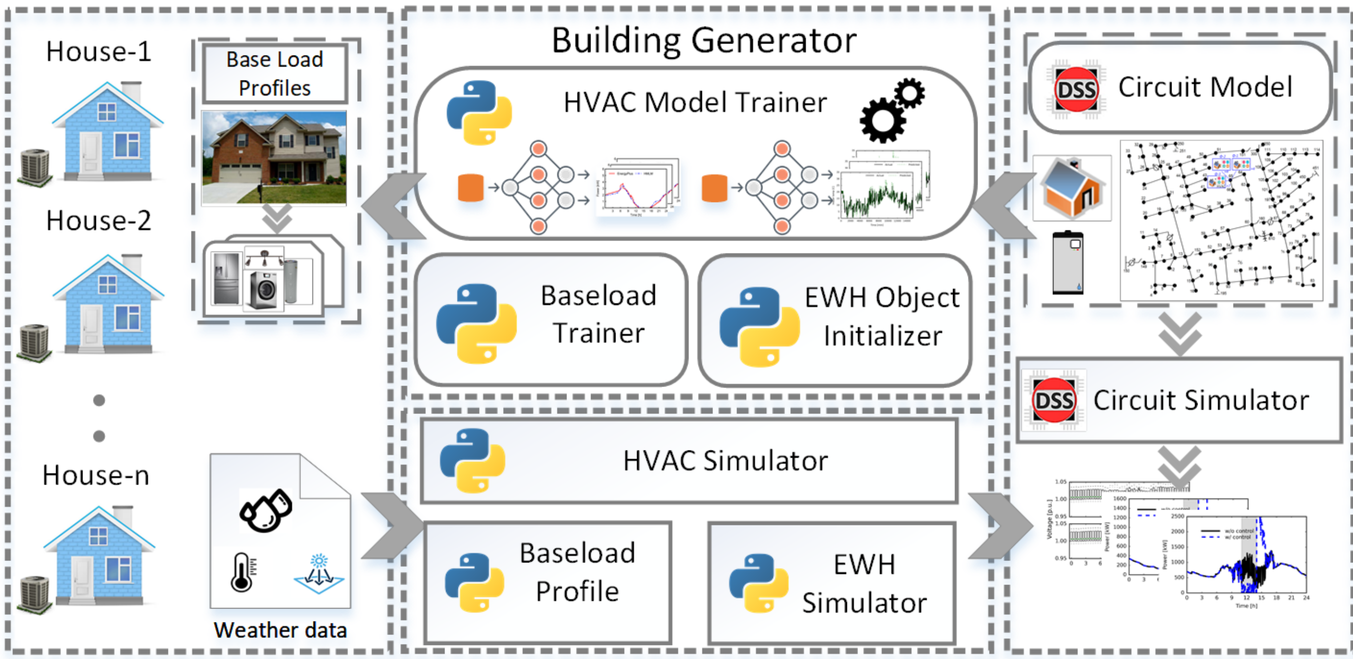

Figure 11. Proposed synthetic community-scale modeling based on modular HVAC, EWH, and baseload AI machine learning and multi-physics modeling. Detailed smart component models, as discussed in the paper are combined to represent am individual home and entire neighborhood.

most important for future developments. Within this paper black box, white box, and grey box models have been considered for smart home DR applications. Scalable and computationally efficient black or grey box models have been identified for further development as they enable larger community-wide DR studies. The methods discussed for training black box models for HVAC systems have the great advantage of only requiring a minimal data set.

In particular, ML models, such as those based on LSTM algorithms, have been shown to provide satisfactory day ahead forecasts for weather driven loads including HVAC and lighting at the hourly and minutely resolution. Modular physics-based models of EWH have been demonstrated to shift significant portions of daily total demand through HEMs controls. Human behavior tied appliances or baseload demand, which account for a relatively low proportion of the total load, are the most challenging to adjust through DR because of human expectations and routines. The authors recommend further DR studies on the major appliances of HVAC and EWH as the use of electric heat pumps is further expanding.

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