2019 Building Performance Analysis Conference

Seminar 13 - Advanced Methods for Grid Integration of High-Performance Residential Communities

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Presenters

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Optimal Rooftop PV Placement in Net Zero Energy Communities

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Machine-Learning-based End-Use Energy Consumption Estimation for Residential Buildings

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Physics-based White-Box Dwelling Model for Building-to-Grid Integration Study

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A Hierarchical Control System for Enhancing Reliability and Resilience of Residential Communities

Learning Objectives

- Describe the challenges in grid integration of residential communities with high PV penetration levels
- Present novel solutions to the challenges and the guidelines for grid integration of future residential communities
- Determine how to optimally place PV panels across a community
- Understand the level of model complexity needed for different applications

Motivation – Increasing PV Penetration

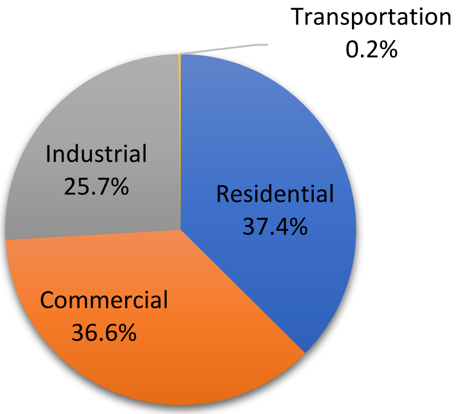
More electricity from renewable sources

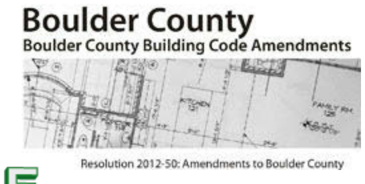
- Over 100 cities target 100% renewable by 2030-2050
- Solar will supply 10-20% of the U.S. electricity by 2030
- Residential electricity usage is larger than any other sector

Net zero energy (NZE) homes and communities are emerging

- California’s Title 24: all new homes will be NZE by 2020
- Boulder County, CO: all new homes to be NZE by 2022

2017 U.S. Electricity Consumption by Sector





Boulder County

Boulder County Building Code Amendments

Resolution 2012-50: Amendments to Boulder County

TITLE 24

CA Compliant

Challenges

Challenges brought by high penetration of PV

- Every home in an NZE community may have 3-10 kW PV
- Distribution system may experience issues such as overvoltage, voltage flicker, and degraded power factor
- Potential solutions: curtailment, storage, flexible loads
    - Curtailment is commonly used but it hurts the economics
    - Battery storage is still expensive for most homeowners
    - Flexible loads have potential but need coordination

Major limitations in existing solar plus technologies:

- Insufficient understanding of behind-the-meter assets
- Immature coordination strategy for heterogeneous assets
- Deficient grid impact analysis

Solution

NREL is developing a hierarchical control system to address the challenges and enhance grid reliability

This seminar consists of four integral presentations that cover different aspects of a solution to the challenges:

- **PV Sizing**: Optimal Rooftop PV Placement in NZE Communities
- **Control-Oriented Building Modeling**: Physics-based White-Box Dwelling Model for Building-to-Grid Integration Study
- **Load Estimation:** Machine-Learning-based End-Use Energy Consumption Estimation for Residential Buildings
- **Community-Scale Control:** A Hierarchical Control System for Enhancing Reliability and Resilience of Residential Communities

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Optimal Rooftop PV Placement in Net Zero Energy Communities

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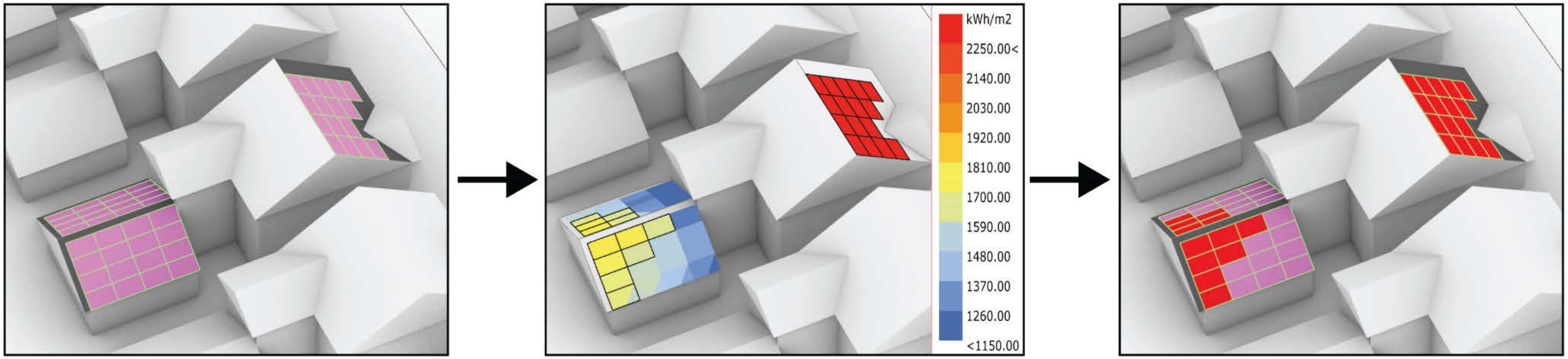
PV Sizing to Meet a Community’s NZE Goal

Automated workflow to size PV to meet the NZE requirement:

1) Optimal rooftop PV panel placement
2) Annual PV energy simulation to calculate the gap for ZNE
3) Size the community PV to fill the gap



(a) Automated PV panel layout

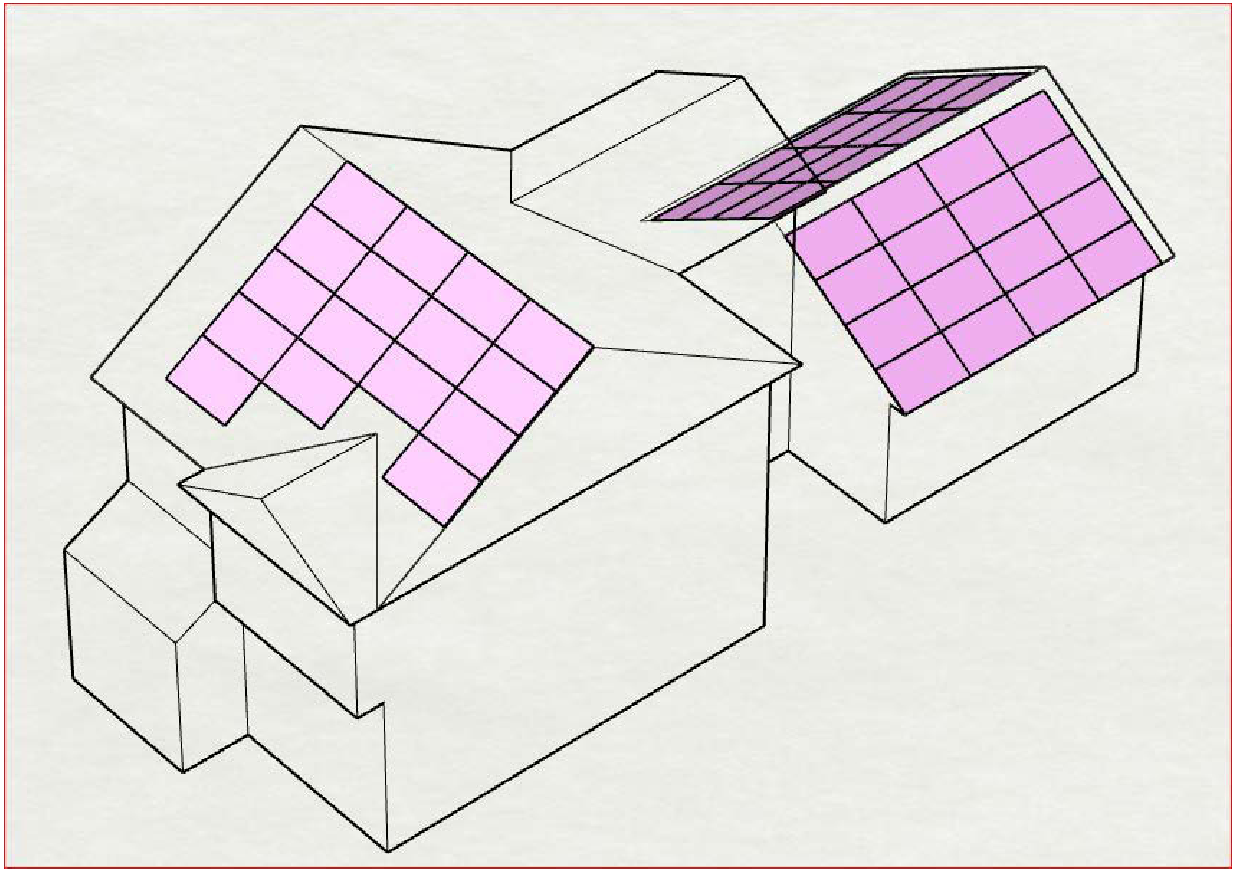
(b) Solar radiation study

(c) Panels selection

1) Optimal rooftop PV panel placement

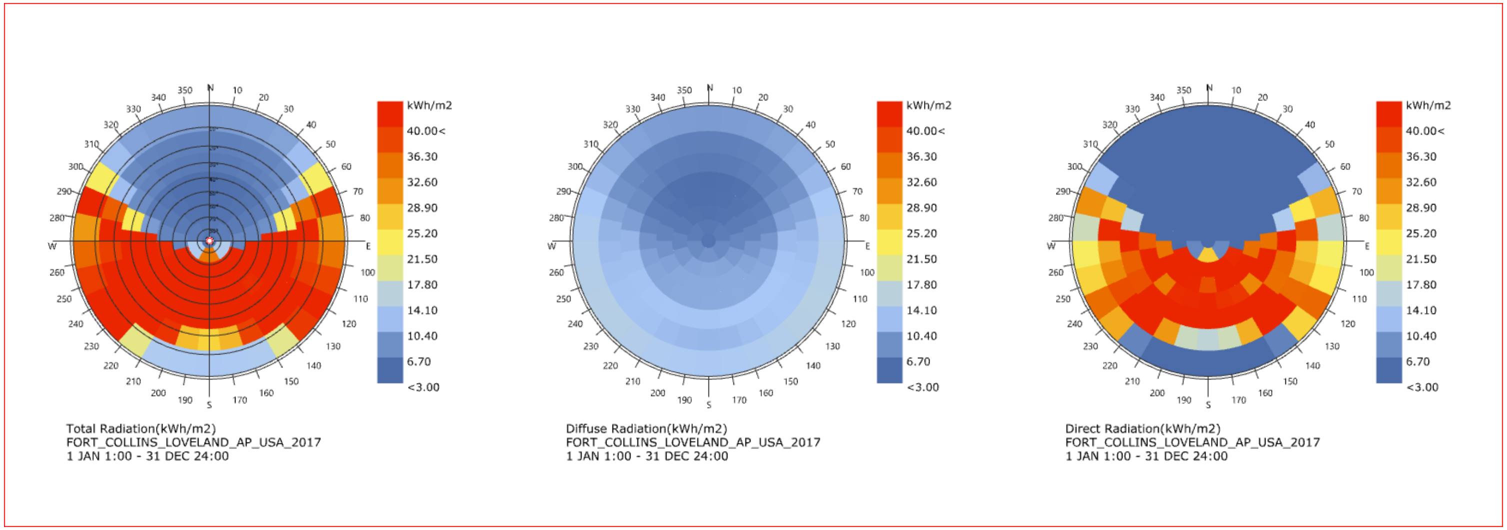
Step 1: Optimal Rooftop PV Panel Placement

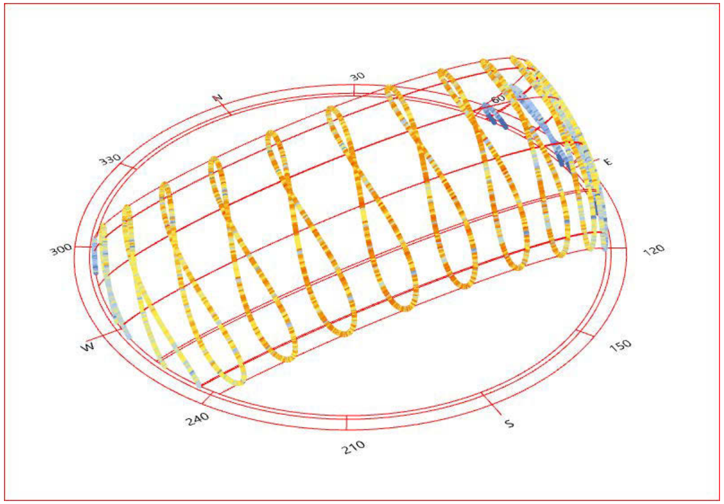
(a) Automated PV panel layout considering roof geometry and panel size

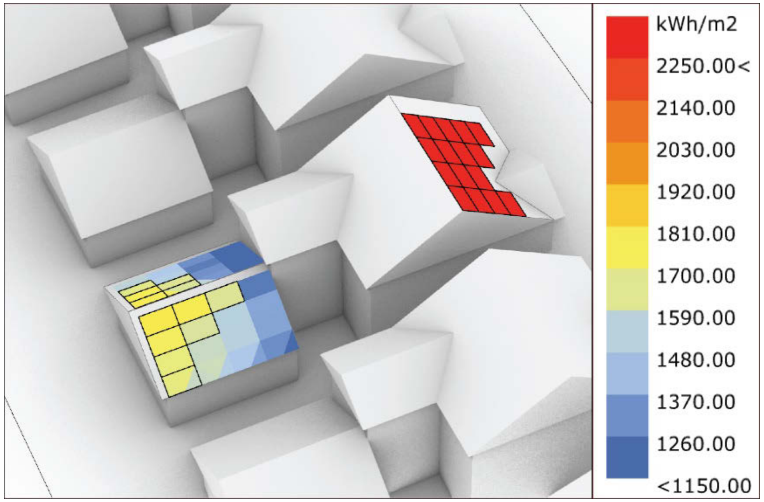


Step 1: Optimal Rooftop PV Panel Placement

(b) Compute the annual solar radiation (kWh) on each panel

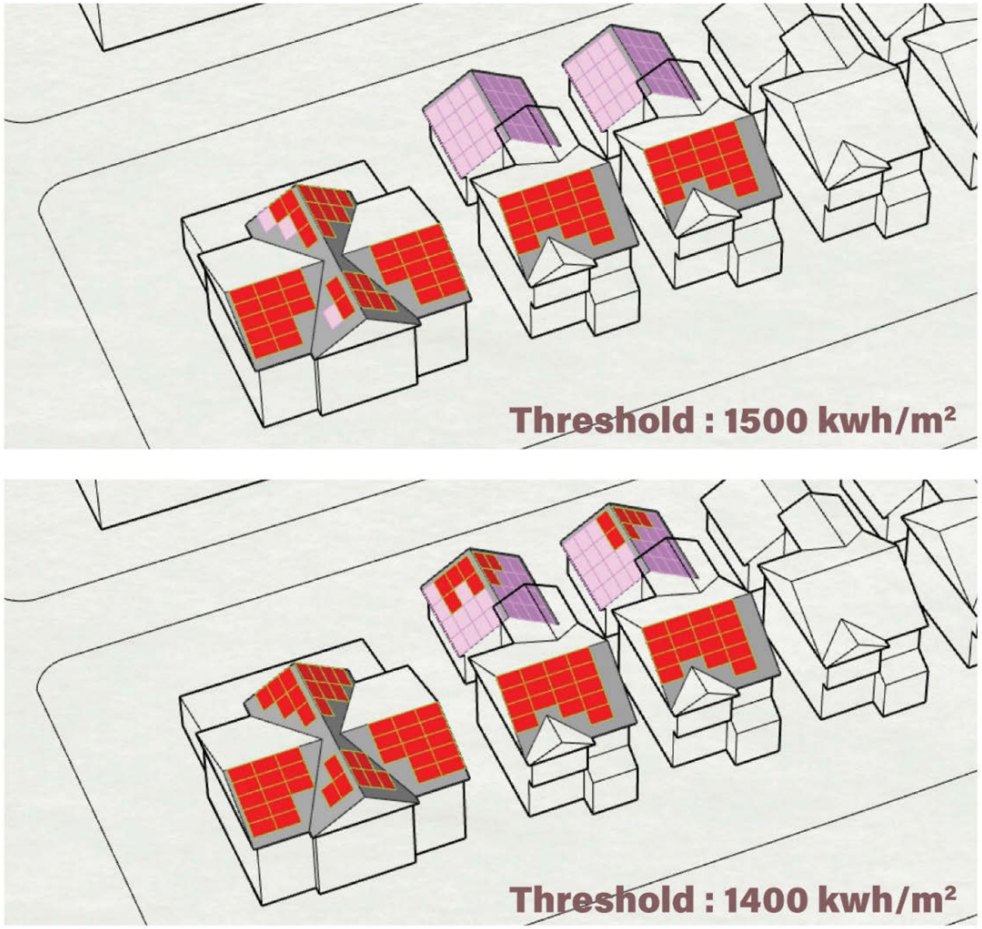






Step 1: Optimal Rooftop PV Panel Placement

(c) Identify the best locations for panel deployment based on a solar radiation threshold



Step 2: PV Energy Simulation

- Annual PV production of the selected panels was calculated using PVWatts
- Typical system losses and PV module settings were used

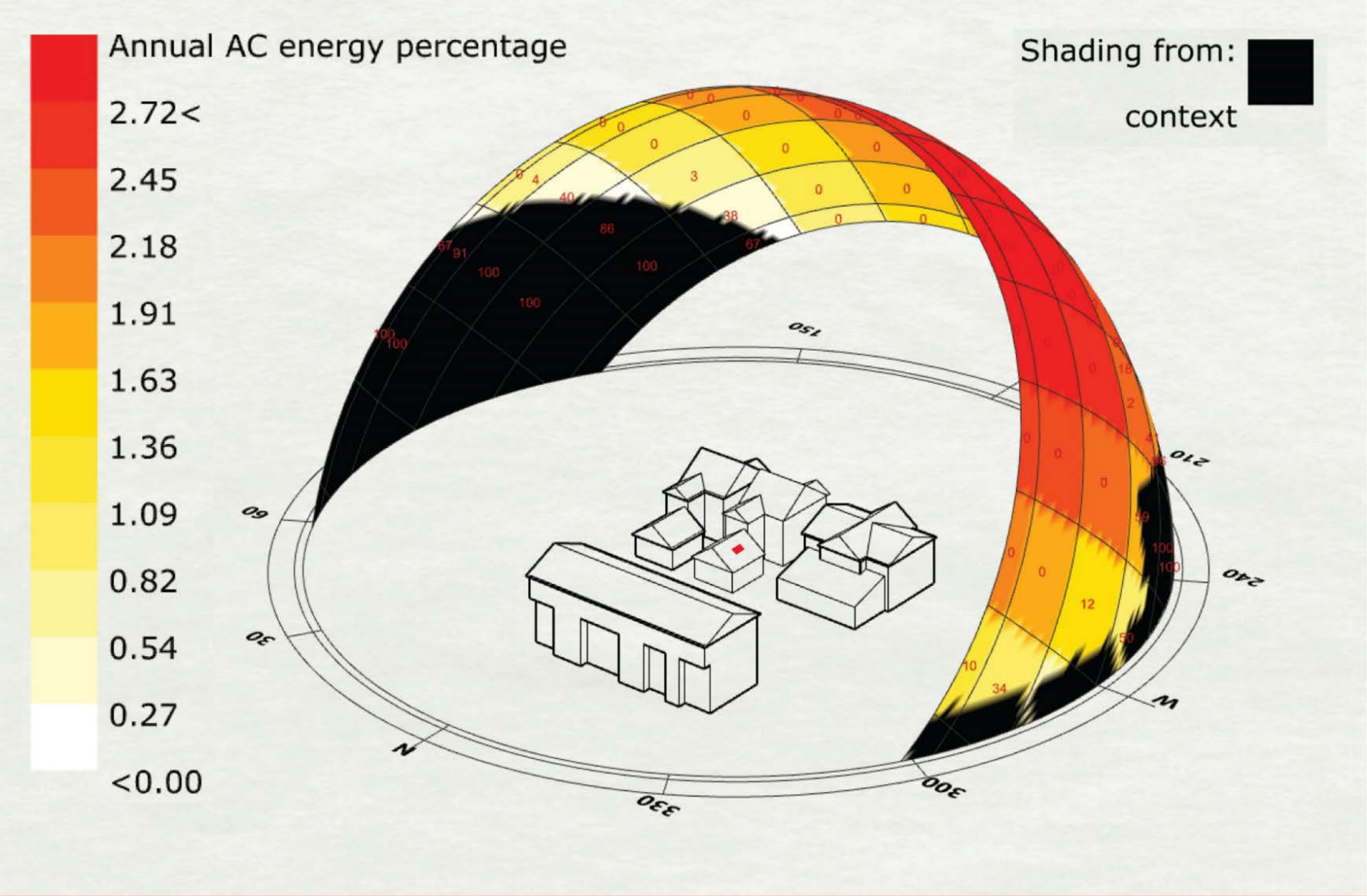
PV model inputs and Assumptions

PV module settings	inputs
Module material	Crystalline silicon (c-Si)
Mount type	Close (flush) roof mount
Module efficiency	18.7 %
Temperature coefficient	-0.5%/C
Module active area %	90%

System Losses Category	Values (%)
Soiling	2
Snow	0
Mismatch	2
Wiring	2
Connections	0.5
Light-Induced Degradation	1.5
Nameplate Rating	1
PV module Age	0
Availability	3

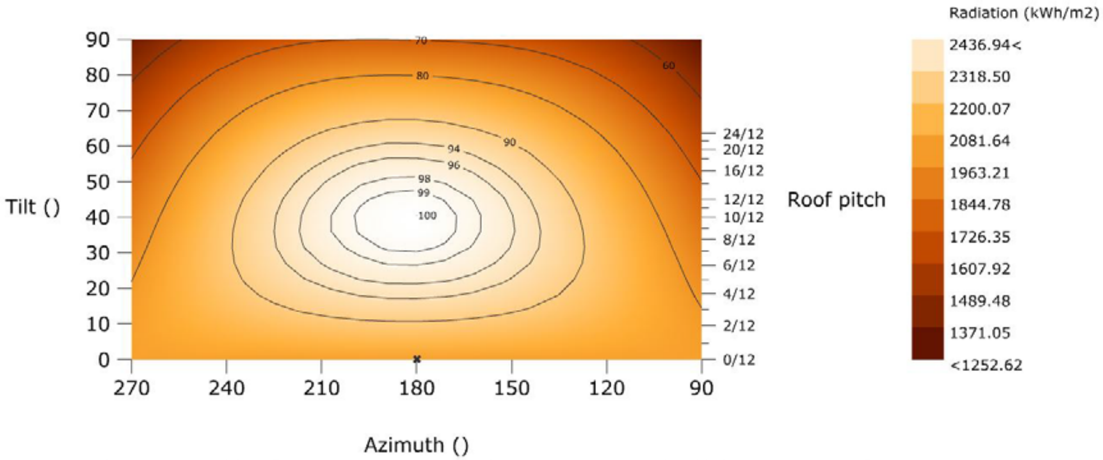
Step 2: PV Energy Simulation

- The losses due to shading were calculated for each PV panel



Step 3: Community PV Sizing

- The selected rooftop PV were not sufficient to meet the NZE requirement when a solar radiation threshold of 1,650 kWh/m^2 or higher was assigned
- The optimal tilt and orientation were calculated for the community PV and the size was determined to fill the gap between the annual energy use and production from rooftop PV

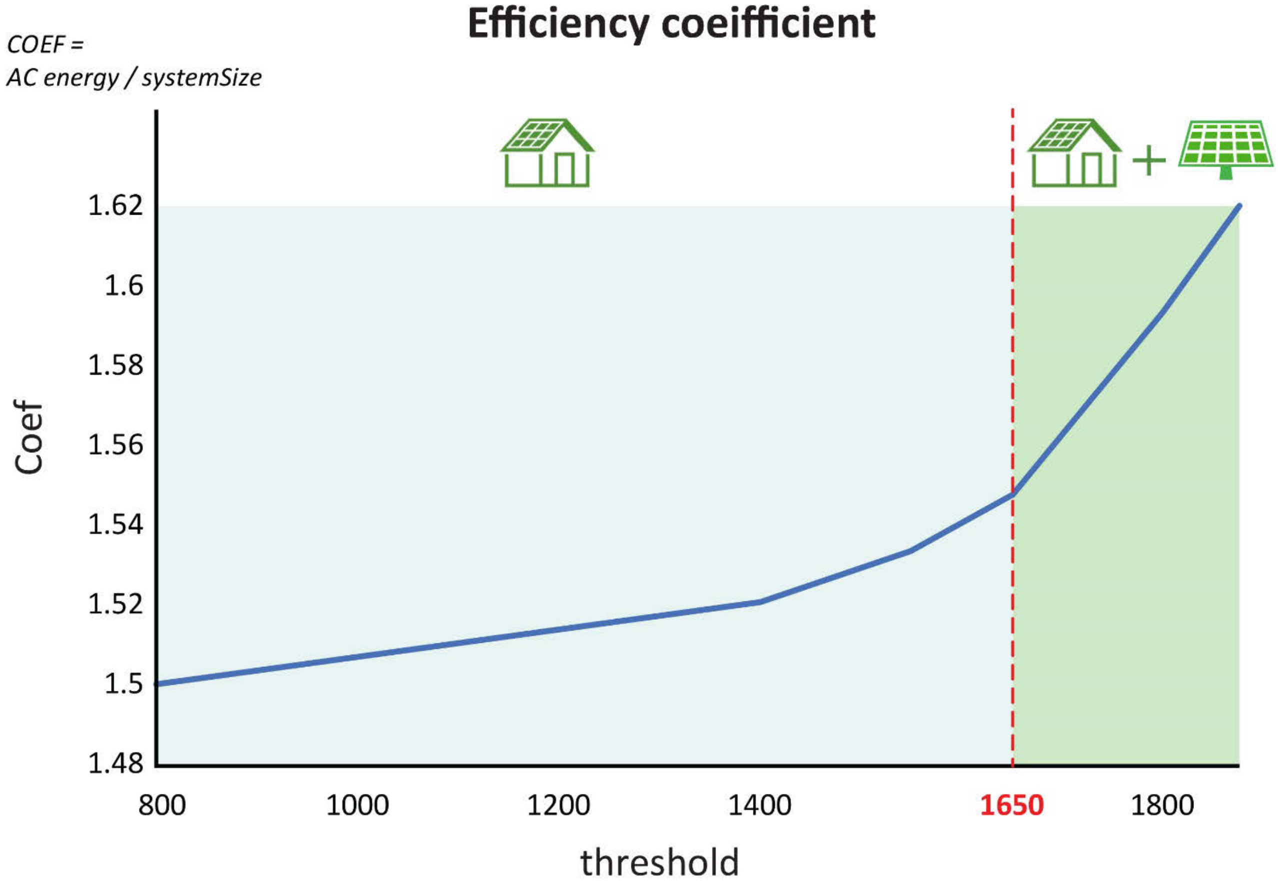


Solar radiation as a function of panel tilt/orientation

Location: FORT-COLLINS-LOVELAND-AP_USA, Latitude: 40.45, Longitude: -105.02
Optimal: Tilt: 40.5, Azimuth: 180.0, Radiation: 2436 kWh/m2, TOF: 100.0, TSRF: 100.0
Analysed: Tilt: 0.0, Azimuth: 180.0, Radiation: 1989 kWh/m2, TOF: 81.6, TSRF: 81.6
Analysis period: whole year

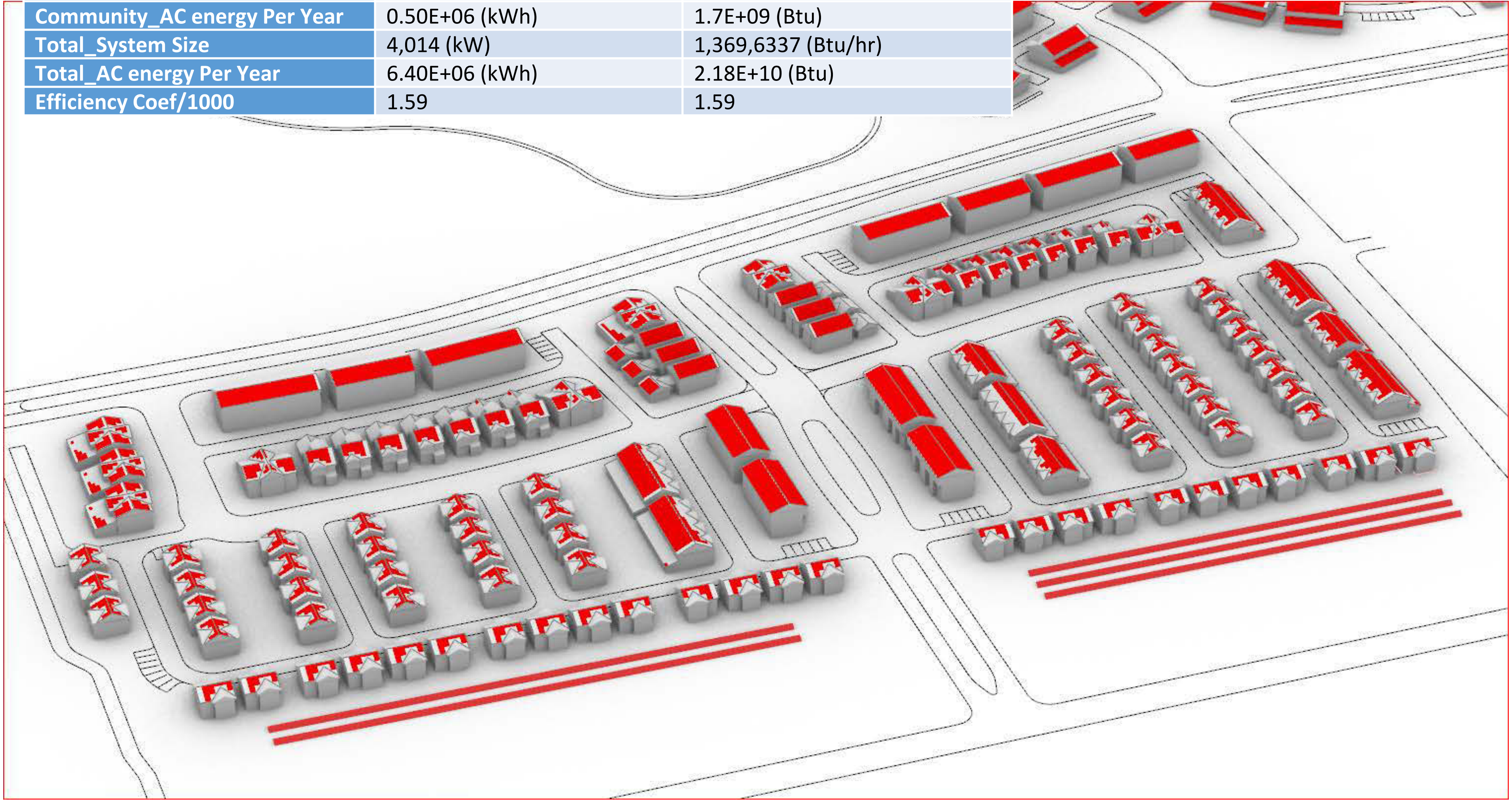
Results

$$\text{Efficiency coeffient} = \frac{\text{total AC energy per year}}{\text{total system size}}$$



Results

Solar Radiation Threshold	1,800 (kWh/m2)	570597 (Btu/ft^2)
Rooftop_System Size	3,761 (kW)	12,833,066 (Btu/hr)
Rooftop_AC energy Per Year	5.90E+06 (kWh)	2.01E+10 (Btu)
Community_System Size	252 (kW)	859,859 (Btu/hr)
Community_AC energy Per Year	0.50E+06 (kWh)	1.7E+09 (Btu)
Total_System Size	4,014 (kW)	1,369,6337 (Btu/hr)
Total_AC energy Per Year	6.40E+06 (kWh)	2.18E+10 (Btu)
Efficiency Coef/1000	1.59	1.59



Conclusion and Future work

Conclusion:

- We present an automated workflow to optimally size and place the PV panels
- The selected rooftop PV and community PV help the community to meet the NZE requirement

Future work will consider additional constraints and objectives :

- TOU pricing
- Minimize PV curtailment
- Balance between battery and PV deployment

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Physics-based White-Box Dwelling Model for Building-to-Grid Integration Study

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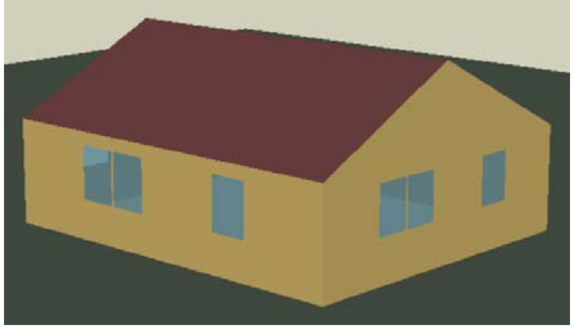
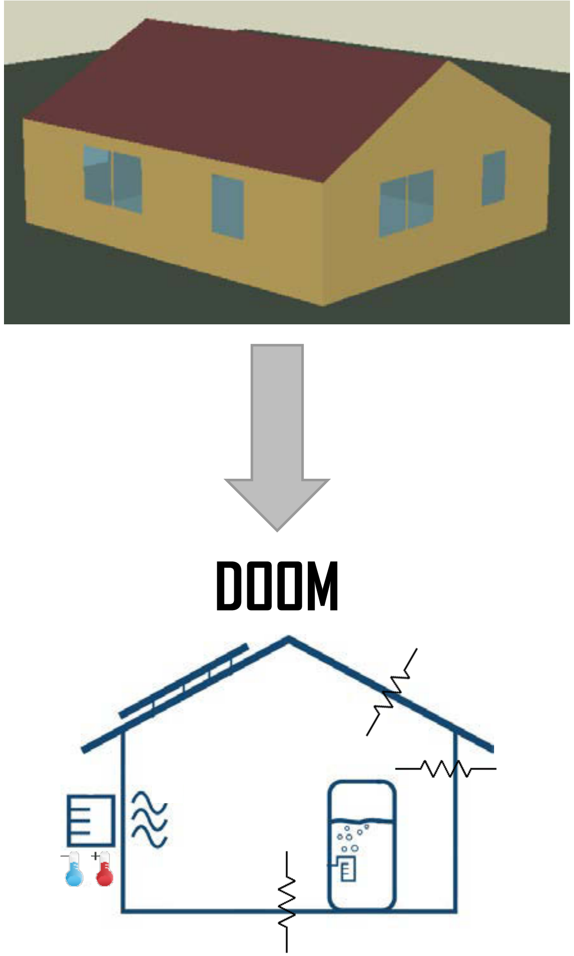
Motivation: Why use a RC model?

- Building simulation engines (E+, DOE-2, TRNSYS, etc.) exist and provide the most detailed models of building physics
- Resistance-capacitance (RC) models allow most of the physics to be captured while providing other advantages
- RC models can run faster and are easier to tailor to specific use cases
    - Ideal for a controls-oriented model because of the faster run time and customization
- This talk discusses a new RC building model created specifically to support control-oriented modeling of a residential community



Motivation: Why ANOTHER RC model?

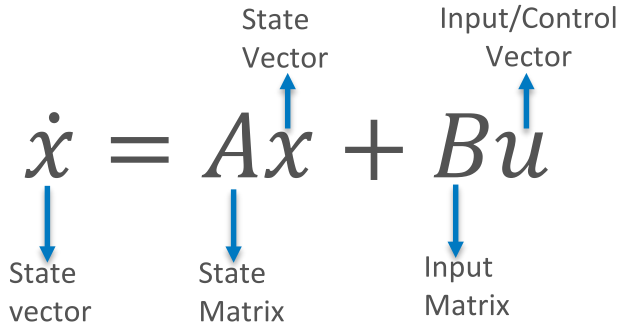
- There are several RC models available in the literature
- A new model (the **D**welling **O**bject-**O**riented **M**odel, DOOM) was created to include several key features:
  - Reactive power
  - **White-box** model (totally based on physics, not tuned with data)
  - Integration with a GUI (BEopt) for fast model creation and ease of use
  - Deadband thermostat control
  - More detailed HVAC models
  - Explicit film coefficients for solar
- Model is tailored to residential buildings



DOOM Features & Functionality

- State space models used to represent the building envelope and water heater
- Detailed HVAC model based on EnergyPlus approach
- Internal gains directly from established residential modeling tool (BEopt)
- Real & reactive power for every end use
- 2 node water heater model
- Full timestep flexibility (down to 1 sec)

State-Space Model



State Vector

Input/Control Vector

$$\dot{x} = Ax + Bu$$

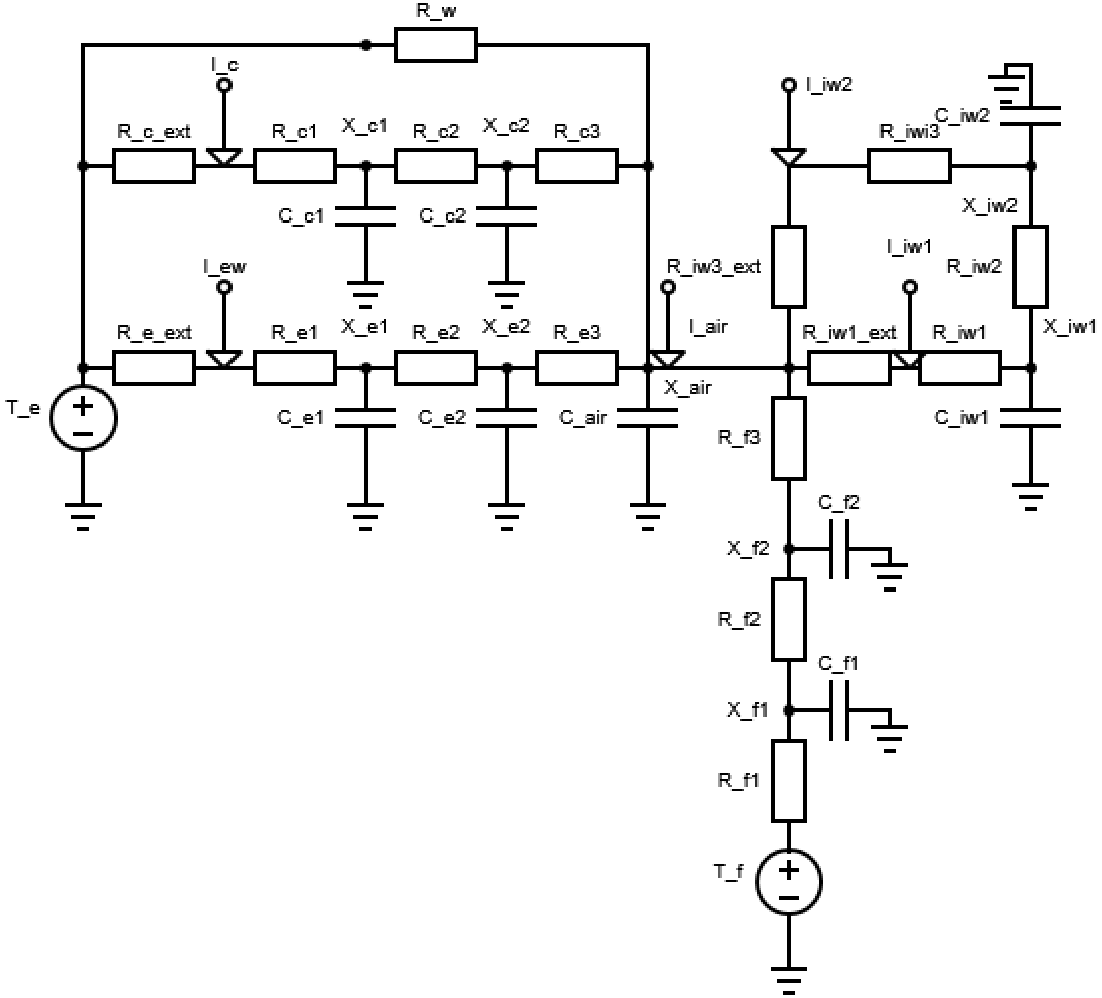
State vector

State Matrix

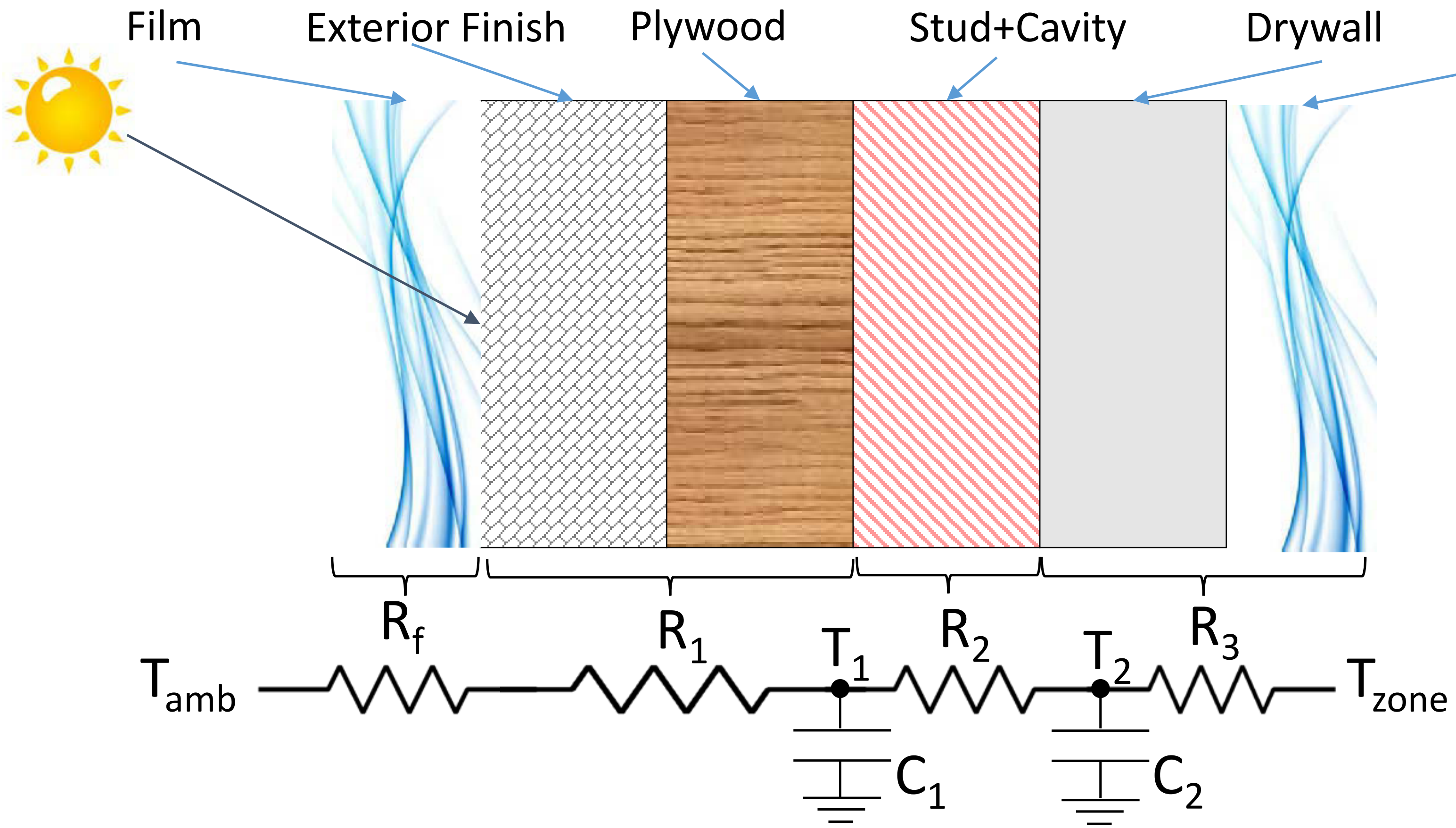
Input Matrix

DOOM is not intended as a replacement to EnergyPlus, but as complimentary for certain controls applications

The DOOM Envelope Circuit Model



DOOM: The 3R2C Approach



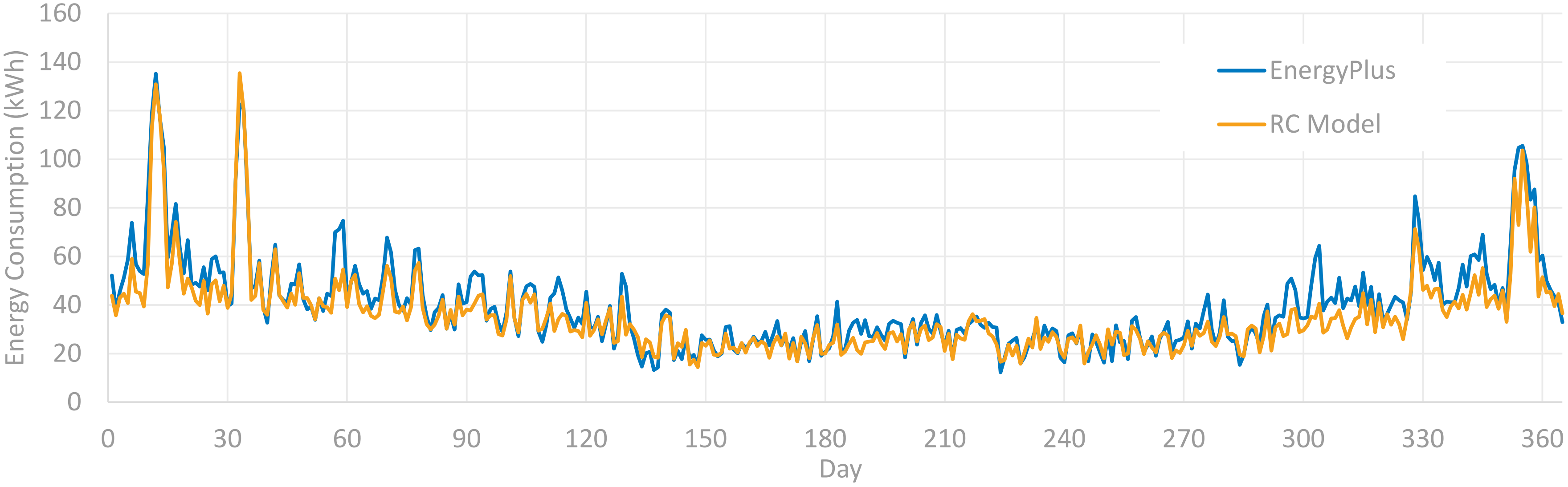
Model Validation Procedure

- Ran a “mini test suite” (similar to the BEopt test suite) to validate the component level models, then did annual simulation
- The test suite approach uses a “minimal” building
  - Superinsulated contructions, no windows, ideal HVAC, no gains/inf/WH
  - Enables one heat transfer path/component model at a time
- Procedure has been used to compare other models to EnergyPlus and found numerous bugs/differences, some expected and some not

Validation: Component Level Results

	BEopt/E+			DOOM			Difference
Category	Heating (kWh/yr)	Cooling (kWh/yr)	Total (kWh/yr)	Heating (kWh/yr)	Cooling (kWh/yr)	Total (kWh/yr)	Total (kWh/yr)
Walls	1046	510	1556	1006	502	1509	3%
Ceiling	161	2216	2377	228	2093	2322	2%
Floor	1949	0	1949	1860	0	1860	5%
Infiltration	513	85	598	541	92	633	6%
Windows	273	1738	2011	107	1499	1606	20%
Gains	0	2145	2145	0	1968	1968	8%
Water Heater	3180	-	3180	3457	-	3457	9%

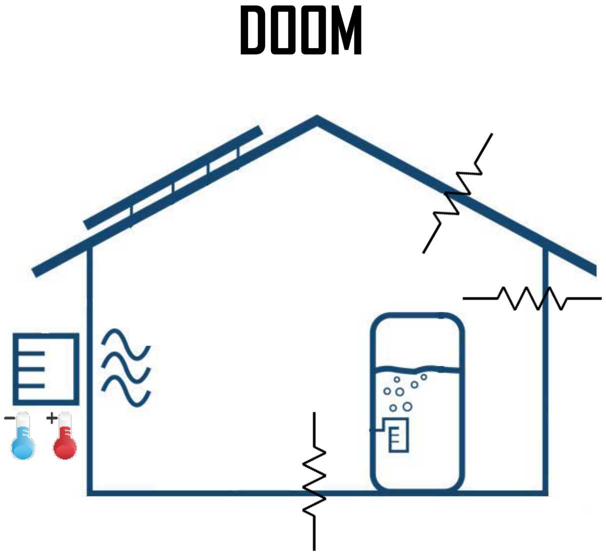
Validation: Annual Results



- Base building is a single family home that's part of the Ft. Collins community
- Annual Energy Consumption Difference: 11%
- Daily Average Energy Consumption Difference: 12%
  - Most of the discrepancy is due to HVAC, could partially be window related

Conclusions

- A new RC building model framework designed for controls purposes has been created and validated against EnergyPlus
    - Tool is designed to be able to be used by people not as intimately familiar with building models
- Development is still ongoing, but the majority of equipment available in residential buildings is incorporated
    - Future updates will increase functionality to allow the simulation of the entire US residential housing stock



Machine-Learning-based End-Use Energy Consumption Estimation for Residential Buildings

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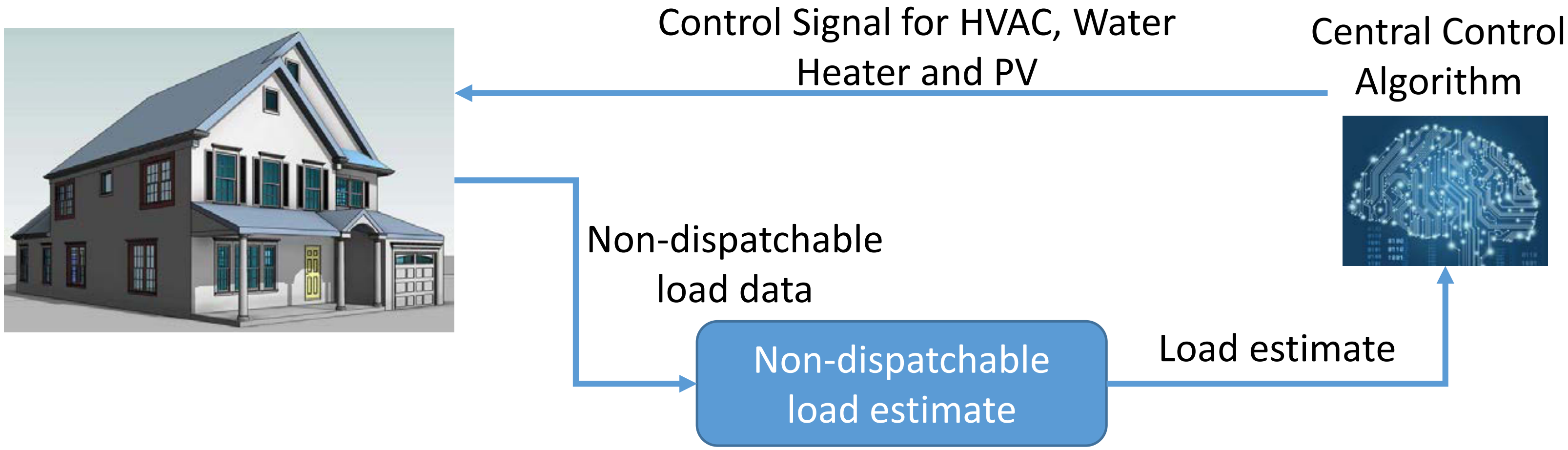
Outline

- Background
- Data
- Algorithms and Variables
- Algorithm Performance
- Conclusion

Research Background

- Non-dispatchable load
  - Include all building loads except for HVAC load and water heater usage
  - Cooking, TV, plug load, lighting, refrigeration etc.

- An accurate estimate of non-dispatchable load is significant in using model predictive control (MPC) in supporting smart grid operation



Control Signal for HVAC, Water Heater and PV

Central Control Algorithm

Non-dispatchable load data

Non-dispatchable load estimate

Load estimate

- Research Objective
- Develop data-driven models for estimating non-dispatchable electric loads to support advanced residential building control

(https://www.pinterest.com/silicongcc/architectural-engineering-services/)
(https://www.leidos.com/insights/what-artificial-intelligence)

Data

- A single-family detached house in the northwest region of the US
- Sub-metered data in 15 mins from May 2012 to May 2013
- 80% training, 20% test

location	Square footage	Floor number	Heating	Cooling	Lighting Fixture Num	Refrigerator	Cooking Equipment
Seattle, WA	2356/219 (sq ft/sq meter)	2	electric FAF	None	18	2008, R/F Top freezer	Electric

Variables and Algorithms

- Variables
  - Noncontrollable load from past 3 timesteps
  - The average noncontrollable load from past 2 weeks
  - Time information – time of a day
- Tested Algorithms
  - Linear vs. Non-linear
  - Parametric vs. non-parametric
- Linear Models
  - Bin Average
  - Multiple Linear Regression
- Non-linear Models
  - Neural Network
  - Gaussian Process
  - Random Forest

Linear Models

- Bin Average Method
  - Baseline
  - Use the average non-dispatchable load in past two weeks to estimate the non-dispatchable load today

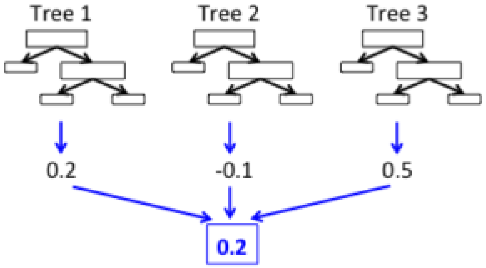
$$y(t) = \frac{\sum_{i=1}^{n} y_i(t)}{n}$$

- Multiple Linear Regression
  - As one of the most common form of linear regression analysis, multiple linear regression is often used to model the relationship between the response variable and multiple independent variables

$$y = \beta_0 + \sum_{p=1}^{k} \beta_p * x_{ip}$$

Nonlinear Models

- Random Forest
  - An ensemble learning (bagging) method for classification and regression
  - Operates by constructing a multitude of decision trees at training time
  - Outputting mean prediction (regression) of the individual trees



(https://www.nosimpler.me/random-forest/)

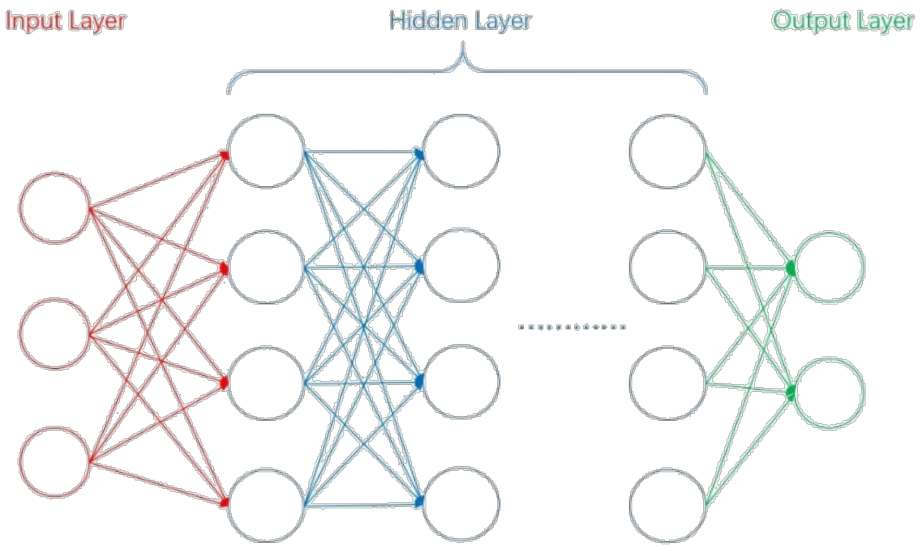
- GP
  - A kernel-based nonparametric regression model
  - Constructed by specifying the covariance matrix k(x,x') of the input data
  - Predicting based on the similarity between the input points and the point we are interested in

$$y^{(i)} = g\left(x^{(i)}\right) + \varepsilon^{(i)}$$

- $g(\cdot) \sim GP(0, k(\cdot,\cdot))$ where $k(\cdot,\cdot)$ is covariance function

Nonlinear Models

- Neural Network
  - Mimicking the way how natural neurons work
  - three major layers, i.e. input layer, hidden layer and output layer
  - Different neuron structures, such as Logistic, ReLU or tanh etc



Algorithm Performance

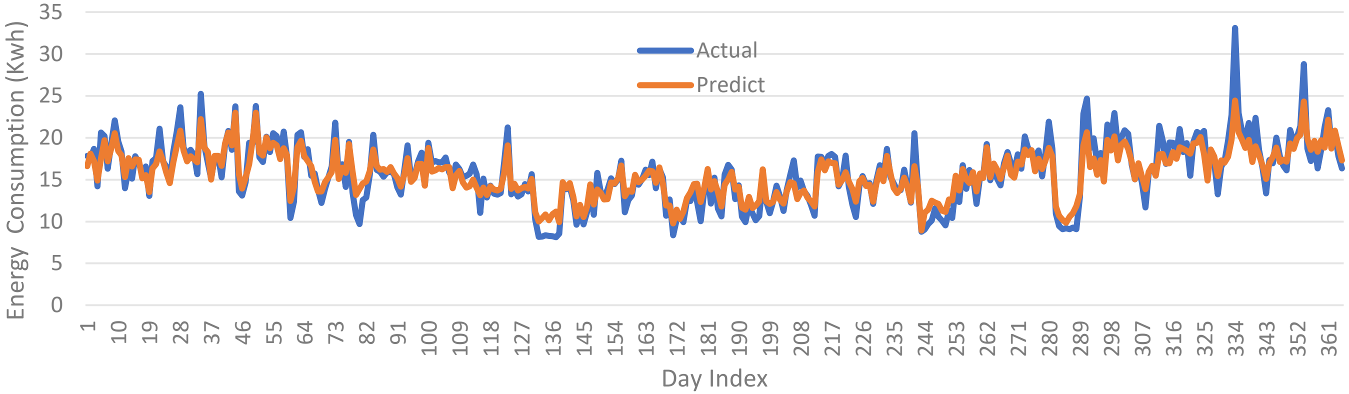
- Training and Test Performance

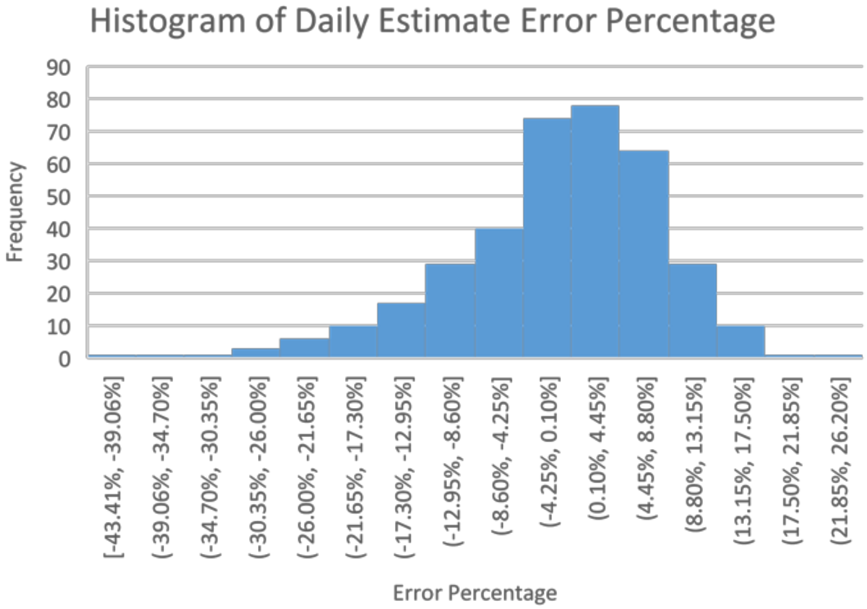
Algorithm Name	Training			Testing		
	MAE	RMSE	R^2	MAE	RMSE	R^2
Bin Average Method	-	-	-	0.209	0.311	0.373
Multiple Linear Regression	0.159	0.251	0.613	0.158	0.242	0.600
Neural Network	0.144	0.228	0.656	0.153	0.246	0.632
Gaussian Process	0.146	0.232	0.662	0.147	0.231	0.640
Random Forest	0.123	0.200	0.753	0.217	0.315	0.325

- Key take-aways
  - Nonlinear method out-perform linear method, but not much
  - The performance of nonlinear methods is comparable
  - Random forest achieves the best performance in training, however, it could easily overfit

Algorithm Performance

- Daily noncontrollable load prediction error





Conclusions

- Both linear and nonlinear methods could be used for estimating non-dispatchable load.
- For linear methods, multiple linear regression is the best approach.
- For nonlinear method, neural network and Gaussian process are the best approaches.
- In estimating the non-dispatchable load, we should be careful to avoid the overfit.

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A Hierarchical Control System for Enhancing Reliability and Resilience of Residential Communities

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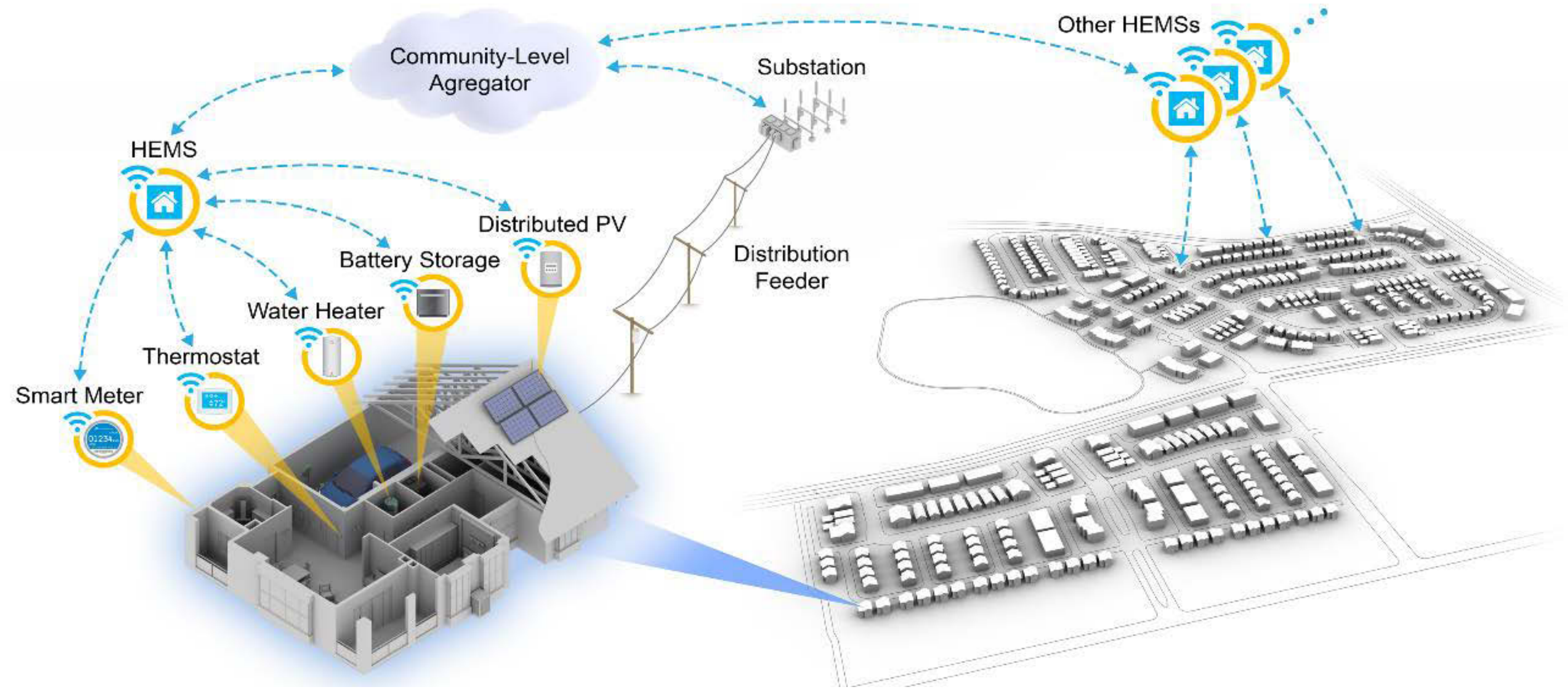
Hierarchical Control System

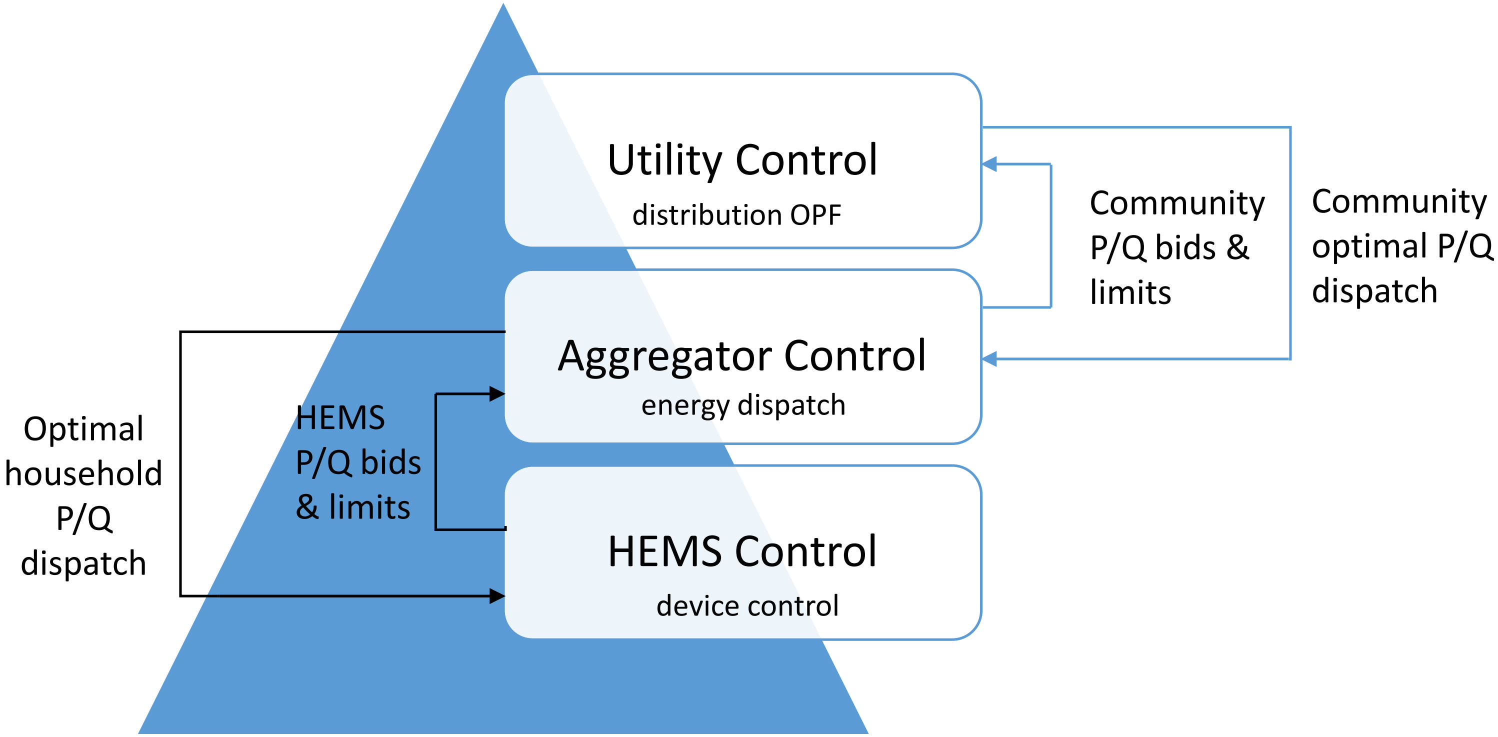
Home Energy Management System (HEMS) + Community Aggregator



HEMS: Manage the behind-the-meter resources and preserve homeowner privacy

Aggregator: Coordinate homes in a community and respond to utility control

Hierarchical Control System



Objectives at different levels:

- HEMS : energy cost, thermal discomfort, home load flexibility
- Aggregator: deviations from HEMS bids and utility dispatch, community load flexibility
- Utility: deviations from aggregator bids and transmission dispatch, utility load flexibility

Simulation Study in an NZE Community

All Phase Totals	
Product	**Number of Lots**
Duplex	28
Two-Story Townhome	103
Three-Story Townhome	85
Single Family Cottage	201
Single Family Detached	81
Total	**498**

- A community model was developed based on the site plan of an actual NZE-ready residential community under development in Fort Collins, CO
- Rooftop PV and community PV were sized following the automated approach
- The control-oriented model presented earlier was used to model the individual homes
- Homes were controlled using **foresee**, a user centric HEMS developed by NREL

Simulation Study in an NZE Community

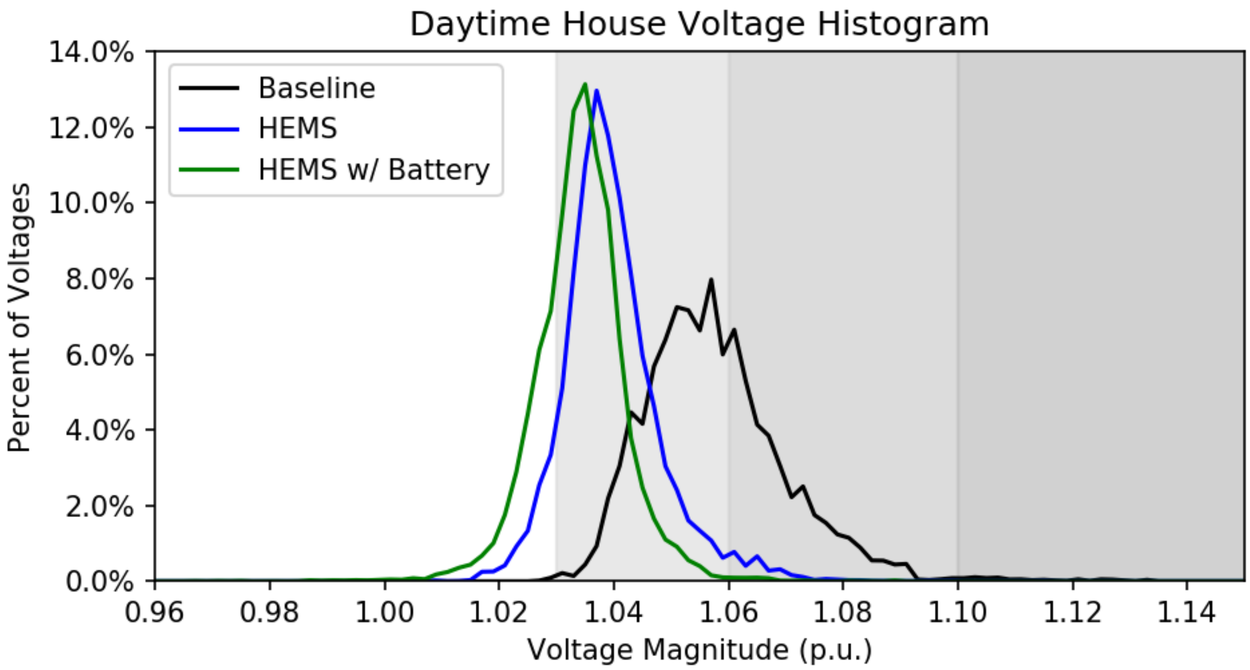
Baseline NZE community with high PV generation

HEMS Use HEMS to schedule flexible loads and smart inverters to self-consume PV

HEMS + Battery Install batteries at homes with severe voltage issue to maximize PV self-consumption

- Every home was modeled as all-electric homes and equipped with air source heat pump and electric resistance water heater
- The mandatory time-of-use rate in Fort Collins was used in the simulation
- Three scenarios were simulated to evaluate the effect of HEMS and battery in addressing voltage issues in the distribution grid without the community aggregator

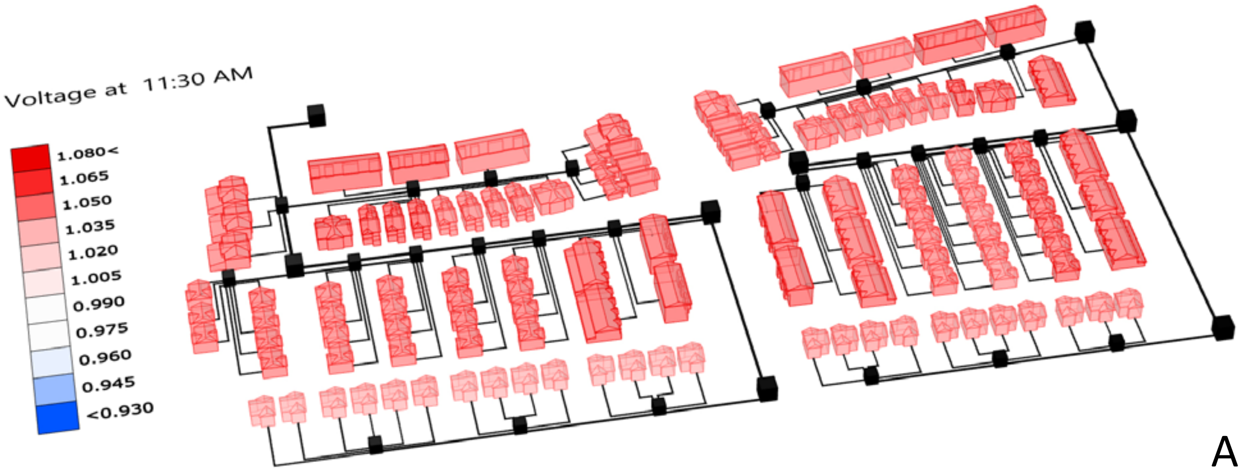
Initial Results – HEMS & Battery



Community network voltage histogram during 10am-2pm

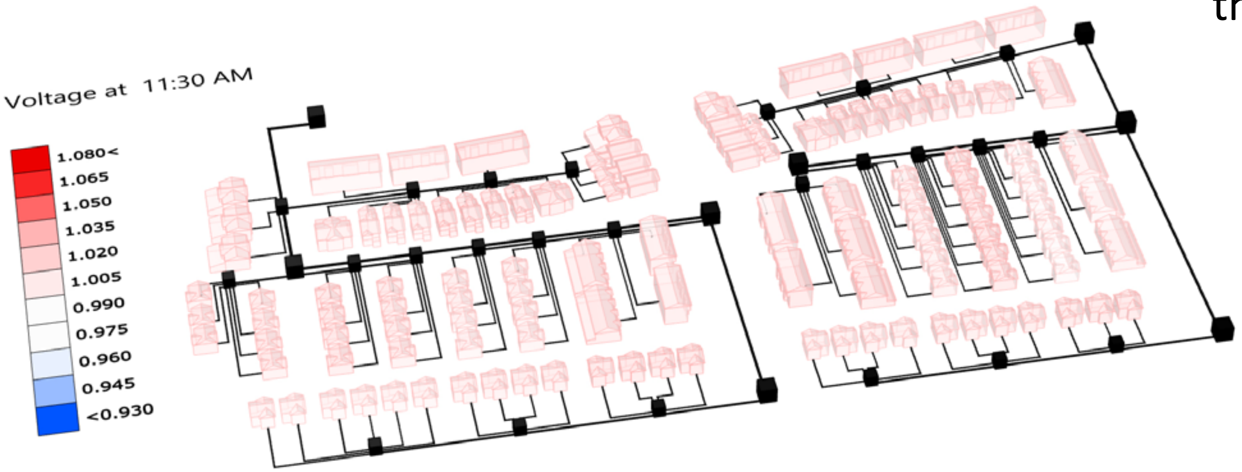
- HEMS was configured to maximize PV self-consumption during the time period when overvoltage was observed in the baseline scenario
- No voltage violation for the **HEMS + Battery** scenario and therefore no PV curtailment

Initial Results - Visualization



No HEMS or Battery

A snapshot of the voltage in the community at 11:30 am



HEMS + Battery

Conclusions

- HEMS with controllable flexible loads was able to significantly reduce the overvoltage in the community network
- Additional battery systems further decreased the overvoltage and eliminated the PV curtailment
- HEMS is more cost-effective in addressing the overvoltage issue compared to battery systems
- Future work will focus on the aggregator and utility control for enhancing grid reliability and resilience

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QUESTIONS?

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