Fine resolution nowcasting of PV and Loads in key sections of the Eversource energy grid



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Background

- PV installed capacity
 - Grid management, market operators
- State-of-the-art models unable to capture PV intermittence
- Clouds are the main drivers of intermittence

PV Installed Capacity 42.0 40 35 41.8 30 41.6 25 LS 20 ≷ 41.4 15 41.2 10 5 41.0 -73.5 -73.0 -72.5 -72.0 Longitude Cumulative Solar PV Installed Capacity in Connecticut from 2005 to 2020 70 285 286 287 288 289 280 281



Observed and Predicted Global Horizontal Irradiance

Objectives

- 1. Establish a monitoring system of PV energy generation in CT
 - Resources: Numerical model (RTMA), Satellite (GOES-R, MODIS products), in situ radiometers –AWIPS
 - Deployment of new observing system –All-sky cameras
- 2. Create a nowcasting system of solar power for distribution grid
 - Evaluate and post-process HRRR model

- 3. Develop and evaluate a data analytic model for load forecasting
 - ML methods using historical load data from ISO/NE



Eversource Energy Center



EVERS

Advance Weather Interactive Processing System

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Meteorological display and analysis package





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Cloud monitoring with All-sky cameras

(a)



- Streaming image data
- Local cloud conditions
- Type of clouds -
- **Cloud cover fraction**
 - **Downward surface radiation**







Case study: Camera data for model bias correction









100 75 50 Cloud Fraction (%) 25 -25 -50 -75 Camera Error(HRRR-Camera) -100Ó 100 200 300 400 500 600 700 800 Time

HRRR vs Camera Cloud Fraction Comparison:DJF 2019-20

Aaron Haeguele's Master's Thesis

PV energy operator in 1-day-ahead scenario: Cost of Reserves needed to mitigate large fluctuations in solar energy supply.

DJF 2019-20	HRRR	HRRR_BC	Climate	Perfect
Expected Expense (E)				
(\$/MW/m^2)	6.50	4.02	12.27	0.007
Economic Value (V)	0.47	0.67	0.00	1.00

Predicting Day-Ahead Energy Demand with Weather Data



Figure: (top two cells) actual vs. predicted hourly energy demand from dummy baseline models ('the demand at 9 AM tomorrow will be the same as 9 AM today'. (bottom two cells) actual vs. predicted hourly energy demand from our best deep learning model (a recurrent neural network with a novel resampling technique to improve accuracy.)



Energy Demand



Synthetic/Resampled Energy Demand

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Figure: novel treatment of the hourly energy data forces the deep learning model to focus on rare/high energy demand observations. This technique prevents overfitting by the deep learning model.

When predicting hourly energy demand 24 hours into the future, the Average Percentage Error was:

- Baseline model: 14.5% error (2021)
- Deep learning model: 4.8% error (2021)

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Deliverables and Timeline

- 1. AWIPS System, and deployment of Cameras: AY 2022
- 2. Bias corrected solar energy products of the HRRR model: AY 2023

 Selection, evaluation and implementation of ML Solar Energy Forecast model: AY 2022





Improved Data Assimilation Methods

Steve Albers





SCADA and AMR Data for Demand-Side-Management

The goal of demand-side management is to encourage the consumer to use less energy during peak hours, or to move the time of energy use to off-peak times such as nighttime and weekends



- Household
- Community
- Utility scale

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• National Level

END





Timeline of Deliveries

- Deploy, test, validate monitoring sensors for detecting and predicting major changes in the renewable energy generation within the Eversource distribution network, especially in the location of PV energy sources.
- Test, validate and prototype analysis techniques, e.g. combine observations with physical models to create fine resolution analysis of the state of the surface energy in targeted domains to monitor energy demand.
- Establish a data flow scheme for real-time monitoring and display of meteorological information for energy management systems.
- Develop models to upscale the relationship between energy generation and load for various urban areas (residential, industrial, commercial).





Tasks

Task 1: Establish the sensor network and display system of renewable energy

Task 1.1. Build backbone observing network of renewable energy for Eversource Energy. Task 1.2. Install and adapt the National Weather Service AWIPS system to display conditions and products of PV energy in the Eversource distribution grid.

Task 2: Develop analysis and nowcasting system of renewable energy

Task 2.1. Install and adapt a data assimilation scheme to process PV radiation data and produce forecasts from 1 to 6 h in advance with 30 mins cycles in targeted domains.

Task 2.2. Bias-correct and downscale the HRRR model from hourly, 3-km to 15-min, 100m on targeted domains.

Task 3: Build the data analytics model for load forecasting at county and state scale

Task 3.1. With the use of ISO data and Green Bank PV data perform deep learning image composites across CT for various hours and seasons to determine the relationship between meteorological and environmental variables and population behavior.

Task 3.2. Use neural network methods to understand energy demand on selected urban areas where data usage is available.

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Data Requirements

- Eversource Energy Engineering department to provide models and data, or help to get data from third-party energy suppliers, for load and distributed generation.
- Connecticut Green Bank has collaborated with Eversource and provided the multi-year, high resolution data (5 or 15-minute interval AC, DC voltage, current, real power and reactive power, and ambient data) in Locus database for a subset of the 13,000 PV systems installed in CT. More data might be requested if needed.
- Meteorological data and parameters necessary for this project will be requested to NOAA during the study process.



