Simulation of Smart Home Loads for Large Scale DR and VPP Studies using Synthetic Data from Hybrid ML Black Box Models

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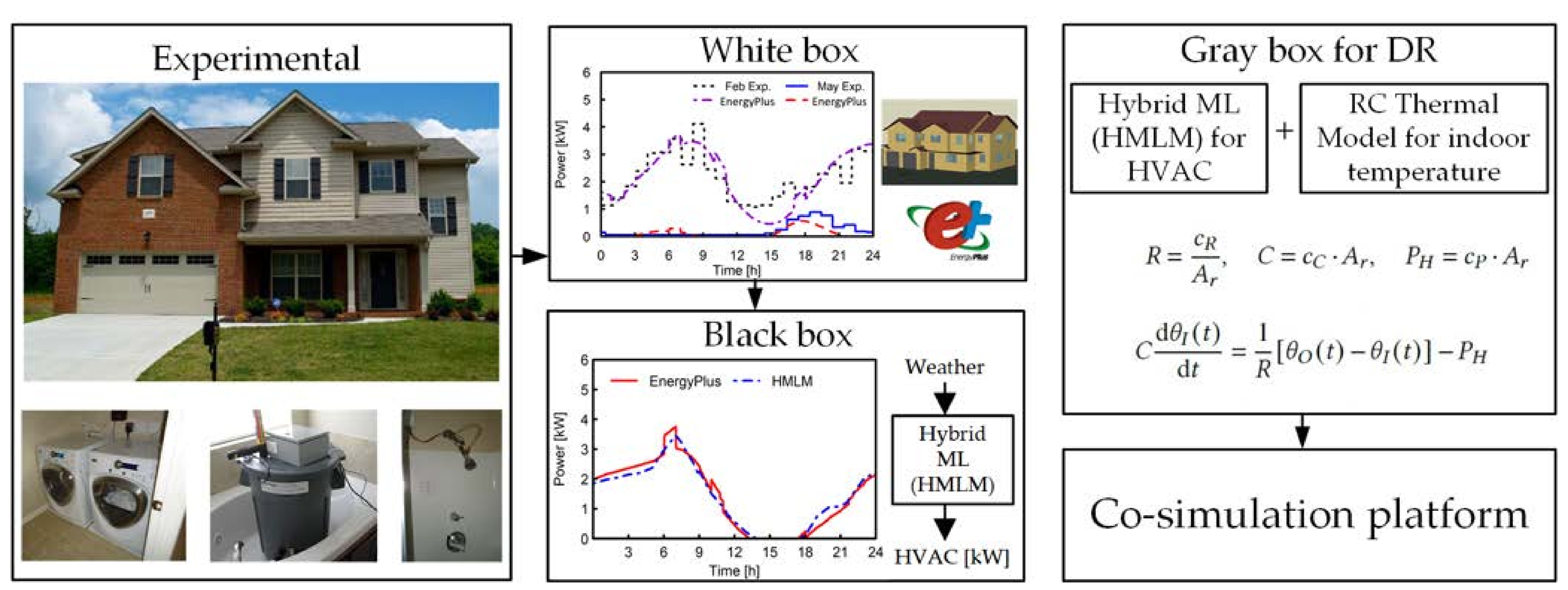
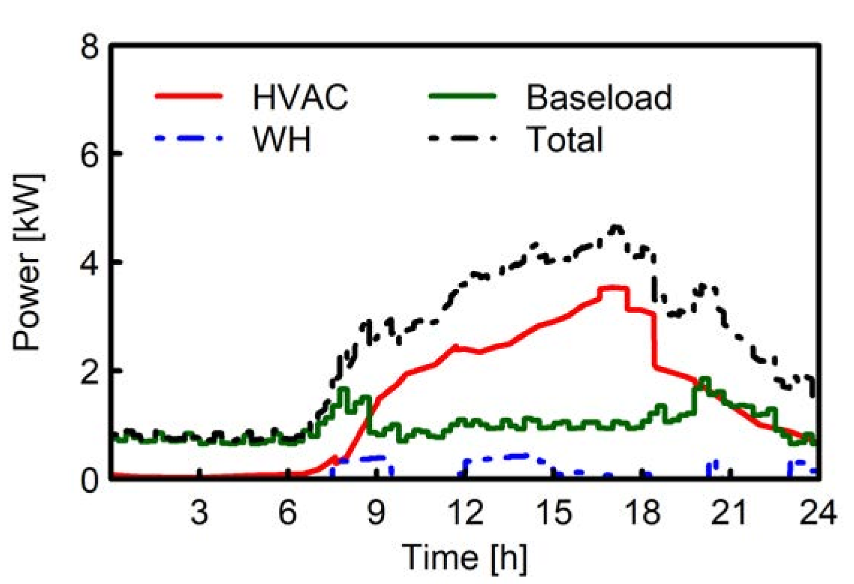
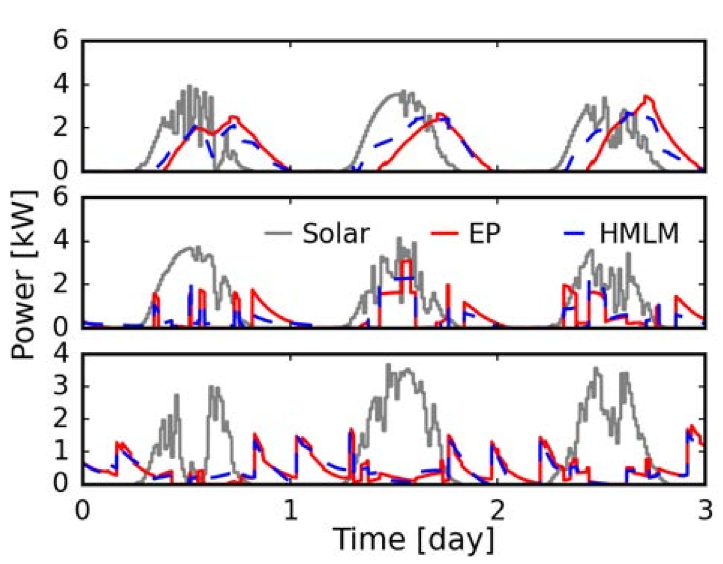
Problem Formulation

- Objective of this poster is to use black box models to approximate widely used white-box model synthetic data of smart home
- Residential load in the United States was 22% of the total energy used in 2020, making it of interest for demand response and load shifting tactics to reduce environmental impact and cost.
- Of this residential demand Heating Ventilation and Air Conditioning (HVAC), makes up the majority with up to 40%
- A calibrated EnergyPlus model of an HVAC system was replicated using a machine learning (ML) model that can facilitate faster simulation
- The basis of the HVAC model is on the temperature difference between the outdoor and the temperature setpoint, which approximates the indoor temperature.

Application of Black Box Home Models in VPP



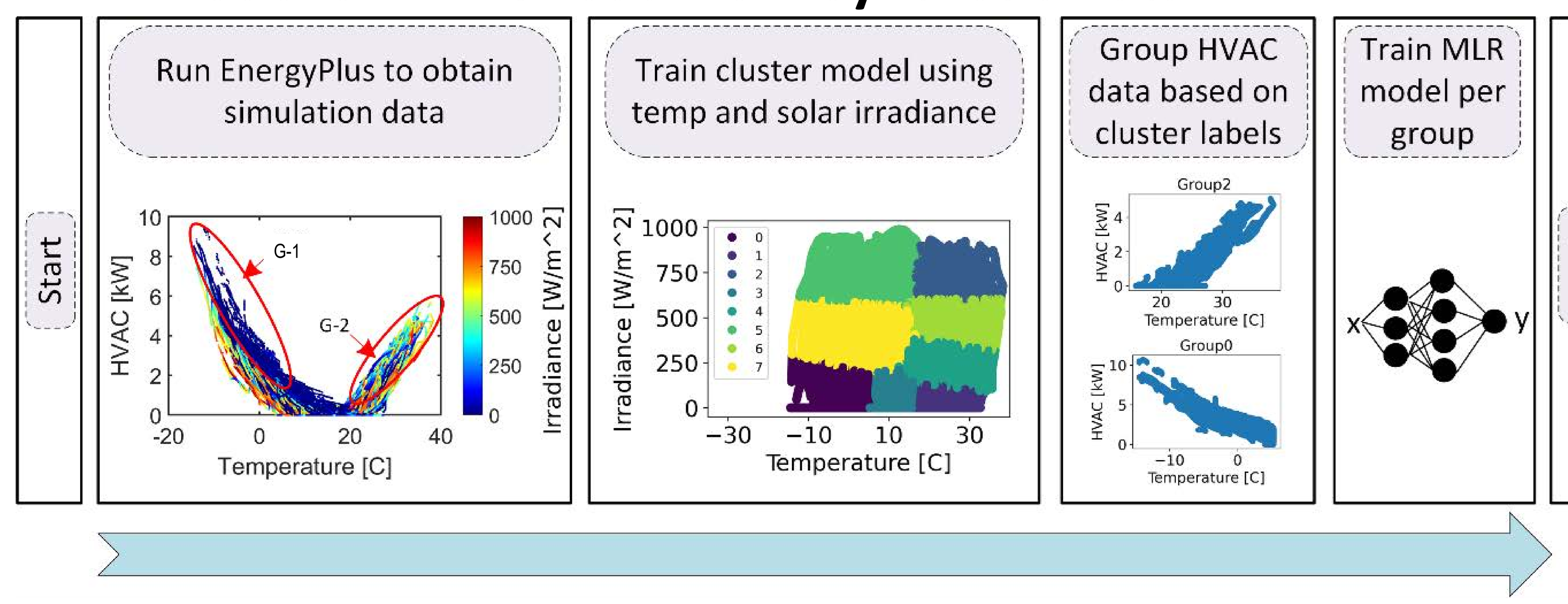




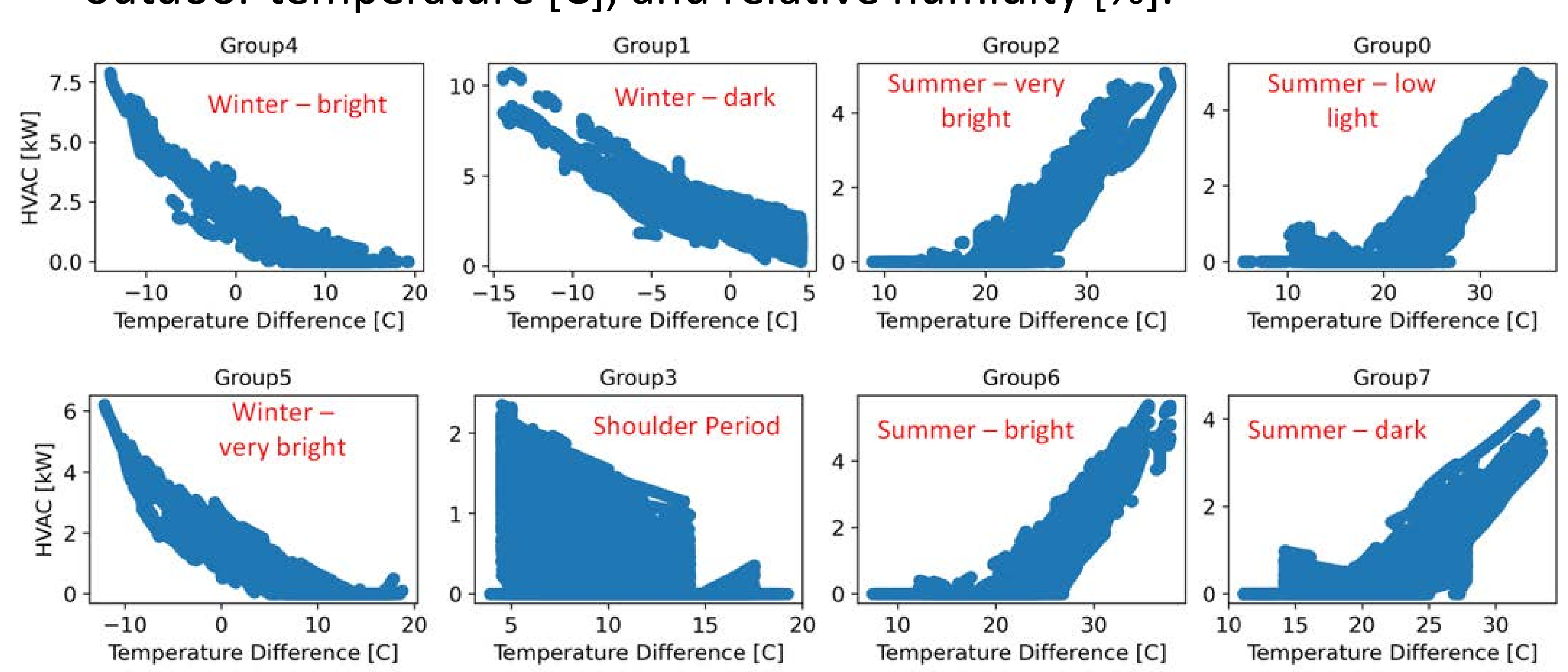
$$P_{tot} = HVAC + WH + Baseload$$

- Renewable Energy integration requires detailed studies to align variable generation times, increased distributed energy storage, and demand response controls
- Solar generation is highly dependent on the weather minute to minute including cloud cover, so a co-simulation platform would benefit of fast accurate models at the minutely level
- Example Total synthetic load for a home based on the proposed HMLM model of a conventional HVAC system with high load, typical experimental baseload, and an high efficiency Heat Pump Electric Water Heater (HPEWH) for use virtual power plant (VPP) studies.

ML Model of HVAC Load from Synthetic Data



- Hybrid ML model 2 parts:
  1. K-means clustering model: organizes the solar irradiance and outdoor temperature inputs into 8 groups of similar data to isolate linear HVAC relationships.
  2. Multiple Linear Regression (MLR): learns the linear relationship between the HVAC and solar irradiance, outdoor temperature, and relative humidity per each group
- Inputs to the Hybrid ML model are solar irradiance [W/ m^2], outdoor temperature [C], and relative humidity [%].

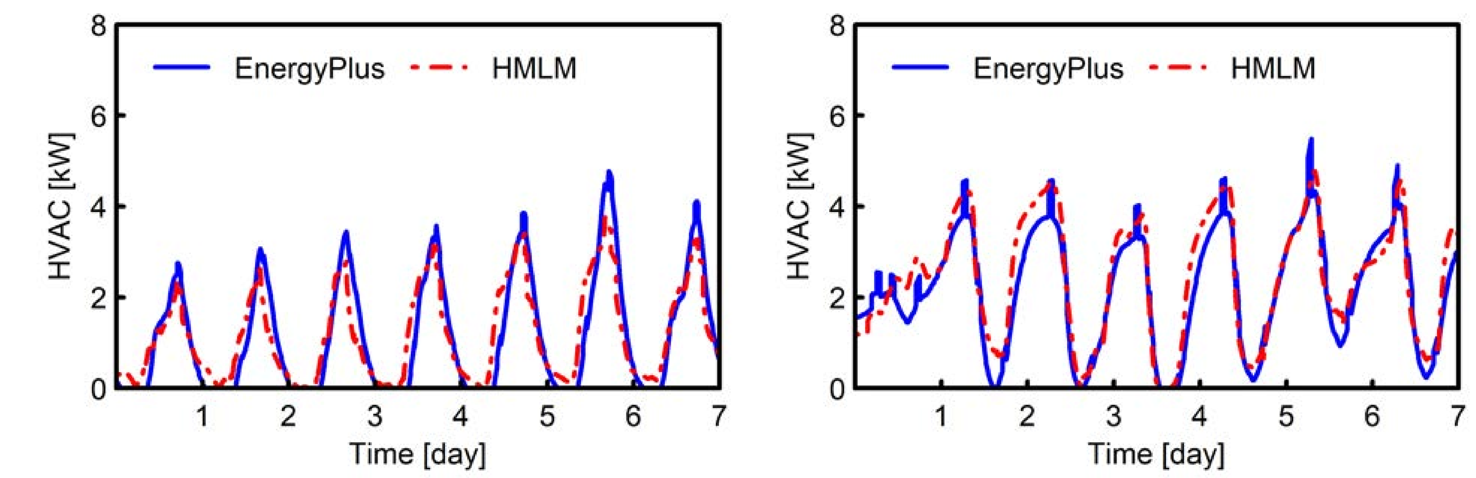


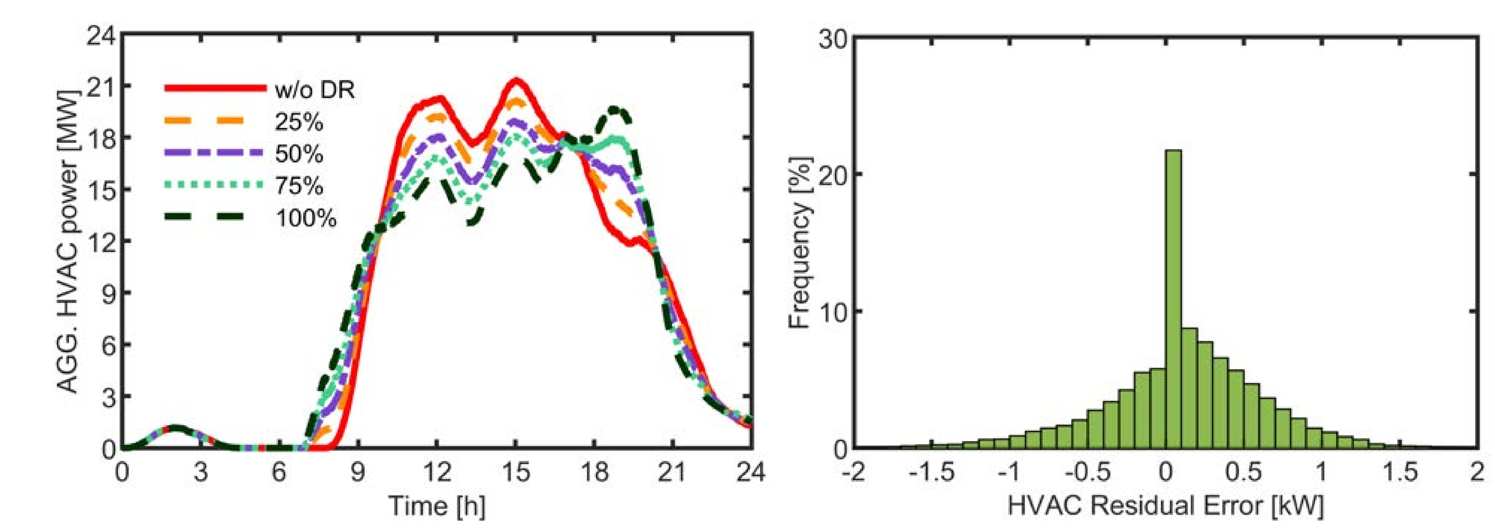
- For the eight groups identified, each represents a different weather pattern that the HVAC will have to operate in
- The accuracy of the Hybrid ML model is affected by the peak load magnitude with shoulder months as the most difficult to calculate.

Season	Group	MAE [kW]	MSE [kW^2]	RMSE [kW]	R2 [-]	Average HVAC [kW]	Maximum HVAC [kW]
Summer (hot low light)	0	0.447	0.385	0.620	0.722	1.012	4.661
Winter (cold and dark)	1	0.478	0.336	0.580	0.608	2.538	7.661
Summer (bright hot)	2	0.562	0.510	0.714	0.585	1.137	4.418
Shoulder	5	0.196	0.097	0.312	0.036	0.183	1.537
Winter (cold and middle brightness)	4	0.360	0.228	0.478	0.669	0.829	3.771
Winter (cold bright)	3	0.310	0.152	0.390	0.431	0.477	2.193
Summer (hot and middle bright)	6	0.509	0.434	0.659	0.714	1.330	4.778
Summer (hot but dark)	7	0.224	0.141	0.375	0.651	0.374	3.700
All year	All	0.359	0.248	0.498	0.812	0.991	7.661

Case Study for Smart Homes

- The historical 2013 synthetic data generated by EnergyPlus for the HVAC system, is compared to the output from the Hybrid ML model using the same weather inputs.
- Fig Left: July 12 – 18, 2013 (Summer week)
- Fig Right: January 17 – 23, 2013 (Winter week)





Conclusions

- Co-simulation of residential load major appliances such as HVAC offers potential for demand response and synergistic alignment with renewable energy resources
- The two-part hybrid ML model proposed in this poster preforms with less than 10% Mean Absolute Percent Error (MAPE) and 70% of time instance calculations have an error within 0.5 kW.
- It is the most accurate in the summer on hot bright days, corresponding with solar generation
- Total home can be modeled in a co-simulation framework through synthetic data by summing the HVAC load predicted, a WH load and a baseload profiles from example smart homes.

Future and Ongoing Work

- Utilize the total home loads as a community demand response and load shifting study
- Assess Home Energy Management (HEM) controls with EV batteries and the synthetic total home profile.

Acknowledgement

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