Artificial Intelligence-based Short-term Electric Load Forecasts for Experimental Smart Homes including HVAC and PV Components

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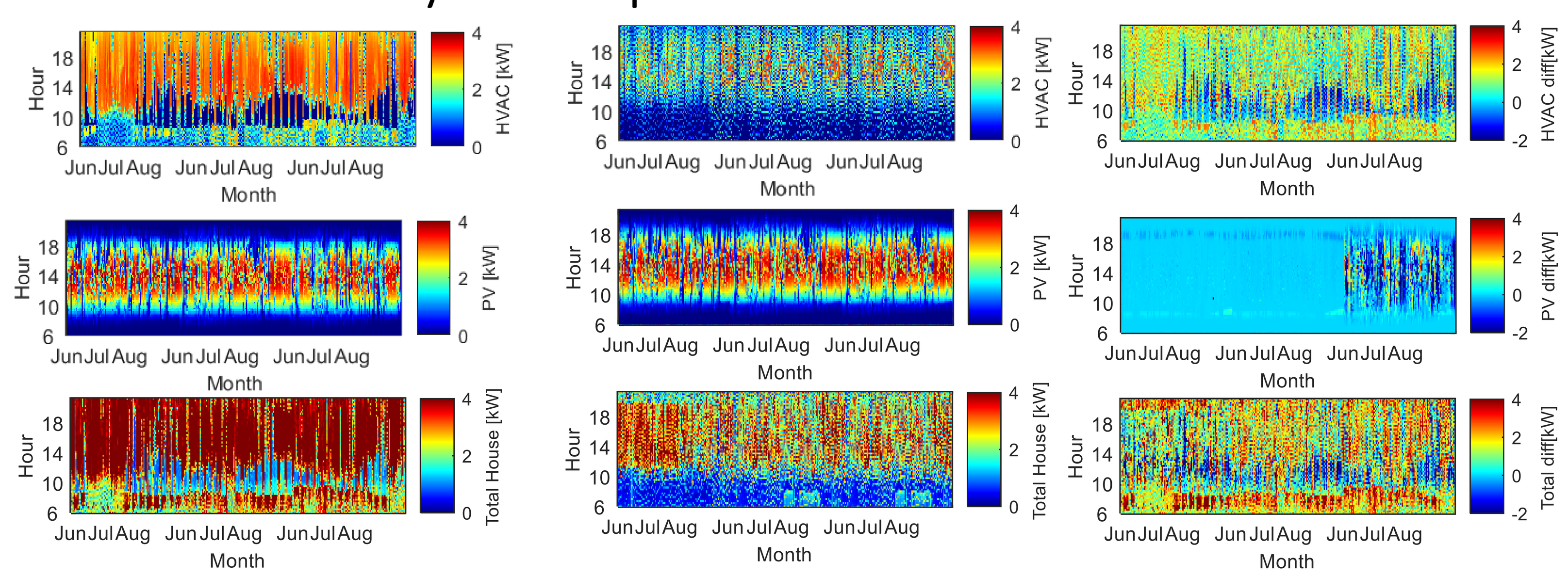
Problem Formulation

- To predict electric load of the total average power as well as individual components for two residencies from experimental data
- Individual residential forecasting is difficult due to high variability of appliance usage and random human behavior influences.
- Separate the HVAC load from total load as a desired profile using weather relationship and minimum HVAC load at night
- Data driven approach to reduce the amount of information about the home required.

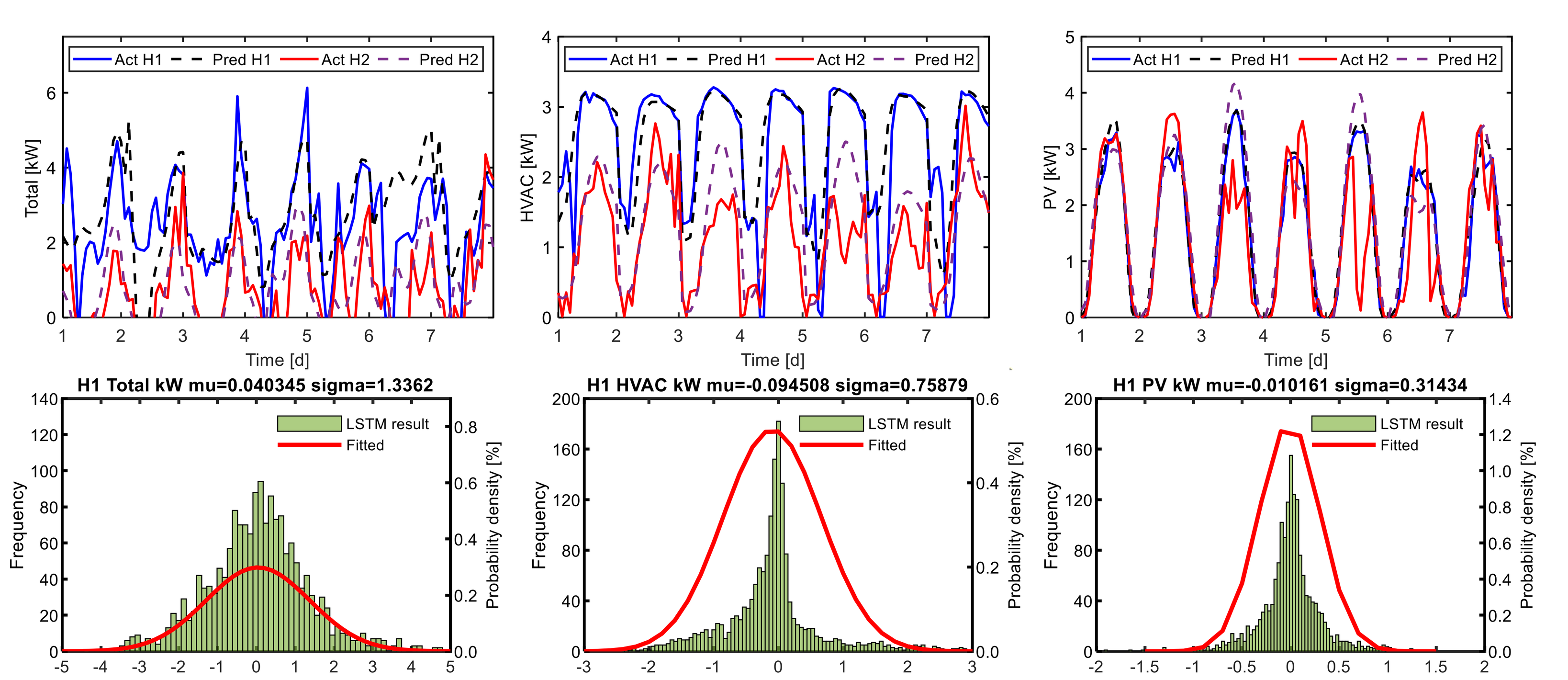
SHINES Field Demonstration Homes

- Experimental 15-minute data in the summer integrated to hourly timestep and isolated the daylight hours from 6am to 9pm only to reduce variability of ML inputs



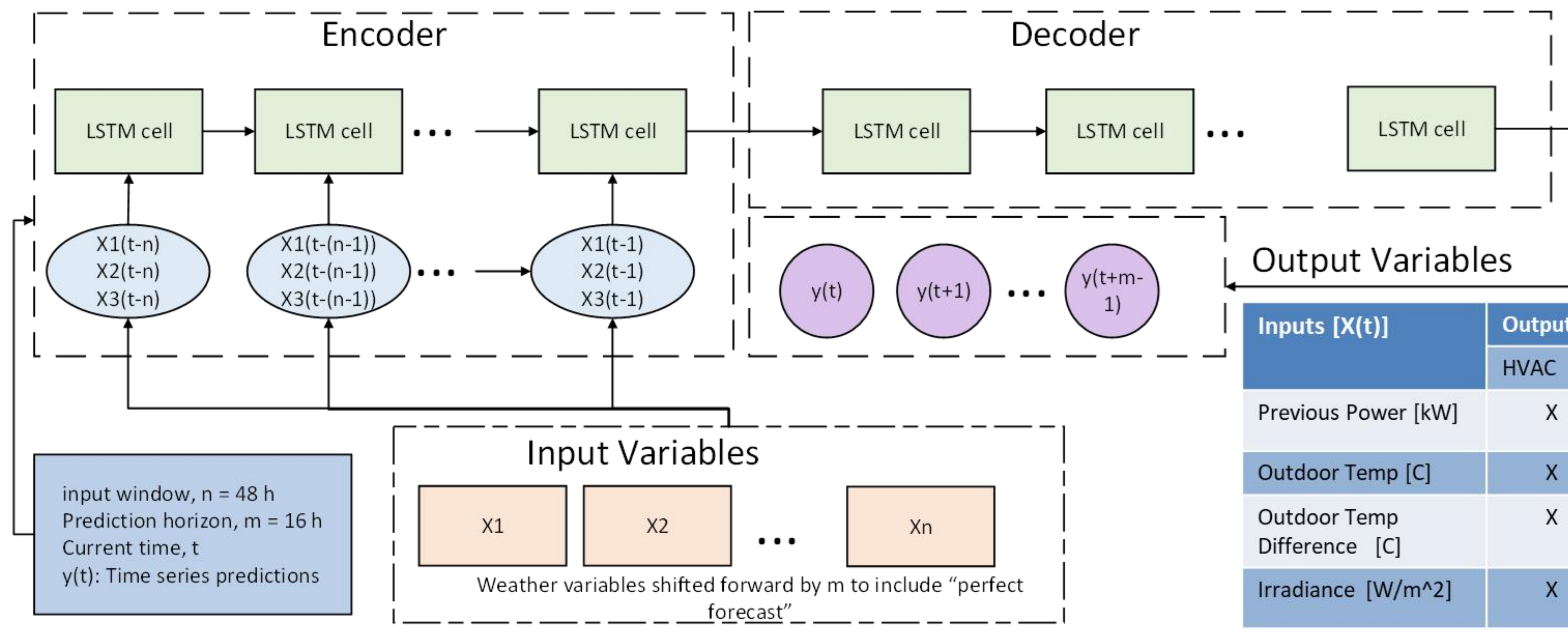
LSTM Encoder-Decoder Model with "Perfect Forecast"

- Model selected is a Recurrent Neural Network (RNN) that is known for identifying long term dependencies
- Structured to predict the next day-time period based on the previous 3 days of energy average power usage, the previous two days of weather data, and one future day of weather parameters
- Future day of weather data is the "perfect forecast"
- Model trained on the two previous summers to predict the 2020 season, example predictions July 31st to August 6th:



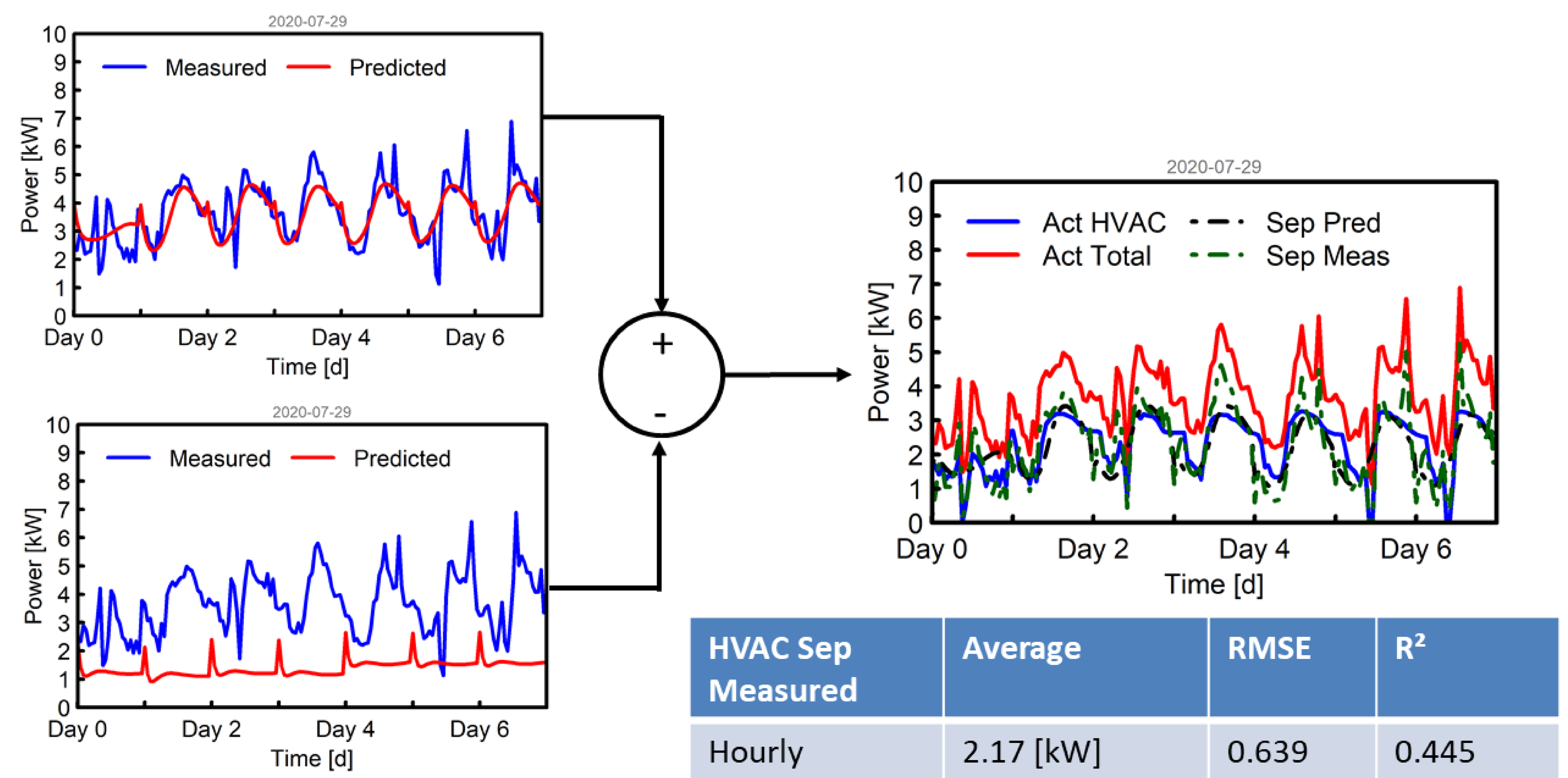
Day ahead	HVAC		Total kW		Solar kW	
	kW	%	kW	%	kW	%
H1 RMSE	0.8	22.8	1.2	10	0.3	6.6
H2 RMSE	0.5	13.8	1.1	9.1	0.9	20

$$RMSE = \sqrt{\sum_{i=1}^{n}(X_{act,i} - X_{pred,i})^2}$$



Inputs [X(t)]	Output [y(t)]		
	HVAC	Total	Solar
Previous Power [kW]	X	X	X
Outdoor Temp [C]	X	X	X
Outdoor Temp Difference [C]	X	X	
Irradiance [W/m^2]	X	X	X

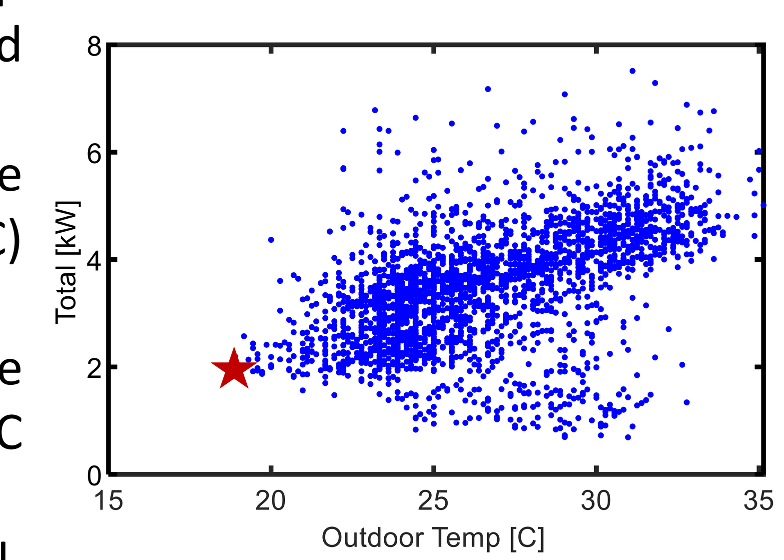
HVAC Separation from Smart Meter Data



HVAC Sep Measured	Average	RMSE	R^2
Hourly	2.17 [kW]	0.639	0.445
Daily	51.6 [kWh/day]	5.72	0.665

A method to separate the HVAC load from total smart meter data:

1. For a given residence, establish the LSTM model for the relationship between total load, temperature and solar irradiance
2. Determine the "Temperature for the minimum HVAC load" (TmHVAC) from hourly load "V-shape curve"
3. Estimate using LSTM model the baseload corresponding to TmHVAC and 0 irradiance
4. Separate HVAC power from the total, measured or forecasted, by subtracting the predicted baseload from step 3.



Connection to HEMS Applications

- Electric load forecasts such as these can be used with HEMs to schedule appliance loads such as HVAC to be during times of renewable energy generation
- HVAC separation serves to estimate for both users and the utility when a large portion of residential use occurs
- It also would allow for demand response to be implemented in more common homes without dedicated circuits for HVAC energy monitoring

Conclusions

- HVAC and solar predictions are satisfactory with the most frequent error near zero.
- Each prediction distribution of residual error for the Total, HVAC, and PV predictions are centered around zero
- The influence of human behavior can be seen in the Total predictions as the distribution is much more spread out and loads such as lighting are considered
- Novel two-step HVAC separation method to predict HVAC load based only on smart meter data performs as well as forecasting from historical HVAC measured data, and may represent a significant contribution to field deployment.

Future and Ongoing Work

- fine tune the mathematical method for selecting the TmHVAC and publish a full paper to provide other researchers an opportunity to verify HVAC separation method with addition homes and climates

Acknowledgement

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