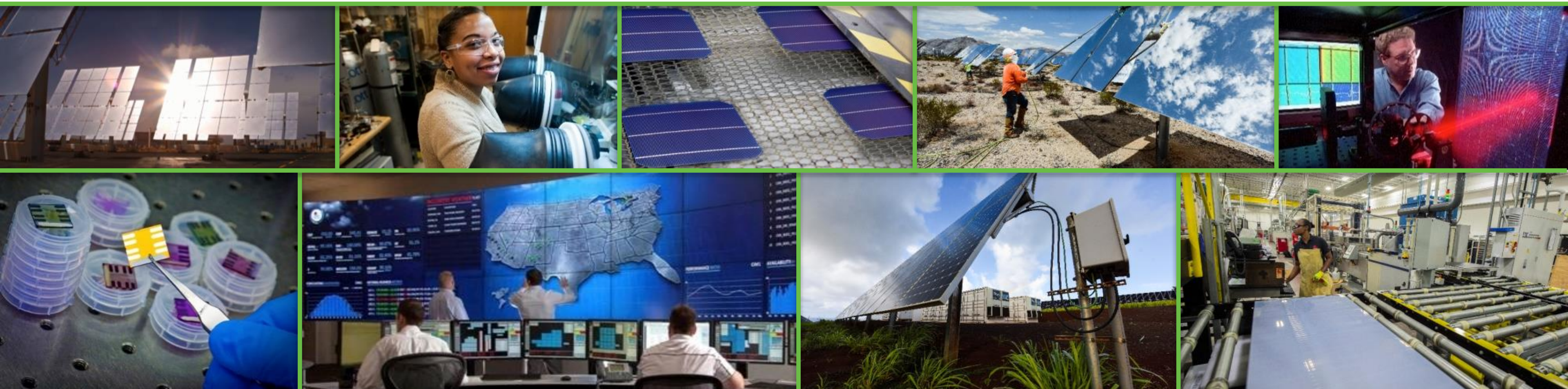
U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

Solar Forecasting Workshop

Day 2

Solar Energy Technologies Office



U.S. DEPARTMENT OF
ENERGY

Office of
ENERGY EFFICIENCY &
RENEWABLE ENERGY

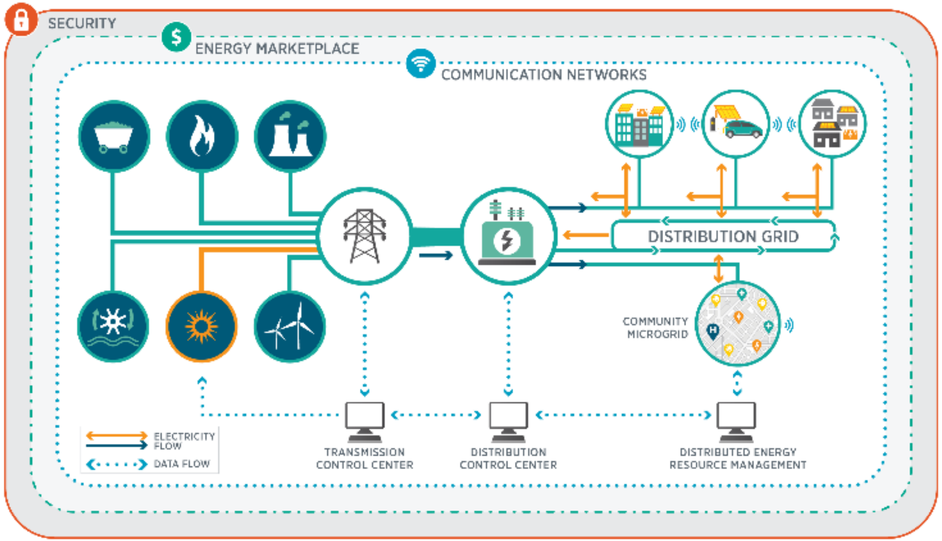
DOE Solar Forecasting R&D Past, Present, Future

Guohui Yuan

Systems Integration, SETO / EERE / DOE

SETO Systems Integration (SI) Program

The Systems Integration (SI) subprogram supports early-stage research, development, and demonstration (RD&D) of technologies and solutions – focusing on technical pillars **data, analytics, control, and hardware -** that advance the **reliable, resilient, secure and affordable** integration of solar energy onto the U.S. electric grid.



Achieving 100% Decarbonized Power System

SETO System Integration Key Research Areas

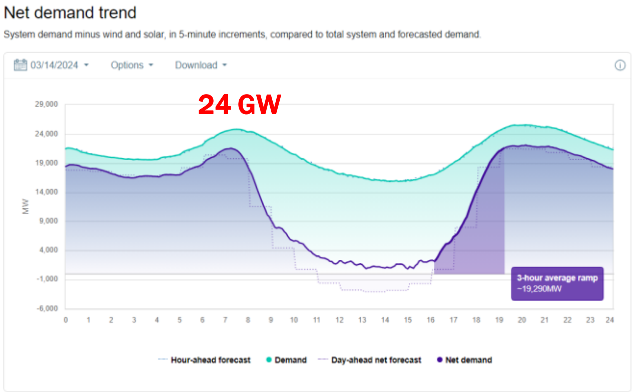
~$55M annual budget, ~90 active RD&D projects

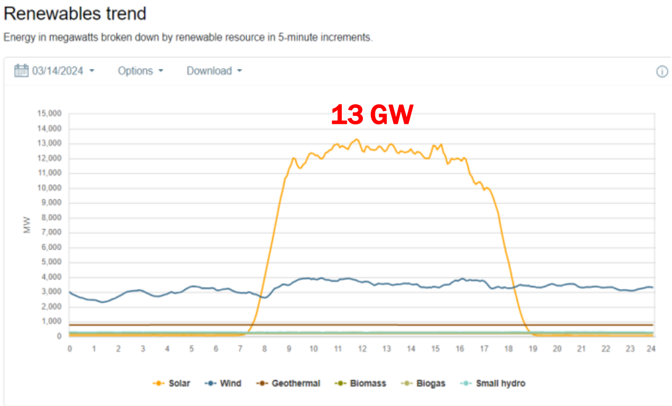
System Planning	System Operation	Resilience & Cybersecurity	Enabling Technologies
• Power system modeling • PV plant and inverter modeling • Solar resource data & solar forecasting • Resource adequacy • Production cost modeling • Reliability and interconnection standards	• Real time situation awareness • State estimation and power flow • System and inverter control • System protection, stability, risk management • Grid services and system flexibility • DER integration and aggregation of PV, ESS, EV, and buildings • SW tools -EMS, ADMS, DERMS, MGMS	• Resilience planning and benchmark metrics • Resilient microgrids and DER-based solutions • Measurement & Verification, and cost/benefit analysis • Cybersecurity R&D and assessment tools for device, plant, and system • Cybersecurity standards • Stakeholder education and information sharing	• Power electronics • Energy storage • Data analytics and AI/ML • Sensing and communication • High performance computing and cloud-based tools • CHIL and PHIL testbeds

Managing Solar and Wind Generation Variability and Uncertainty

Wind + Solar ~100%

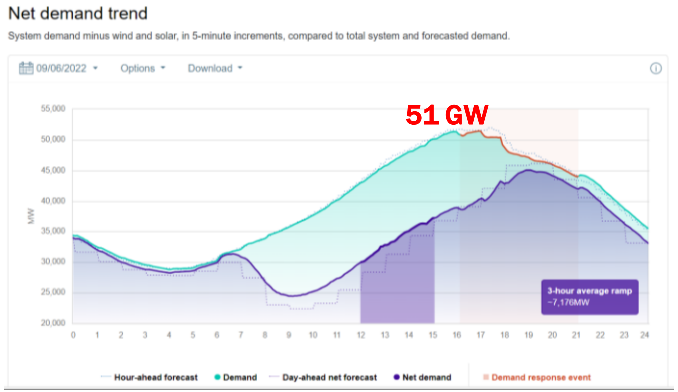
March 14, 2024
Load 16.5 GW
Solar 12.5 GW
Wind 3.5 GW
Wind + Solar ~100%

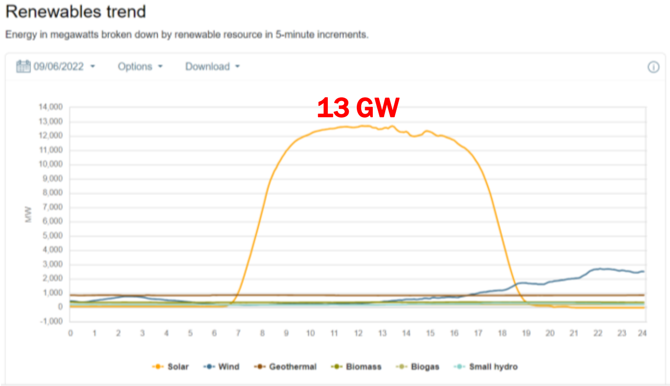




Historical System Peak

September 5-7, 2022
Load ~51 GW
Solar~13 GW
Wind ~0.7 GW
Wind + Solar 20-30%





Unlocking the Value of Solar Forecasting

Round 1: October 2021, Solar Forecasting Prize
https://www.energy.gov/eere/solar/american-made-solar-forecasting-prize
Round 2: February 2023, Net Load Forecasting Prize (Open)
https://www.energy.gov/eere/solar/american-made-net-load-forecasting-prize

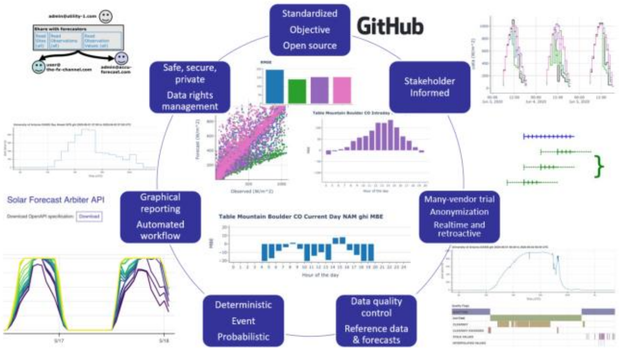
(Winners announced at RE+ 2023)

Solar Forecasting Funding Programs (2013 & 2017)

- Improve irradiance forecast
- Improve power forecast & utility integration
- Create benchmarking tools

Solar Forecast Arbiter

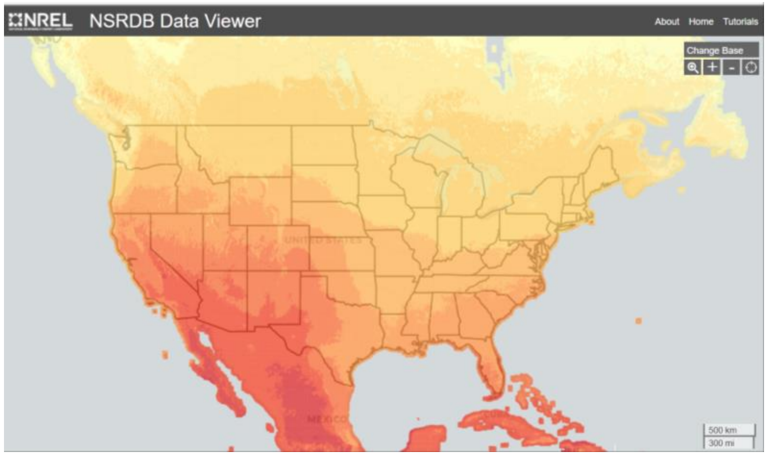
A paradigm shift in forecast evaluation



(Source: University of Arizona/EPRI)

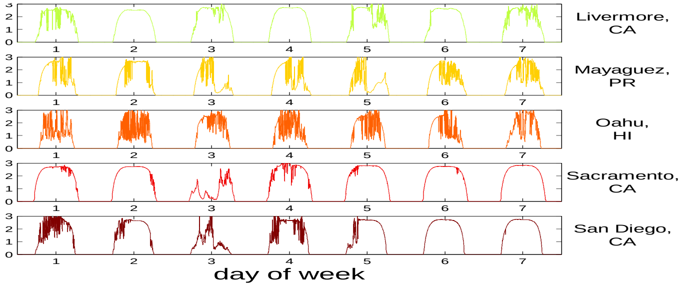
Solar Generation Variability and Uncertainty

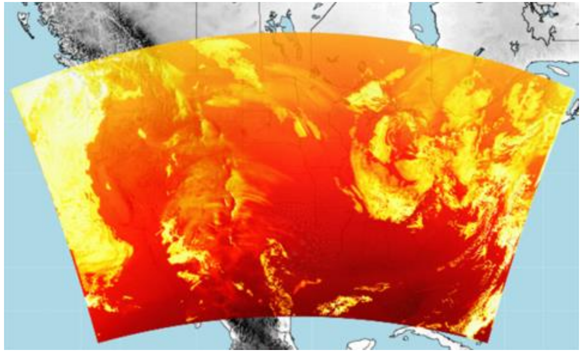
Solar Irradiance Data (GHI, DNI):
- Historical = NSRDB
- Real time = satellites and ground sensors
- Future = forecast



2019 Annual Mean of GHI from NSRDB (2km x 2km, 5 min, Terabytes) [Home - NSRDB (nrel.gov)]

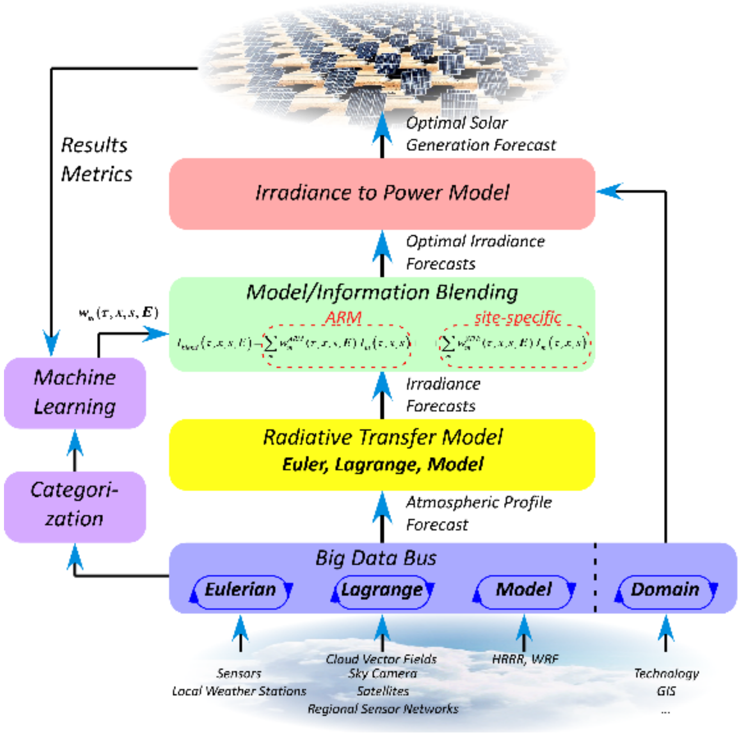
Sample measurements (1 min)





[WRF-Solar® | NCAR Research Applications Laboratory | RAL (ucar.edu)] ***Run on HPC***

AI/ML for Solar Forecasting



- Using big-data technologies;
- Applying deep machine learning to blend outputs from multiple models
- Leveraging ARM and/or SURFRAD/ISIS data sets
- Integrating with ISO operation
- Gridded Forecast Improved by 25%

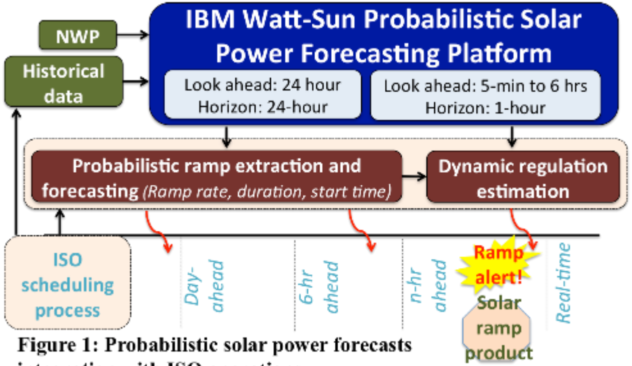


Figure 1: Probabilistic solar power forecasts integration with ISO operations

IBM Watt-Sun: Deep Learning for Solar Forecasting

SETO Systems Integration RD&D Activities

Enabling large-scale solar deployment while maintaining reliability

- *FY22 Grid Services FOA* – demonstration of grid services provided by IBRs; bulk power **system protection**
- *FY22 RACER FOA* – community resilience planning and technology demonstration
- *FY22-FY24 SETO Lab Call* - **transient/dynamic modeling**, open data, solar database (NSRDB), reliability and cybersecurity standards
- *FY21 SI & Incubator FOA* - grid-forming consortium, **BTM solar integration**
- *FY20 SETO FOA* - resilient community microgrids, PV cybersecurity, hybrid PV plants, **AI/ML applications**
- *FY19-FY21 SETO Lab Call* – *grid* planning & operation, power electronics, sensing and communication, solar+X
- *FY19 GMLC Lab Call* - resilience models, sensing and measurement, **PV cybersecurity**
- *FY19 SETO FOA* - system protection, grid services, grid-forming inverter control, PV cybersecurity
- *ASSIST FOA* – **situation awareness**, and resilience for critical infrastructures
- *Advanced Power Electronics FOA* - Improving inverter efficiency, reliability, control; WBG
- *GMLC-RDS Lab Call* - Resilient distribution system design, demonstration, and value analysis
- *Solar Foresting II FOA* – **irradiance forecast, power forecast**, validation framework, operation
- *ENERGISE FOA* – **state estimation, OPF**, DERMS, field demonstration
- *SHINES FOA* – dispachable solution for **optimal control** of solar PV, energy storage, and dynamic building load

What’s Next?

DOE Solar Forecasting Workshop

Amber Motley
Director, Short Term Forecasting

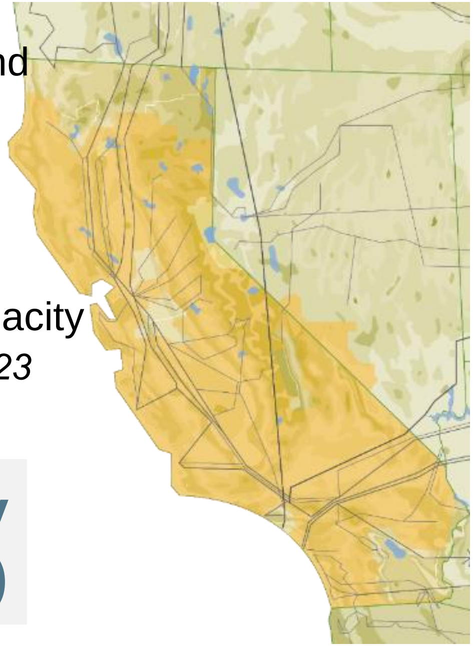
July 10th, 2024

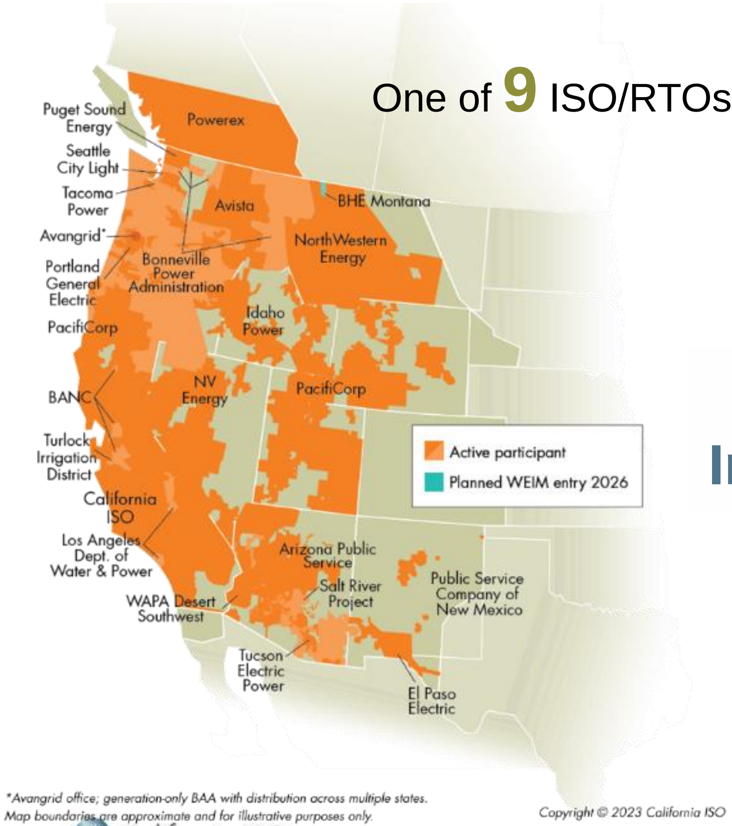
California ISO

52,061 MW record peak demand
(Sept. 6, 2022)

One of **9** ISO/RTOs in North America

76,184 MW power plant capacity
Source: ISO's Masterfile, August 2023





Western Energy Imbalance Market (WEIM)

22 participating entities

925,568 metric tons of CO_2 avoided

California ISO BAA Renewables

Historical statistics and record (as of May 30, 2024)

Solar peak **NEW!**
18,787 MW
May 13, 2024 at 11:55 am

Previous record:
18,673 MW, May 9, 2024

Wind peak
6,465 MW
May 28, 2022 at 5:39 pm

Previous record:
6,265 MW, March 4, 2022

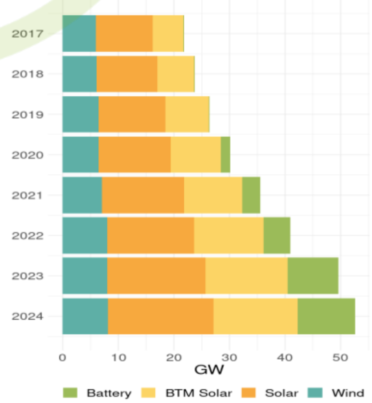
Peak percentage of renewables compared to demand
117.3%
April 20, 2024

Previous record:
107%, June 2023

Number of Renewable Resources: **529**

MW Forecasted Large Scale Renewables: **27,872 MWs**

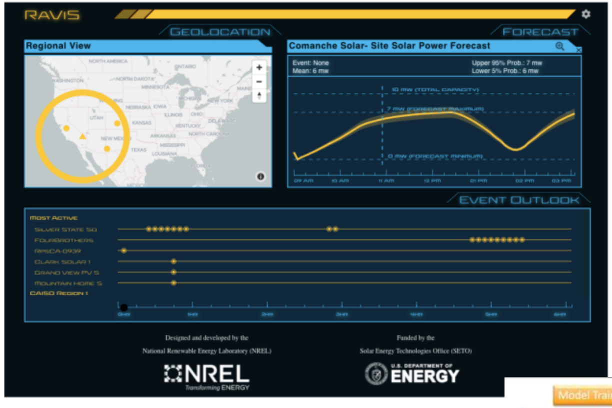
MW Capacity Behind-the-Meter Solar: **16,200 MWs**



Values are approximate as of May 2024

ADVANCEMENTS

DE-EE0008215: Uncertainty Requirement Research



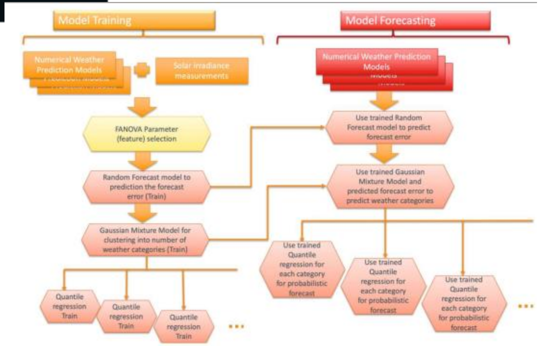


Fig. 9: Model blending Flow chart Overview

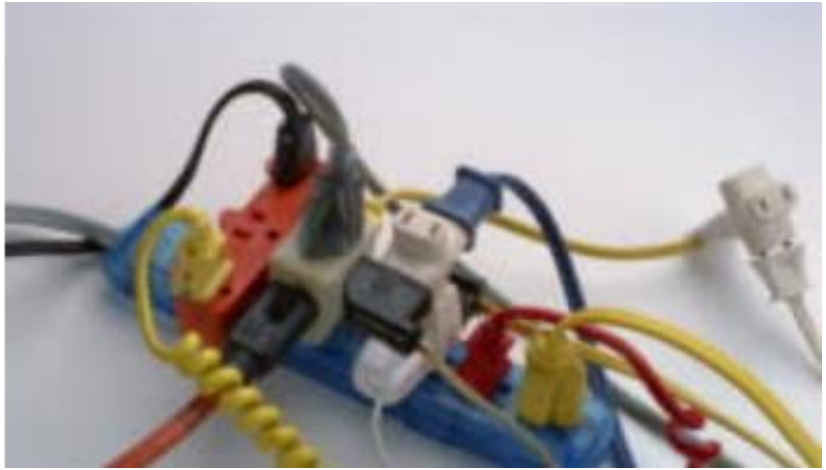
OPPORTUNITIES

Opportunity Agenda

- Implementation Considerations
- Smoke
- Renewable Forecasting
- Probabilistic Forecasting
- Distributed Energy Forecasting

Implementation Considerations

AI Multi Vendor Optimization

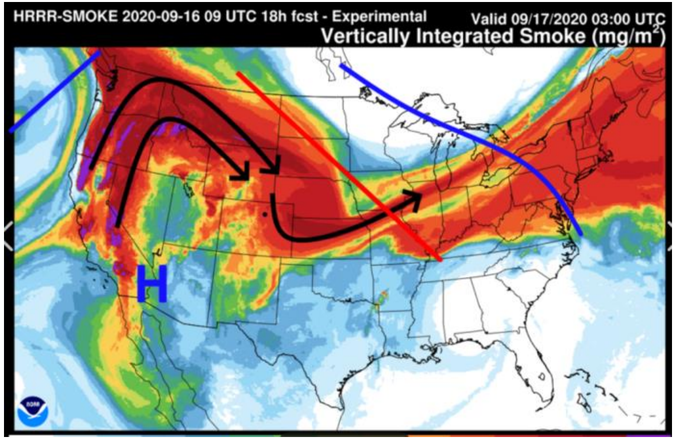


As forecasting products evolve it is critical we can streamline the data hookups, inputs, cleaning, validations, and use throughout all the systems that lead to the outputs and then the actions taken by operations and markets.

Data Validation and Data Monitoring

Better Weather Forecasting Accounting for impacts to Fire on critical weather variables

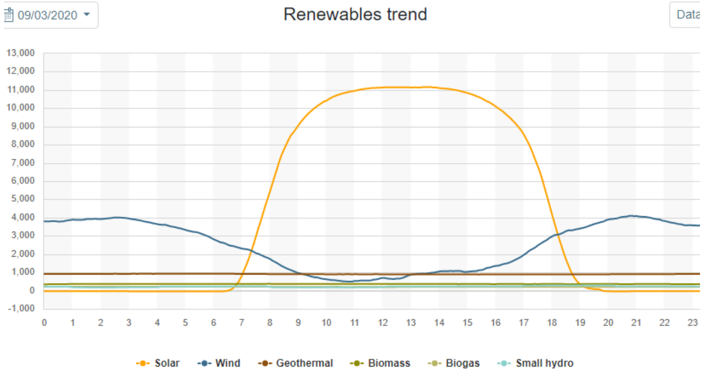
Only One Short Range Model accounts for Smoke



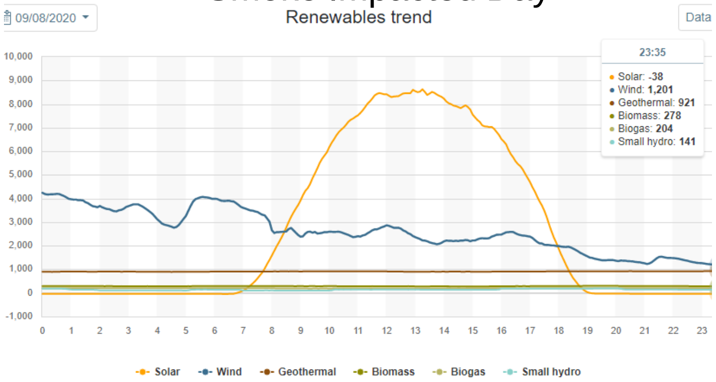
[High-Resolution Rapid Refresh (HRRR) (noaa.gov)]

Currently there is a lag to account for smoke and soot impacts in the renewable forecasts; this lag is different for different vendors.

Minimal Smoke Impacted Day



Smoke Impacted Day



Renewable Forecasting without Actual Telemetry Information

- For periods where resources are required to follow Dispatch Operational Targets (DOT) renewable forecasts exclude telemetry data
  - Can occur for multiple hours across consecutive days and have a large impact on forecast quality
- High Sustainable Limit (HSL) can still be used during these periods as one input to train the forecast -> improvement in external forecast

HSL Quality	External forecast error	External forecast error Follow DOT
Bad	9.7%	11.6%
Good	7.8%	**7.3%**

Good HSL – Renewable Forecasts (including persistence) can use HSL as input into forecast even during follow DOT

Forecast stays reasonable

Bad HSL – Vendors exclude actuals excluded from forecast during times of follow DOT

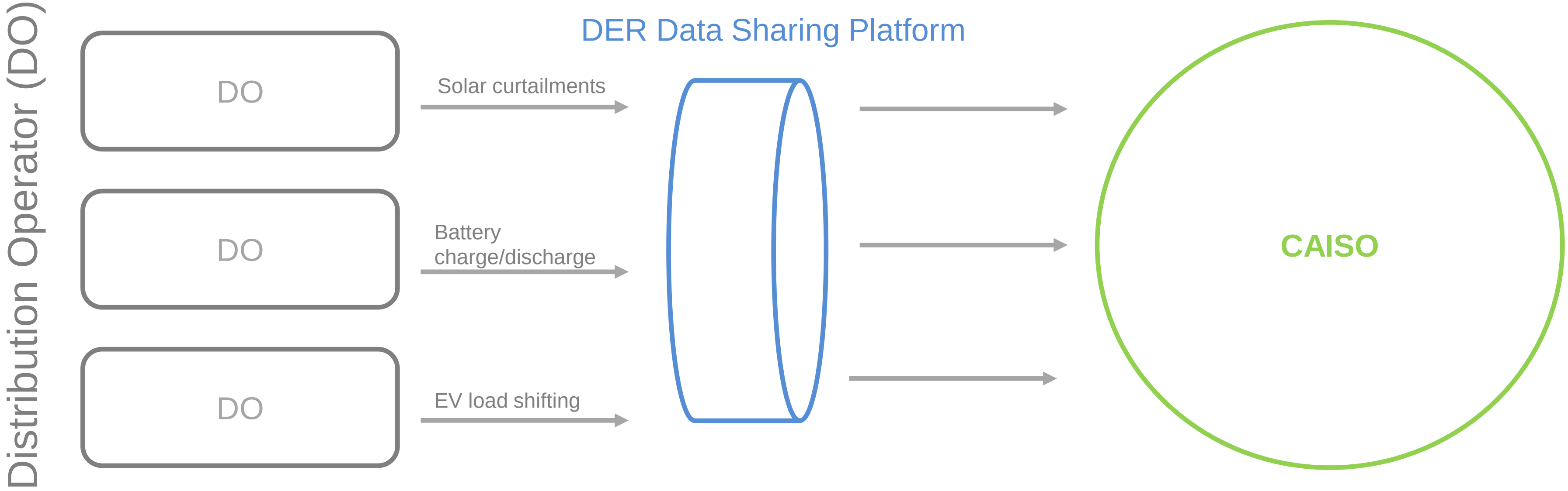
High forecast bias

Vendor forecast
HSL
Telemetry
Supplemental Energy
Δ = follow DOT

Ensuring resource provide good quality HSL data is critical to utilize for forecasting. Ensuring tools available to identify bad data is critical.

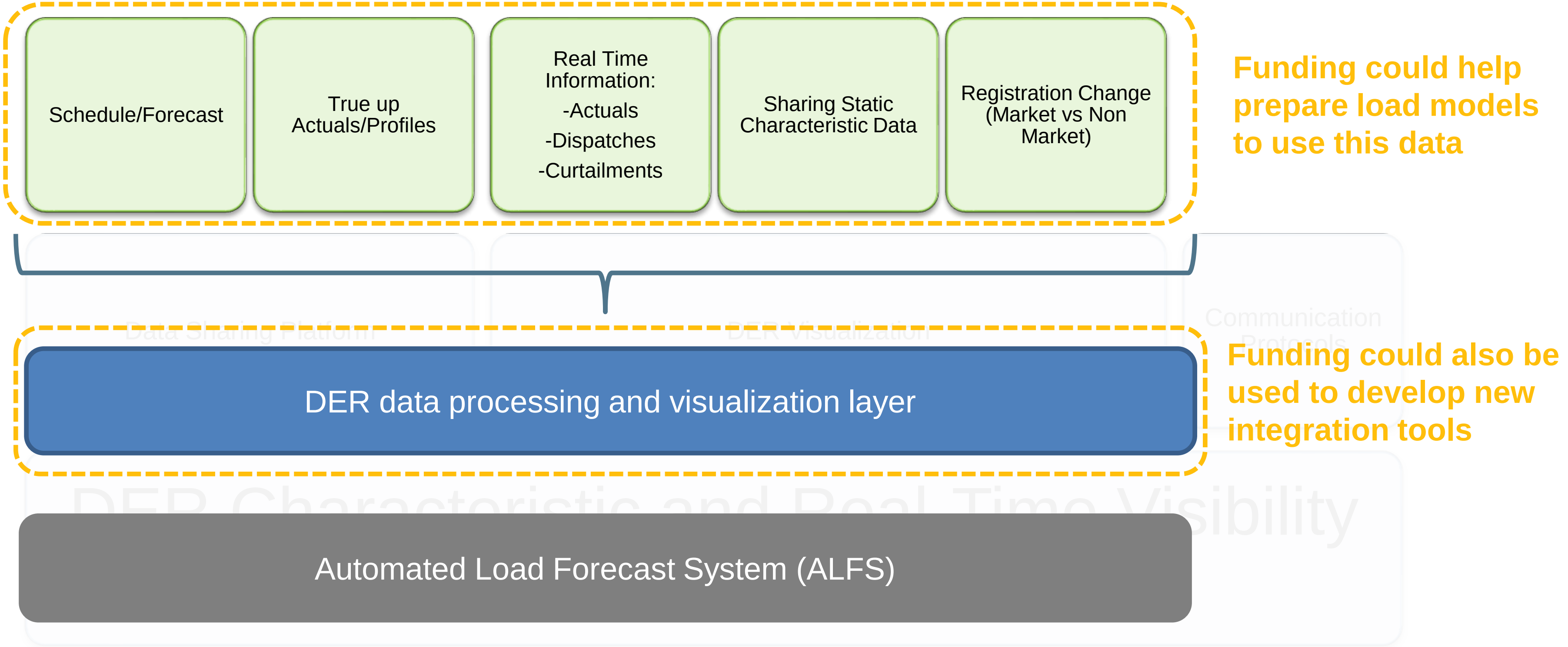
Probabilistic forecasts help us **manage uncertainty**. Adapting for **conditions** helps us balance cost with risk.

CAISO will need visibility data for DERs used to manage distribution system level constraints



DER data sharing between Distribution Operators and CAISO is crucial since Distribution Operators may dispatch DERS to manage distribution system constraints.

Building the architecture to integrate DERs for grid operations



Tools of the Future: Connecting the pieces through automation

ISO Panel

07/10/2024

BTMPV Forecasting Overview

Solar Forecasting Workshop 2024

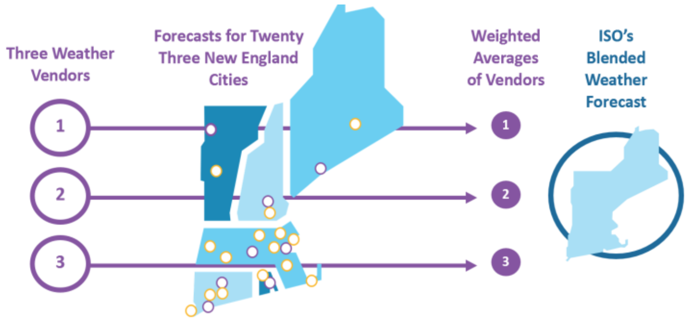
Michael Fontaine

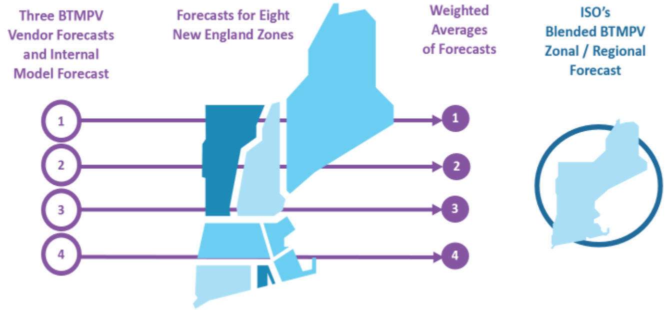
SUPERVISOR, OPERATIONS FORECASTING

ISO NEW ENGLAND LOAD FORECAST TOOL

- *ISO New England has an internally built tool with which to construct and produce Load Forecasts.*
- *In addition to creating the New England Load Forecast, this tool allows Forecasters to analyze, build and blend custom Weather and BTMPV forecasts & profiles from multiple sources.*
- *It also allows Forecasters to create reports pertaining to Weather, BTMPV, and Load Forecasting*

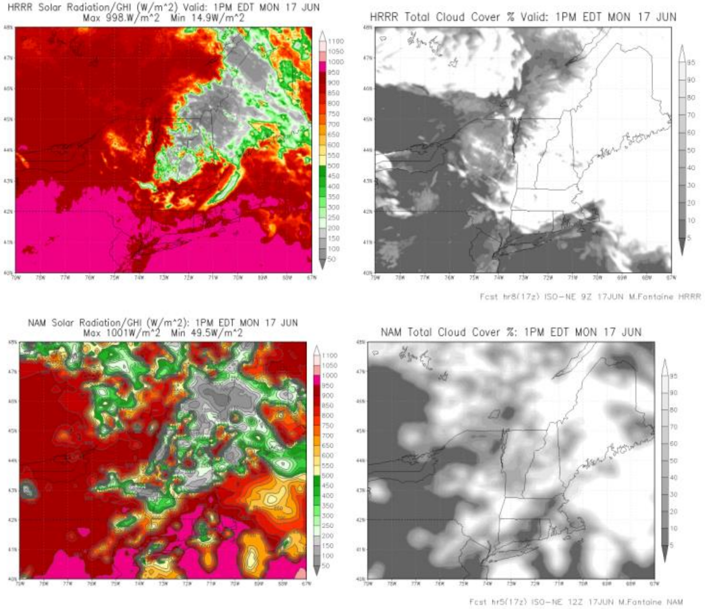
BTMPV Forecast Steps





- Evaluate New England weather
- Multiple weather forecasts and observations for 23 Cities
- Blend and Adjust to a single Weather Forecast
- Evaluate BTMPV forecasts and observations
- Multiple BTMPV forecasts for 8 N.E. Zones
- Blend and Adjust to a single BTMPV Forecast
- With Weather and BTMPV Forecasts created, multiple Load/Demand Forecast models are then run using these inputs

Analysis of Weather Prior to BTMPV Forecast



- Load Forecasters stay weather forecast diligent
- Review of multiple NWP models to compare forecast convergence and divergence, including irradiance and cloud cover parameters
- Forecasters then review forecasts and discussions from several weather vendors as well as forecasts and technical discussions from the National Weather Service

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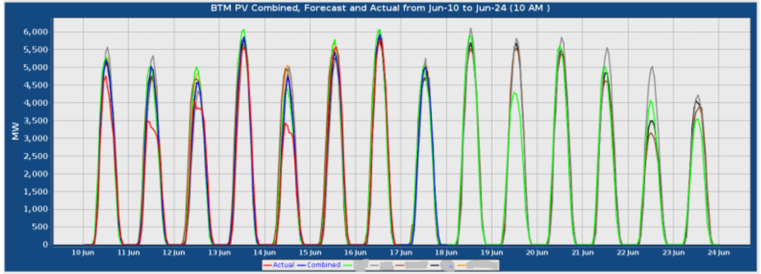
Analysis of BTMPV Forecast Performance

- Forecasters review daily automated reports on previous BTMPV performance
- These reports show the Forecaster the past performance of individual BTMPV models
- The reports also show the performance of the Forecaster's blended BTMPV Forecast.

ISO new england BTMPV Status Report For Production FCSTDBP As of 2024-Jun-17 03:02 AM

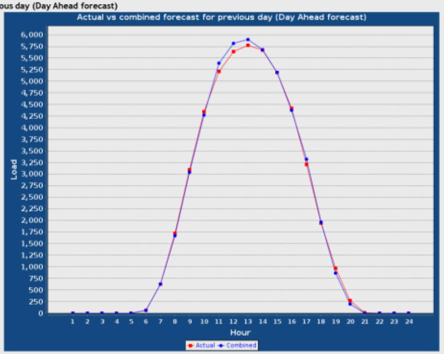
Files or Data received in the last 24 hours

Type	Service	No of Files	Latest Timestamp
Actual	[illegible]	1	2024-06-17 01:46:42
Forecast	[illegible]	6	2024-06-17 03:00:54
Forecast	[illegible]	8	2024-06-17 03:00:30
Forecast	[illegible]	8	2024-06-17 03:00:27
Forecast	[illegible]	4	2024-06-17 03:01:28



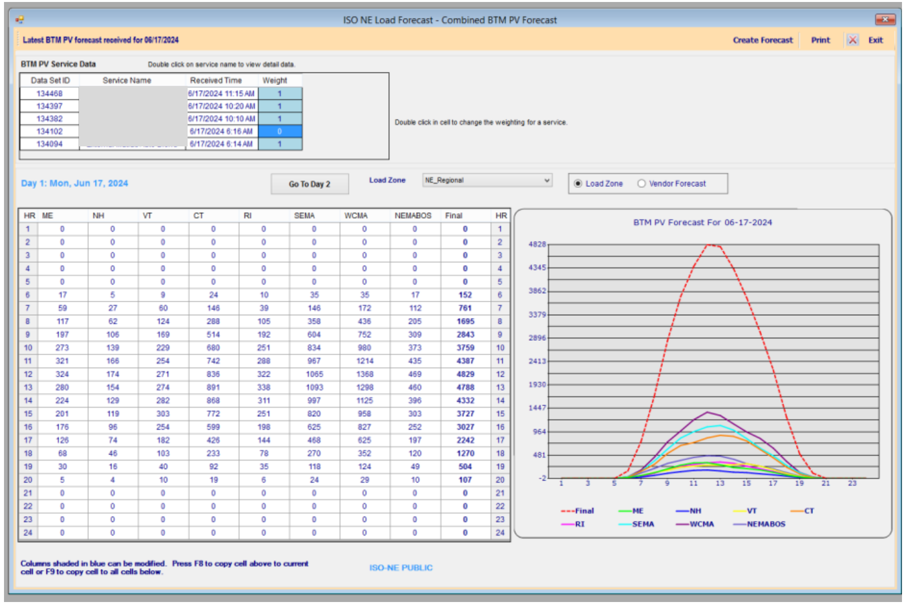
Actual vs combined forecast for previous day (Day Ahead forecast)

Date	Hour	Actual	Combined
06/16/2024	1	0.0	0.0
06/16/2024	2	0.0	0.0
06/16/2024	3	0.0	0.0
06/16/2024	4	0.0	0.0
06/16/2024	5	0.0	4.0
06/16/2024	6	61.0	59.0
06/16/2024	7	625.0	626.0
06/16/2024	8	1718.0	1667.0
06/16/2024	9	3096.0	3036.0
06/16/2024	10	4343.0	4275.0
06/16/2024	11	5211.0	5395.0
06/16/2024	12	5638.0	5817.0
06/16/2024	13	5779.0	5898.0
06/16/2024	14	5672.0	5680.0
06/16/2024	15	5195.0	5196.0
06/16/2024	16	4423.0	4374.0
06/16/2024	17	3202.0	3317.0
06/16/2024	18	1942.0	1964.0
06/16/2024	19	966.0	863.0
06/16/2024	20	275.0	200.0
06/16/2024	21	5.0	0.0
06/16/2024	22	0.0	0.0
06/16/2024	23	0.0	0.0
06/16/2024	24	0.0	0.0



Building / Blending BTMPV Forecast

- Once the Forecaster has evaluated Weather conditions they can then build a BTMPV Forecast
- The Forecaster will import the latest Forecasts.
- Forecasts are for 8 New England Zones
- Forecasts are 24 Hourly
- Forecast are for 7 Days



Data Set ID	Service Name	Received Time	Weight
134468		6/17/2024 11:15 AM	1
134397		6/17/2024 10:20 AM	1
134382		6/17/2024 10:10 AM	1
134102		6/17/2024 6:16 AM	0
134094		6/17/2024 6:14 AM	1

HR	ME	NH	VT	CT	RI	SEMA	WCMA	NEMABOS	Final	HR
1	0	0	0	0	0	0	0	0	0	1
2	0	0	0	0	0	0	0	0	0	2
3	0	0	0	0	0	0	0	0	0	3
4	0	0	0	0	0	0	0	0	0	4
5	0	0	0	0	0	0	0	0	0	5
6	17	5	9	24	10	35	35	17	152	6
7	59	27	60	146	39	146	172	112	761	7
8	117	62	124	288	105	358	436	205	1695	8
9	197	106	169	514	192	604	752	309	2843	9
10	273	139	229	680	251	834	980	373	3759	10
11	321	166	254	742	288	967	1214	435	4387	11
12	324	174	271	836	322	1065	1368	469	4829	12
13	280	154	274	891	338	1093	1298	460	4788	13
14	224	129	282	868	311	997	1125	396	4332	14
15	201	119	303	772	251	820	958	303	3727	15
16	176	96	254	599	198	625	827	252	3027	16
17	126	74	182	426	144	468	625	197	2242	17
18	68	46	103	233	78	270	352	120	1270	18
19	30	16	40	92	35	118	124	49	504	19
20	5	4	10	19	6	24	29	10	107	20
21	0	0	0	0	0	0	0	0	0	21
22	0	0	0	0	0	0	0	0	0	22
23	0	0	0	0	0	0	0	0	0	23
24	0	0	0	0	0	0	0	0	0	24

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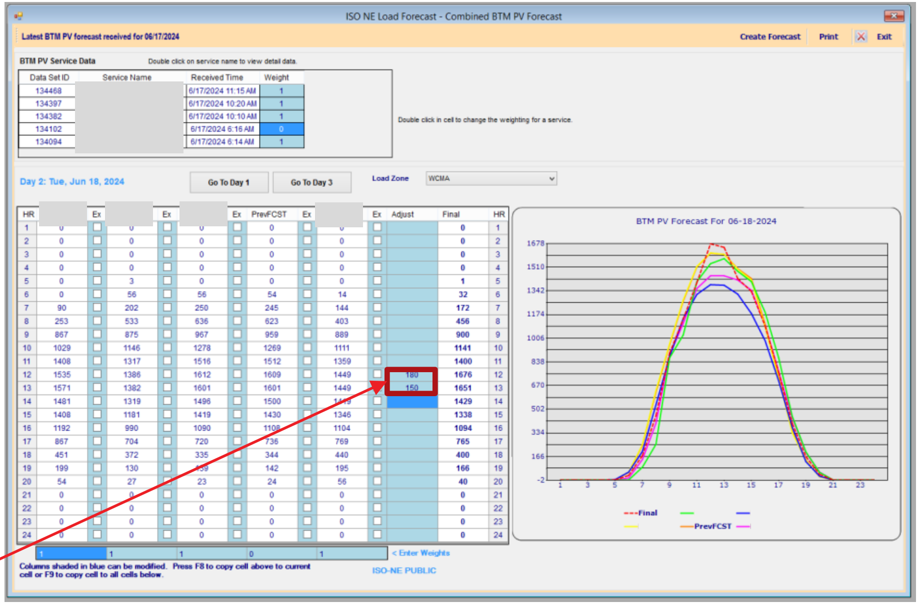
Building / Blending BTMPV Forecast cont.

- After importing the latest Forecasts:
- The Forecaster can weight any forecast globally for all 7 days
- Can weight any forecast on a daily basis for each of the 8 New England Zones, excluding individual hours in individual forecasts as deemed necessary
- Is able to manually add or subtract MW to each Daily Zonal Forecast



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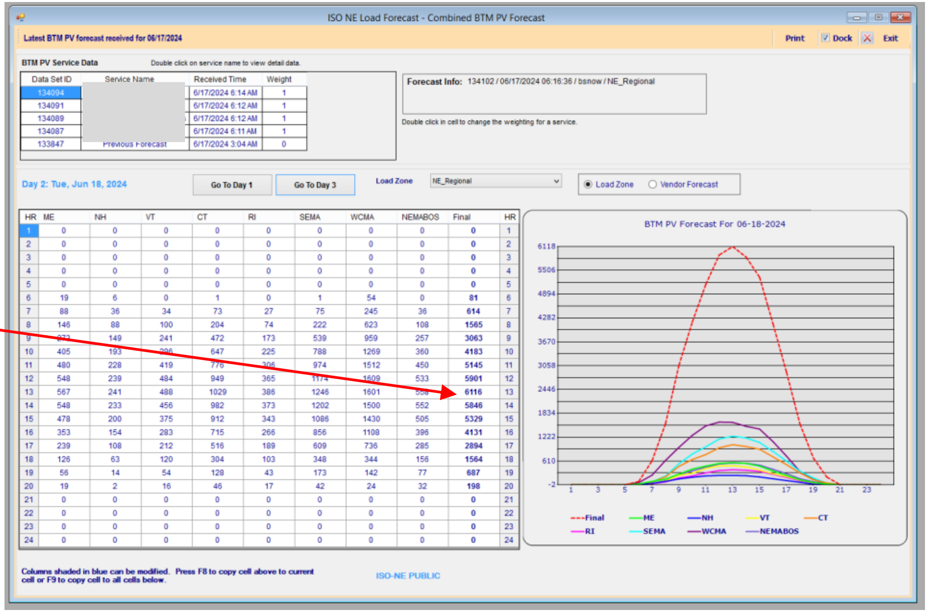
Approving BTMPV Forecast

- Once the Forecaster has finished adjusting and blending of the BTMPV Forecast it is then exported for use in over 14 Load/Demand models to produce Load/Demand Forecasts to blend
- Please note in this particular Forecast over 6100 MW of BTMPV is Forecast
- The largest physical generator in New England is 1247 MW
- New England can import up to 2000 MW from neighboring control areas but is typically limited to 1600 MW or less
- So with an installed capacity of over 6900 MW of BTMPV, accurate prediction of BTMPV becomes of critical importance.



Data Set ID	Service Name	Received Time	Weight
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134091		6/17/2024 6:12 AM	1
134089		6/17/2024 6:12 AM	1
134087		6/17/2024 6:11 AM	1
133847	Previous Forecast	6/17/2024 3:04 AM	0

HR	ME	NH	VT	CT	RI	SEMA	WCMA	NEMABOS	Final	HR
1	0	0	0	0	0	0	0	0	0	1
2	0	0	0	0	0	0	0	0	0	2
3	0	0	0	0	0	0	0	0	0	3
4	0	0	0	0	0	0	0	0	0	4
5	0	0	0	0	0	0	0	0	0	5
6	19	6	0	1	0	1	54	0	81	6
7	88	36	34	73	27	75	245	36	614	7
8	146	88	100	204	74	222	623	108	1565	8
9	273	149	241	472	173	539	959	257	3063	9
10	405	193	296	647	225	788	1269	360	4183	10
11	480	228	419	776	306	974	1512	450	5145	11
12	548	239	484	949	365	1174	1609	533	5901	12
13	567	241	488	1029	386	1246	1601	558	6116	13
14	548	233	456	982	373	1202	1500	552	5846	14
15	478	200	375	912	343	1086	1430	505	5329	15
16	353	154	283	715	266	856	1108	396	4131	16
17	239	108	212	516	189	609	736	285	2894	17
18	126	63	120	304	103	348	344	156	1564	18
19	56	14	54	128	43	173	142	77	687	19
20	19	2	16	46	17	42	24	32	198	20
21	0	0	0	0	0	0	0	0	0	21
22	0	0	0	0	0	0	0	0	0	22
23	0	0	0	0	0	0	0	0	0	23
24	0	0	0	0	0	0	0	0	0	24

34

Why are Weather and BTMPV Forecasts important?

- Weather and BTMPV are the most significant inputs into demand forecasting software.
- With the continued growth of BTMPV in New England, the impact and volatility to demand forecasting accuracy is ever increasing.
- Poor weather forecasts into electrical demand forecast models equals bad electrical demand forecasts.
- Poor BTMPV and Irradiance forecasts equal bad demand forecasts.

What if there's a bad Electrical Demand Forecast?

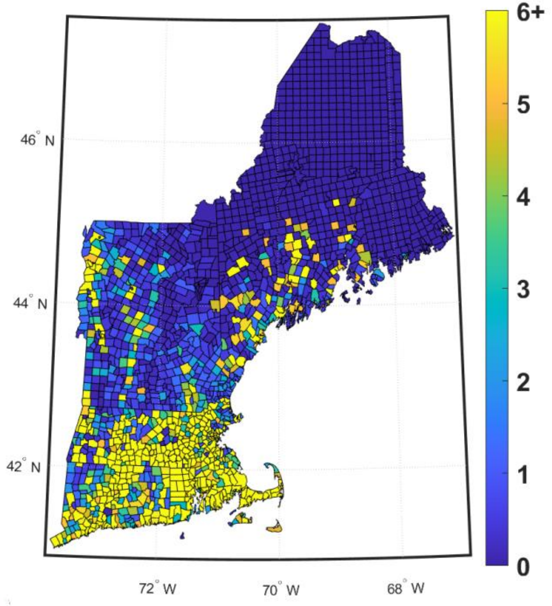
- Poor unit commitment, and potential for inadequate units to cover real time overall demand and real time unit loss emergencies.
- Poor market participant management of generation units and improper fuel procurement with poor financial performance.
- Could cause emergency conditions that may lead to impacts on Life and Property.

PV in Service by State

Through 2023

State	Installed Capacity (MW_{AC})	% of Total
Massachusetts	3,712.0	57.5%
Connecticut	1090.5	15.6%
Vermont	507.0	7.8%
New Hampshire	244.0	3.7%
Rhode Island	400.0	6.2%
Maine	588.0	9.1%
New England Total	**6,451.5**	

Source: [2024 Photovoltaic (PV) Forecast]



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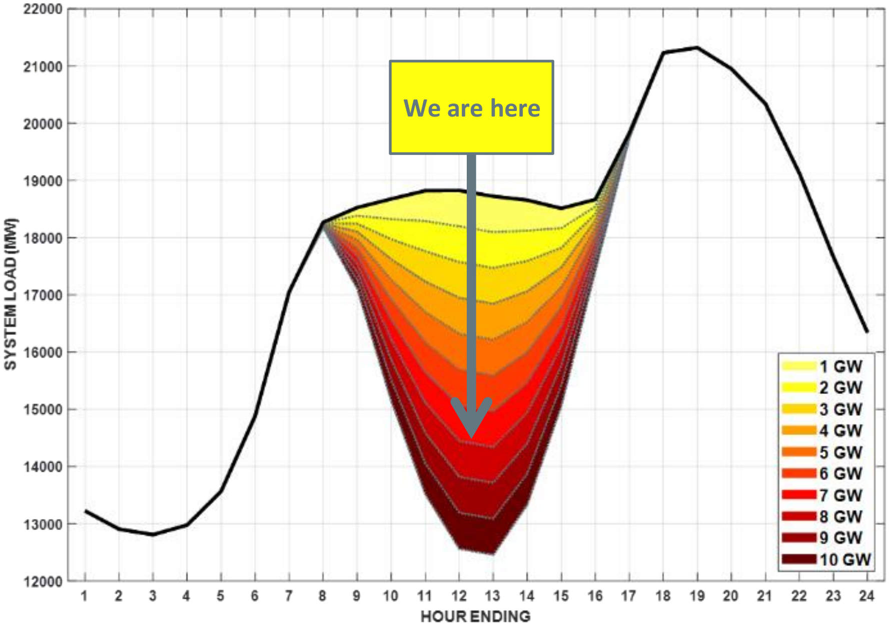
Over 7,000 MW of Photovoltaics in Region by End of Year

- Largest concentration of photovoltaics (PV) is in Central / Eastern MA
- There is 850 MW of large PV facilities visible in front of the meter, however most PV is behind-the-meter and most is not visible to ISO in real time.

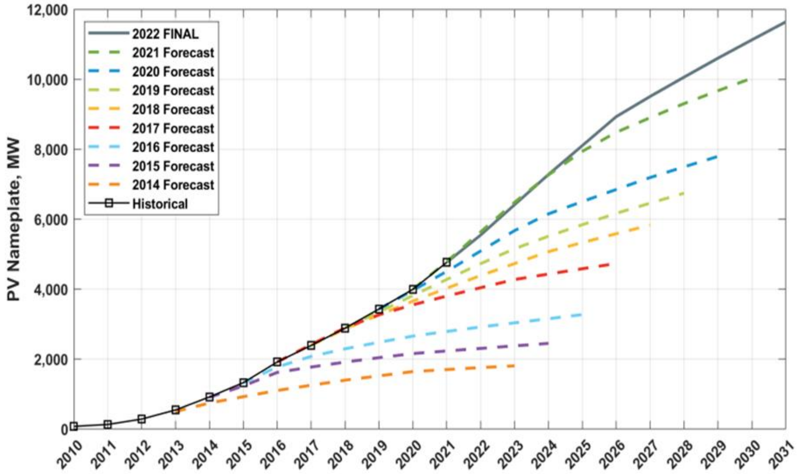


PV Forecast through 2031

End of year forecasts by year

Year	MW of BTM PV
2021	4,767
2022	5,547
2023	6,414
2024	7,278
2025	8,106
2026	8,933
2027	9,493
2028	10,021
2029	10,539
2030	11,033
2031	11,520

Source: [2022 Photovoltaic (PV) Forecast]



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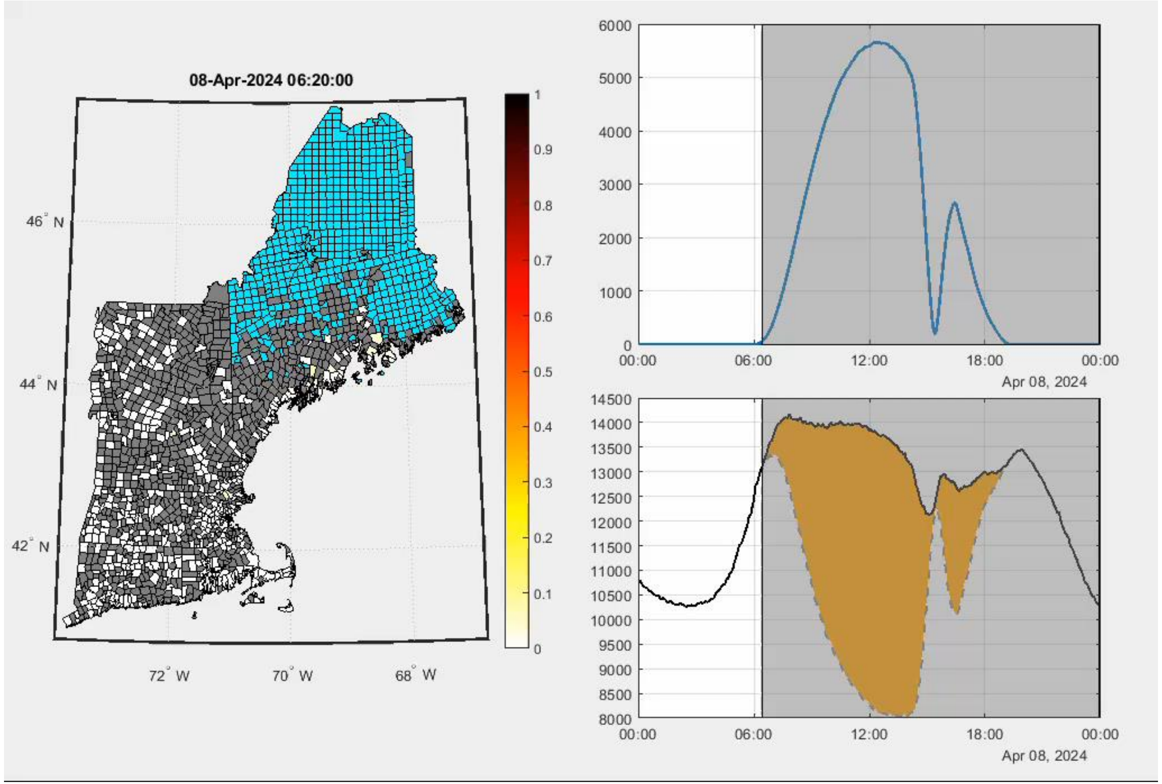
April 8th 2024 Solar Eclipse Impact on the Demand Curve



In Conclusion

Accurate BTMPV forecasts are of critical importance to ISO New England

- With the impact of BTMPV on demand forecasting it is quickly becoming the single most important factor when trying to produce an accurate demand forecast.
- Electric vehicle adoption and battery storage are beginning to grow.
- With financial impacts as well as impacts to life and property, accurate demand forecasting is of prime importance to ISO New England.

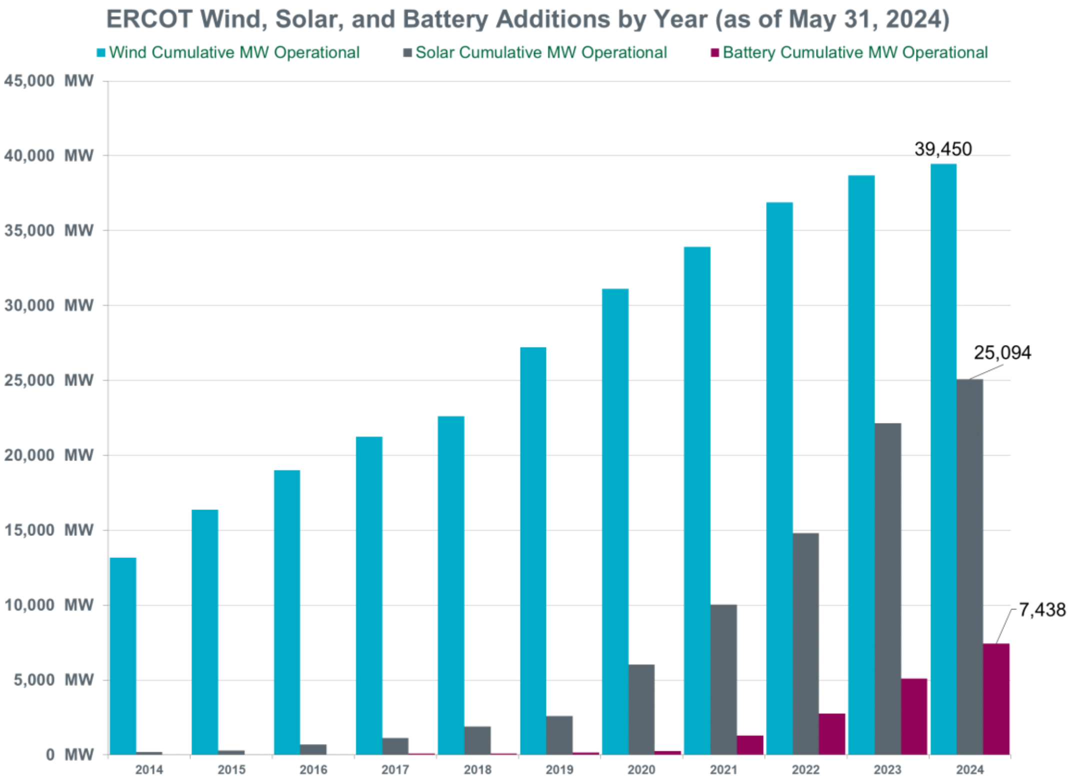
- Thank you from the ISO-New England Forecast team

Solar Forecasting in Operations at ERCOT

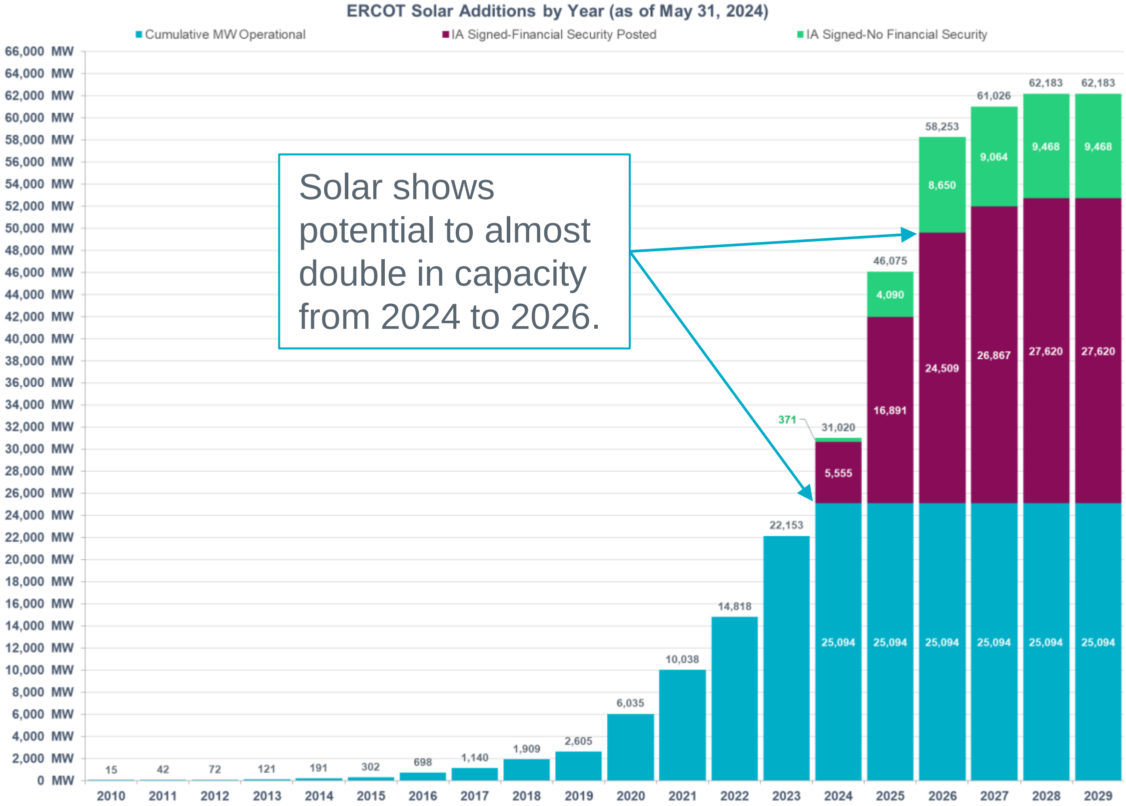
Luke Butler
Manager, Resource Forecasting and Analysis
ERCOT

July 10, 2024

ERCOT Wind, Solar, and Battery Cumulative MW Operational

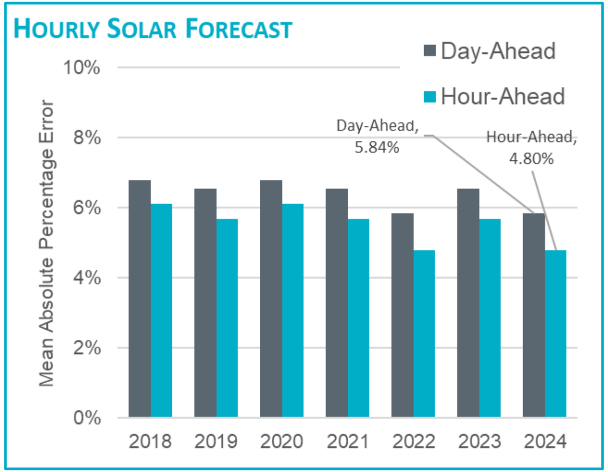


Planned Solar Additions



Solar Forecasts

- ERCOT implemented a centralized forecast for solar in 2016.
  - Second vendor added in 2022
- Model Description
  - Four Hourly Solar Forecasts per Vendor
    - Rolling 168-hr forecast; hourly resolution; updated every hour
    - POE80, POE50 and 2 Extreme Event Forecast are received from each vendor for each solar resource
  - One Intra-Hour Solar Forecasts per Vendor
    - 2-hour rolling forecast; 5-min resolution; updated every 5-min
  - Four 15-min Probabilistic Forecasts
    - Rolling 6-hr forecast; 15-min resolution; updated every hour
    - 50^{th}, 85^{th}, 90^{th}, 95^{th}, 98^{th}.
- Primary Inputs
  - Site geo-location; Met tower geo-location; Wind Speed and Temperature Operational limits; Telemetered site-specific data; Scheduled outages & de-rates; Generic power curves; Weather variables like wind speed/direction, irradiance, cloud cover



*In the graph above, 2024 represents the average forecast error between 01/01/2024 and 03/31/2024

ercot

Monitoring and Assessing Operational Impacts of Renewables in or near Real Time

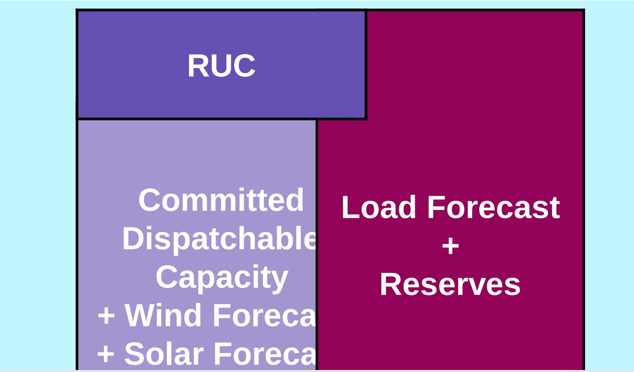
- A new Reliability Risk desk was added in the ERCOT Control Room in January 2017 to meet ERCOT's strategic goal of adapting to the changing resource mix .

- Some tools and studies this desk monitors include
  - **Forecast Presentation Platform** to monitor all renewable forecasts and **select active forecast for studies and dispatch**.
  - PI-based **displays to monitor renewable generation and forecast** at resource, region and system level
  - **Supply and Demand 6-day Grid Outlook and next 24-hour Capacity Availability Tool (CAT)** both use the **active hourly Wind and Solar forecast** and associated **historic over forecast uncertainties** and help gauge **sufficiency of available dispatchable resources to cover the various possible Net Load Forecasts** over the study horizon and **determine if long lead time unit commitment** is necessary.
  - **Intra-hour 5-min Capacity Availability Tool (i-CAT)** uses the active Intra-Hour forecast and help gauge **sufficiency of available dispatchable ramping capability to cover the various possible Net Load Forecasted ramp** over the next 2 hours.

Studies that Use Renewable Forecasts

Unit Commitment studies

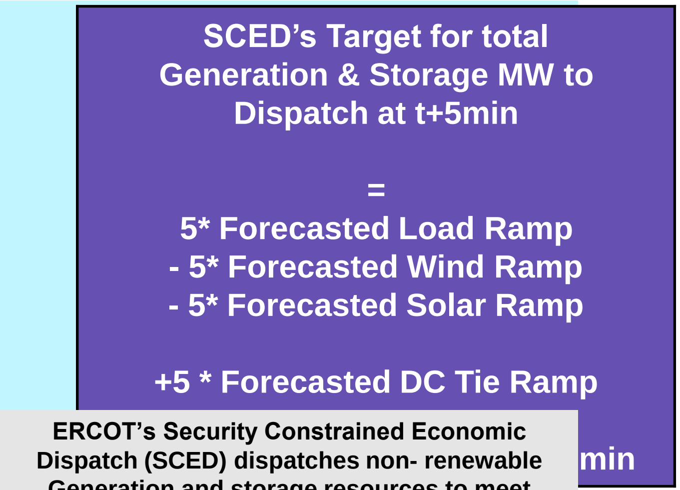
Active hourly Wind and Solar forecast are used in hourly Reliability **Unit Commitment studies** to determine if sufficient capacity is available to cover active forecasted demand plus reserves. Also used in look ahead studies like **Outage Coordination and Next Day Study.**



Reliability Unit Commitment (RUC) studies assess if additional commitments are needed to meet Forecasted Demand + Reserves

Security Constrained Economic Dispatch

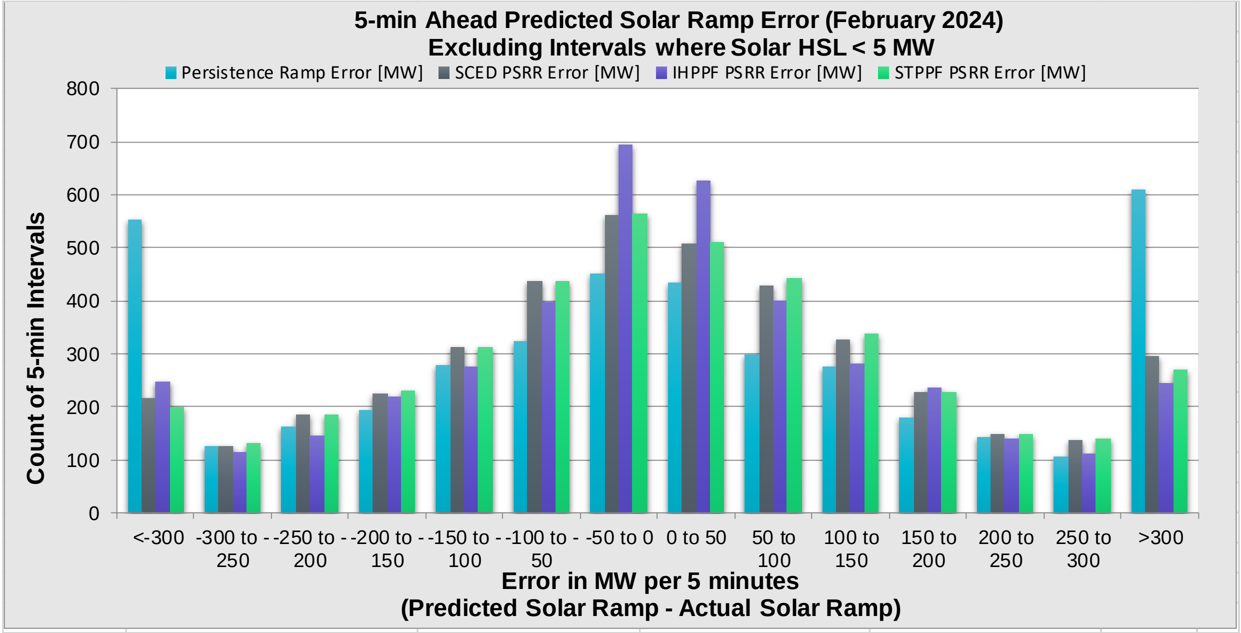
Active Intra-hour 5-min Wind and Solar forecast are used in **5-min Real Time dispatch** preposition dispatchable Resources in anticipation of wind and solar ramps.



ERCOT's Security Constrained Economic Dispatch (SCED) dispatches non- renewable Generation and storage resources to meet forecasted "net" load (load – wind – solar) over the next 5-min

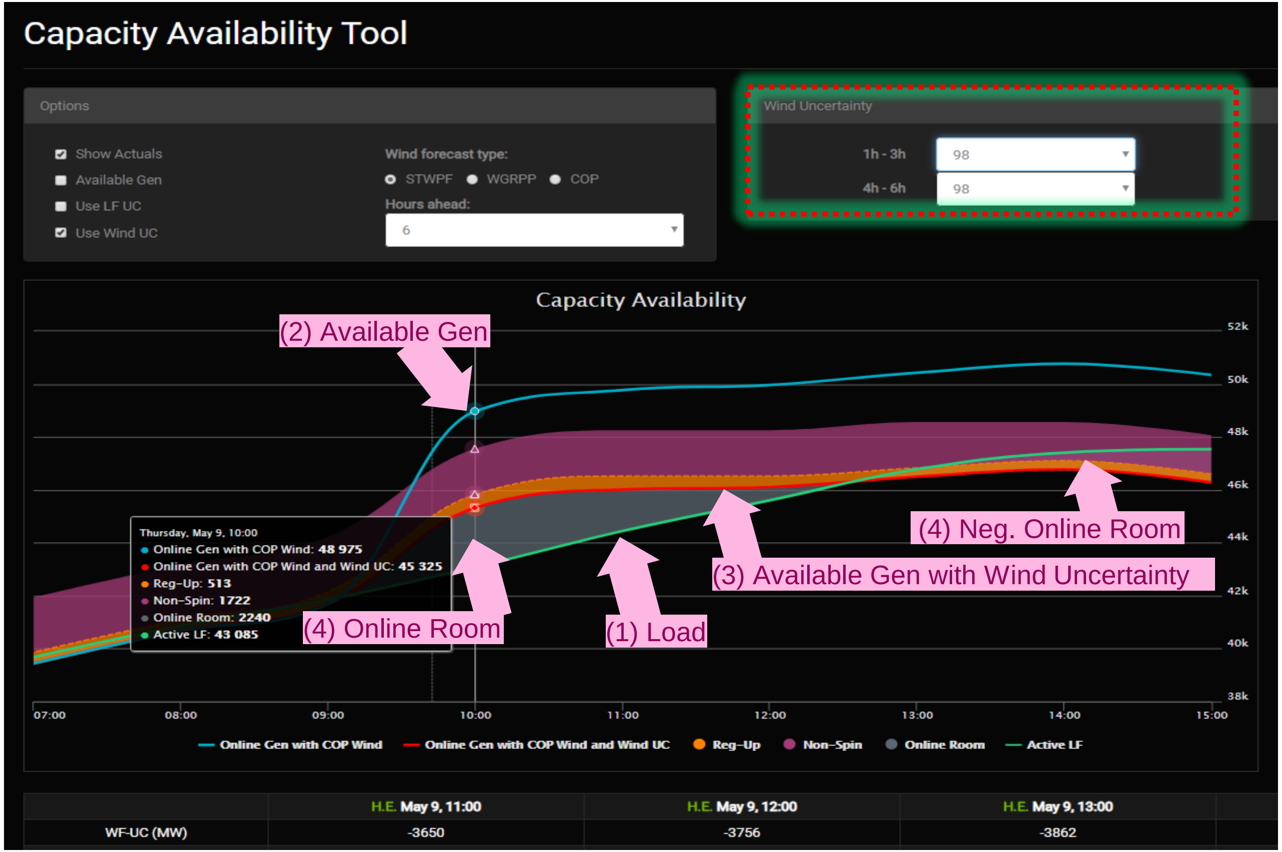
Predicted Solar Ramp Rate (PSRR) Error

Performance Metric	Persistence Ramp*	SCED PSRR	PSRR, IHPPF	PSRR, STPPF
Monthly MAE (MW per 5 minutes)	235	148	140	143
Monthly MAE when 5-Min. Solar Ramp > 100 MW	344	184	171	177



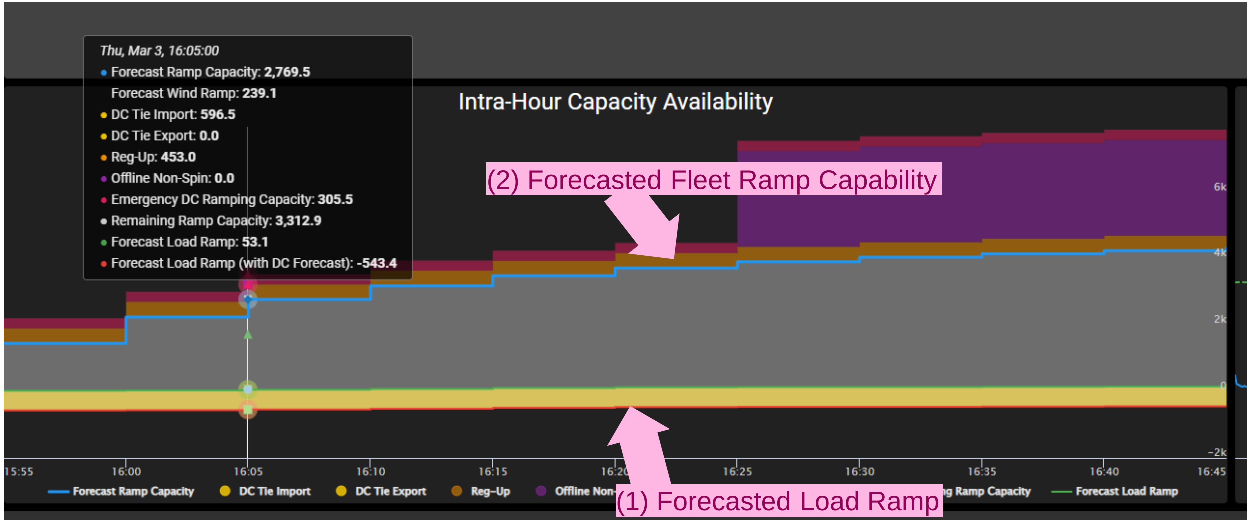
* Persistence Ramp assumes a 0 MW solar ramp

Capacity Availability Tool – "What If" Assessment for next 6 hours



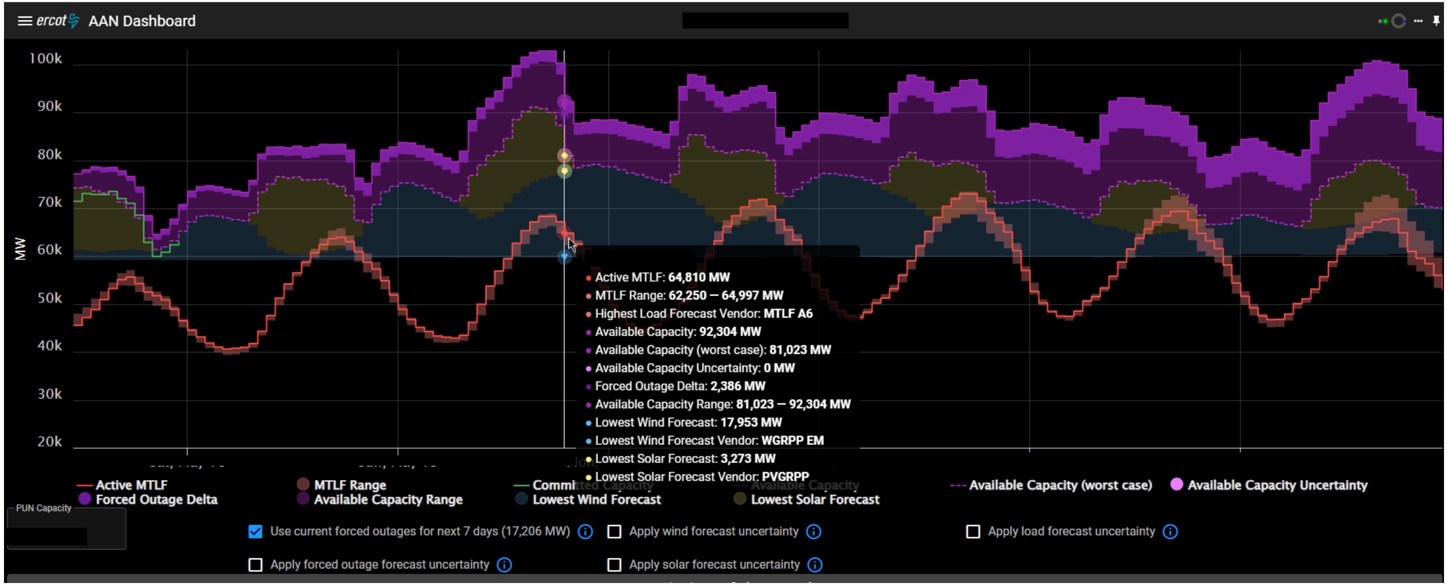
Intra-Hour Capacity Availability Tool – "What If" Assessment for next 2 hours

Monitors forecasted net load ramp in the next two hours and the available ramping capability of the thermal fleet to cover these.



Advanced Action Notice (AAN) Display

Renewable forecasts are a key input to the ERCOT outage scheduling process and the potential decision to reduce planned outages based on projected capacity availability.



Probabilistic Capacity Availability Tool (PCAT) Model

Currently developing a probabilistic approach to quantify risk in capacity assessment.

Input

- Hourly COP Data
- Hourly Load Forecast Data
- Hourly Solar Forecast Data
- Hourly Wind Forecast Data

Extras

- Energy Storage Resources SOC Forecast
- Price Responsive Demand Forecast

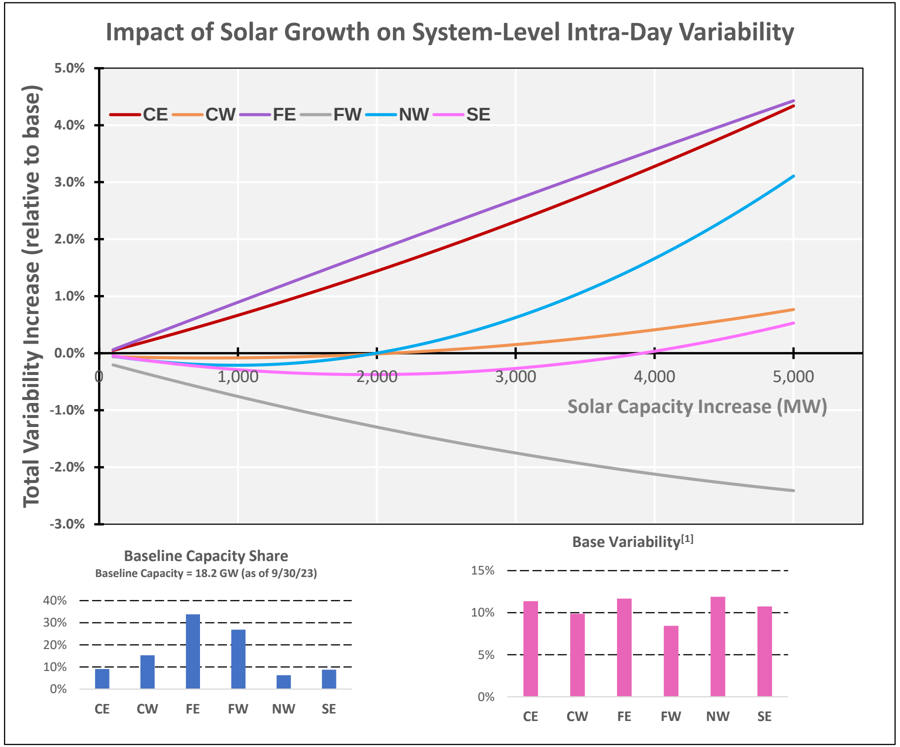
Process

- Calculate uncertainty for load, solar and wind forecast
- Apply the forecast uncertainty for the forecast period (168 hours) with information from history
- Create distribution of net load forecast (*net load = total load – solar – wind*) using Monte Carlo (MC) simulation
- Determine forecasted capacity margin distribution from COP data and MC output

Output

- Event Occurrence Probability – hourly probability of capacity margin falling below certain threshold (168 hours)
- Statistics on forecasted capacity margin (min, max, average, median, k^{th} percentile, etc.

System Solar Intra-Day Variability

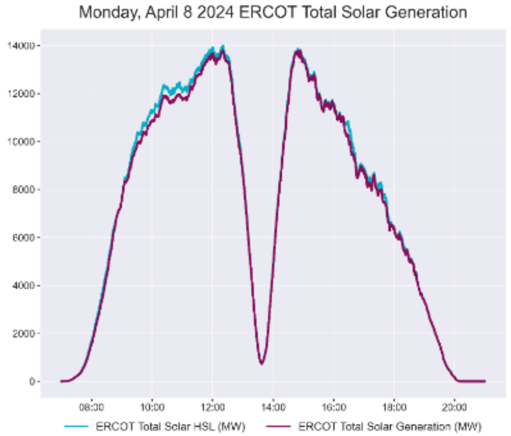


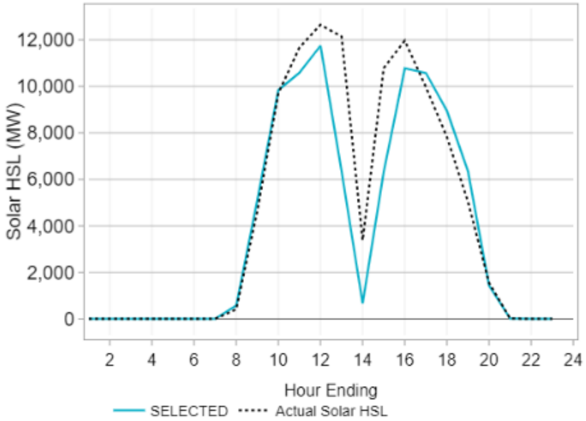
[1] baseline variability metric of the regions (1 sigma / average)
[2] baseline capacity: 18.2 GW as of 9/30/2023 at the system level

- The graph illustrates the increase in intra-day solar variability at the system level with the growth of solar capacity in each region.
- Each line represents the rise in system-level intra-day variability with incremental capacity in that specific region, while maintaining a constant capacity in other regions.
- The intra-day variability (y-axis) is presented relative to the baseline capacity[2]
- The growth in FarEast and CentralEast has the most significant impact on system-level variability. An additional capacity of 5000 MW in either region increases the system variability by approximately 4.3%.
- In contrast, the growth in FarWest leads to a reduction in system-level variability. The addition of 5000 MW decreases the variability by about 2.5%.

April 8 Eclipse Forecast

- On Monday, April 8, 2024, a total solar eclipse passed over Texas from the southwest to northeast direction.
- Solar generation was reduced during the eclipse, dropping from an instantaneous peak of 13.8 GW at the beginning of the eclipse to a low output of 0.7 GW at 1:36 p.m., and then rising to approximately 13.8 GW by 3:10 p.m.
- ERCOT procured additional Ancillary Services (AS), committed additional generation, took manual actions to increase ramping capability, and deployed AS to maintain reliability.





Solar forecasting –

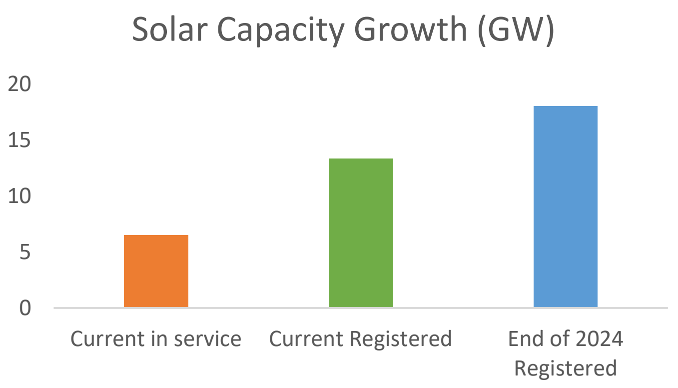
progresses, challenges and needs from MISO perspective

DoE Solar Forecasting Workshop

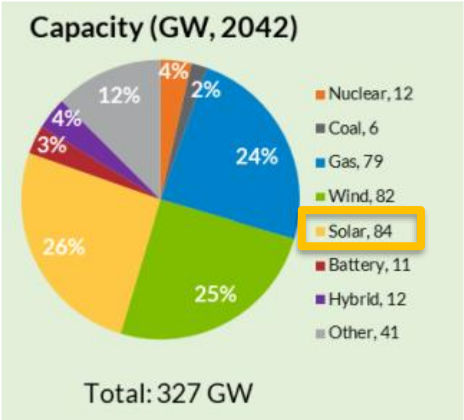
July 9-10, 2024

Accelerating solar penetration increase is a key theme of MISO's transitioning fleet

- Current in-service capacity is relatively low at 6.5GW, but has been doubling from previous year each of past five years (**fast increase**)
- MISO is projected to manage 80GW utility-scale solar by 2040, likely one of the largest among all ISOs/RTOs (**largest penetration by 2040**)
- Solar is penetrated across all MISO three regions from North to the South (**geographic diversity**)



MISO Future 1



Solar forecasting provides important inputs for markets and operations to balance energy and clear reserves

Solar Forecast Inputs	Hourly forecast up to 7-day ahead	Market Participant (MP) Offer	Hourly forecast Day-Ahead	Hourly and 5 min forecasts hours ahead	5min forecast by MISO or MP
Commitment Dispatch Processes	Multi-Day Forward RAC	Day-Ahead Market	Next-Day Forward RAC	Intra-Day RAC and LAC	Real-Time Market and UDS AGC...

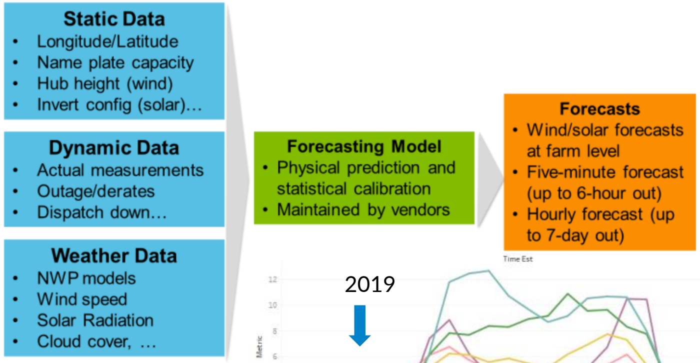
Market Products

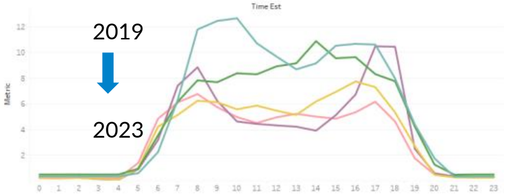
- Next-Day Reserve: *Next Day Uncertainty (Dynamic)*
- Short Term Reserves: *30 minutes – 3 hour (Dynamic)*
- Ramp Capability: *10 – 30 minutes*
- *Contingency Reserve: Largest unit loss*
- Regulation: *4 second – 5 minutes*

Solar forecasting accuracy is a continuous focus and its improvement results in direct market and reliability values

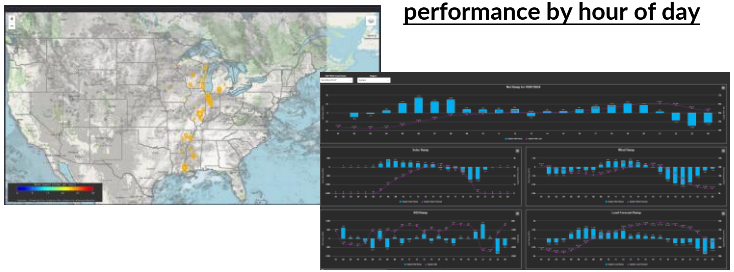
- Solar forecasting accuracy improved across the forecasting timeframes in collaboration with vendor and members

- Situational awareness of solar variability and net load ramping are built for control room operations





<u>**Day-Ahead solar forecasting performance by hour of day**</u>



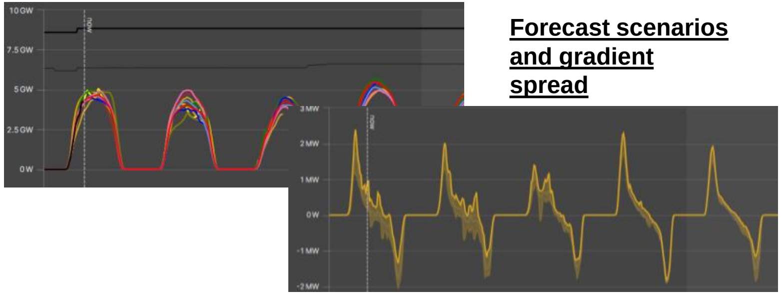
Public

"Probabilistic" solar forecasting is established to quantify uncertainty and used in scenario-based Operations planning

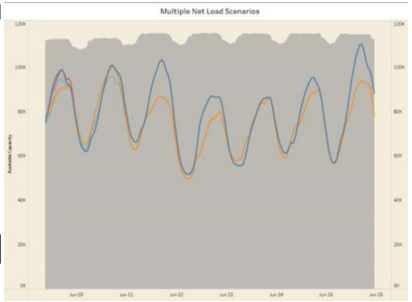
- Multiple NWP based solar forecasting scenarios are established and utilized to quantify uncertainty

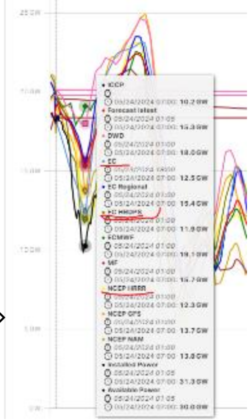
- Multiple scenarios are used in Operations planning to manage uncertainty

- Advanced analytics is being developed to dynamically and optimally ensemble scenarios leveraging real-time conditions



Forecast scenarios and gradient spread



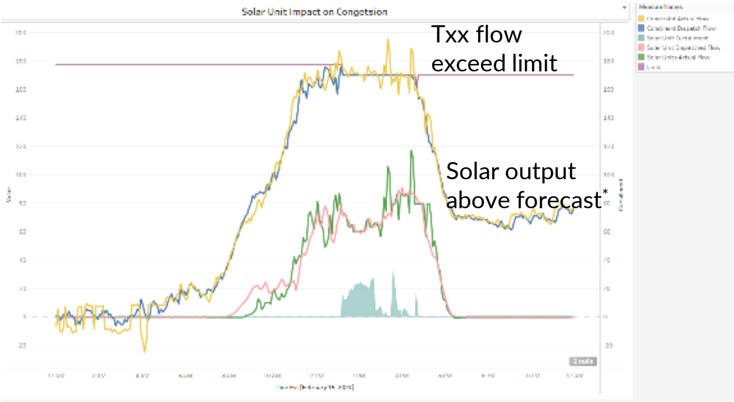


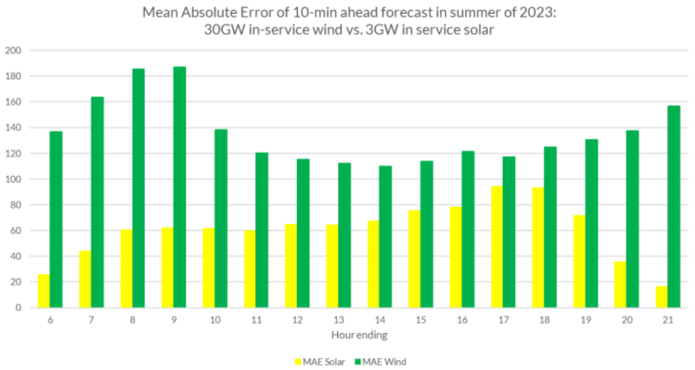
Example of high-resolution NWP models better capture wind drop

Challenges remain in solar forecasting and the errors in the dispatch horizon cause difficulty in managing congestion

- While portfolio level 10-minute ahead solar forecast error averages at 1-2%, significant error can occur at certain farms causing congestion challenges

- Solar is introducing high shorter-timeframe variabilities, and its forecasting error is almost comparable to wind whose capacity is multi-folder higher





*Note: Besides forecast errors, unit not following dispatch can also challenge congestion management as discussed at June 2024 board meeting

With the geographic diversity, solar forecasting is challenged by various weather events

- Cloud forecasting
  - Limited tools available for accurately predicting formation/dissipation/evolution of different cloud types such as convective clouds, marine stratus and fog
  - Both sub-hourly for the dispatch horizon forecast, and beyond the sub-hourly and intra-day for commitment and ops planning horizons
- Snow / snow-free
  - Mainly northern MISO is affected by snow during wintertime
- Dust / smoke
- Thunderstorms
- Convection

- Behind the Meter solar visibility and load forecasting

Improve forecasting during these weather events

Identify leading indicators of high uncertainty to inform dynamic reserve carrying

Questions?

NYISO Solar Forecasting

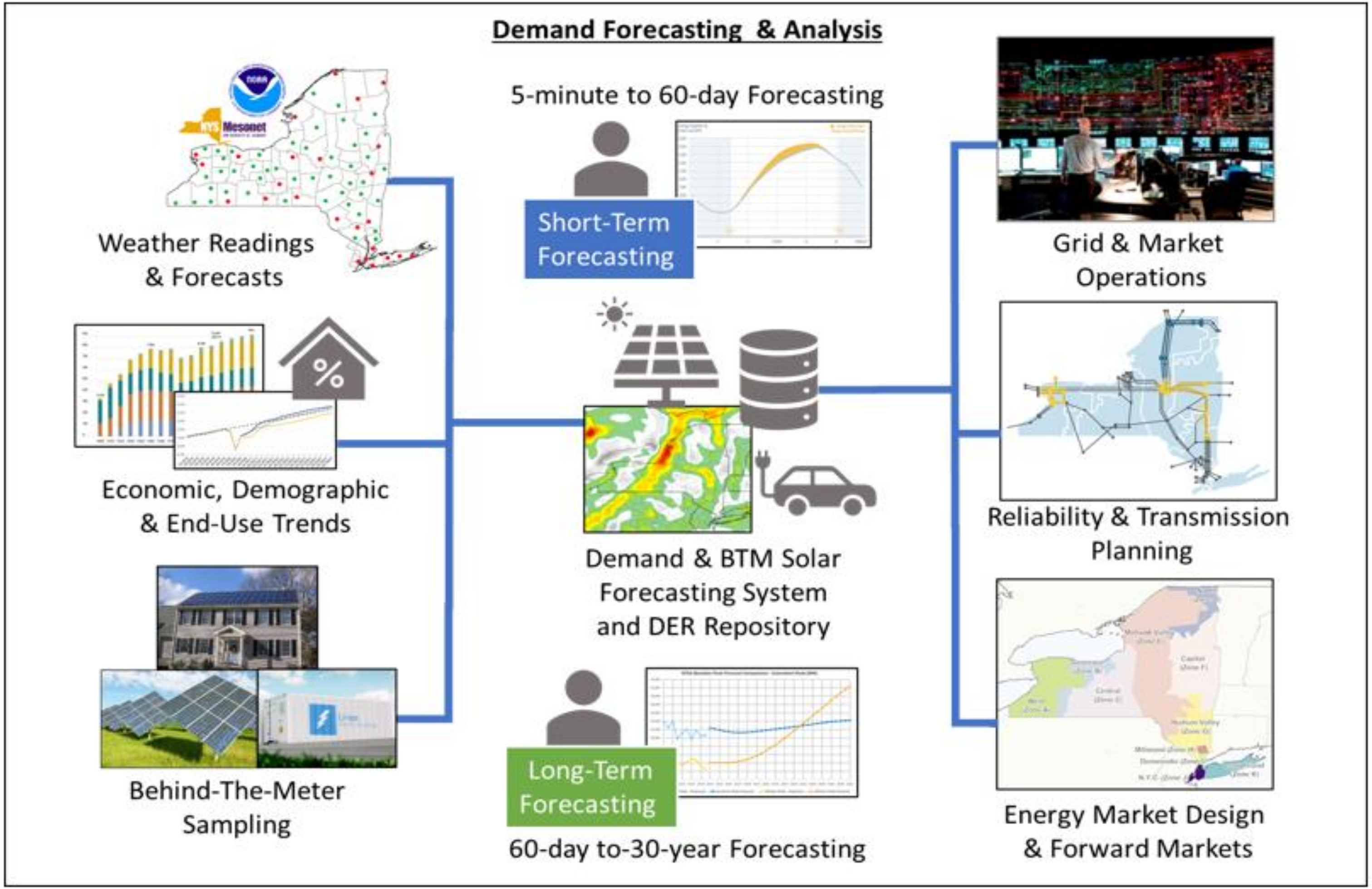
Timothy Duffy
Manager, Demand Forecasting and Analysis
Grid Transition

DOE Workshop on Solar Forecasting
July 9, 2024

Agenda

- Demand Forecasting System
- Renewable Forecasting System
- NYCA Solar Trends
- Future Developments

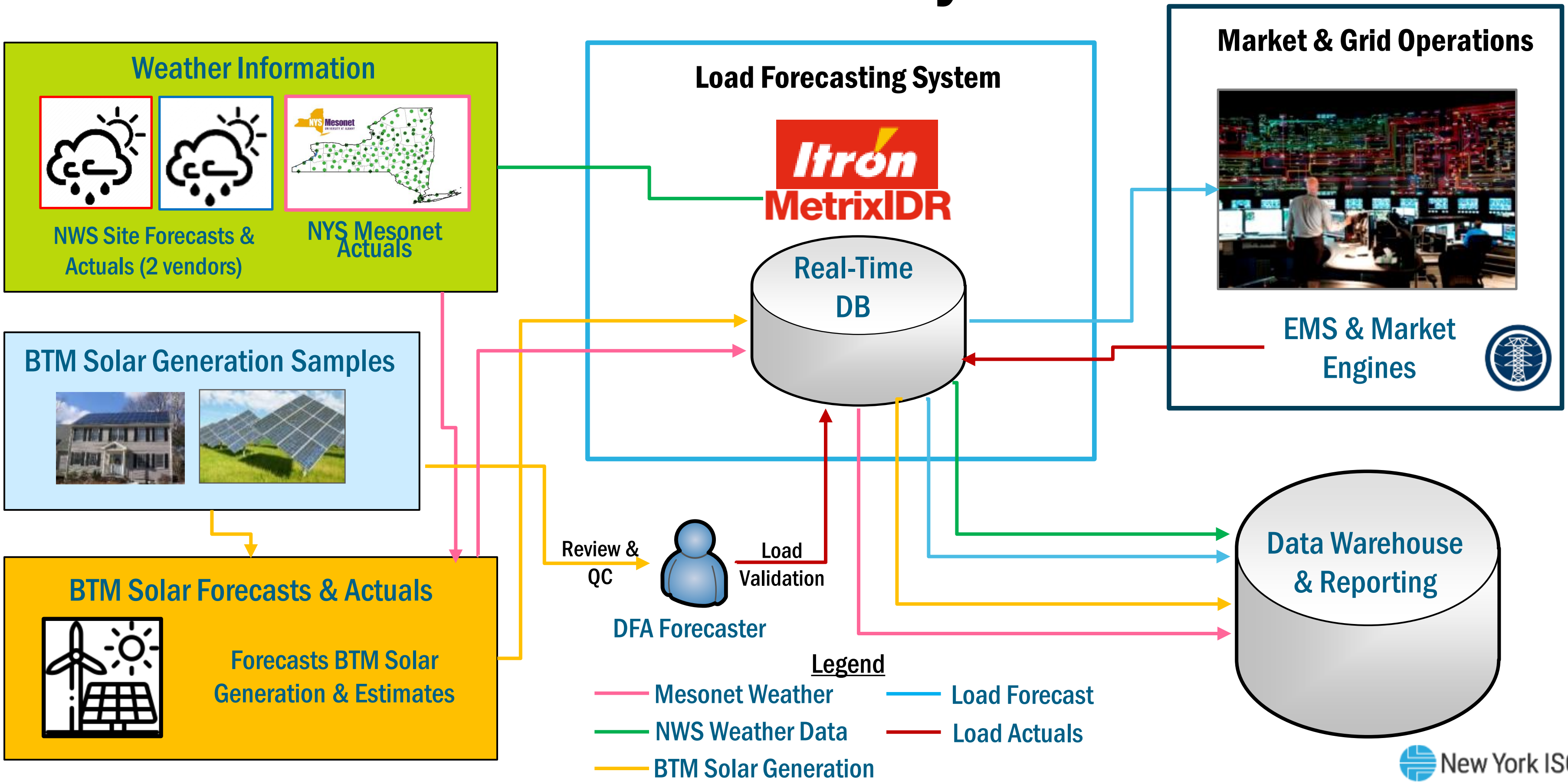
Demand Forecasting System



Demand Forecasting & Analysis
5-minute to 60-day Forecasting
Short-Term Forecasting
Weather Readings & Forecasts
NYS Mesonet
NOAA
Grid & Market Operations
Economic, Demographic & End-Use Trends
Demand & BTM Solar Forecasting System and DER Repository
Reliability & Transmission Planning
Behind-The-Meter Sampling
Long-Term Forecasting
60-day to-30-year Forecasting
Energy Market Design & Forward Markets

New York ISO

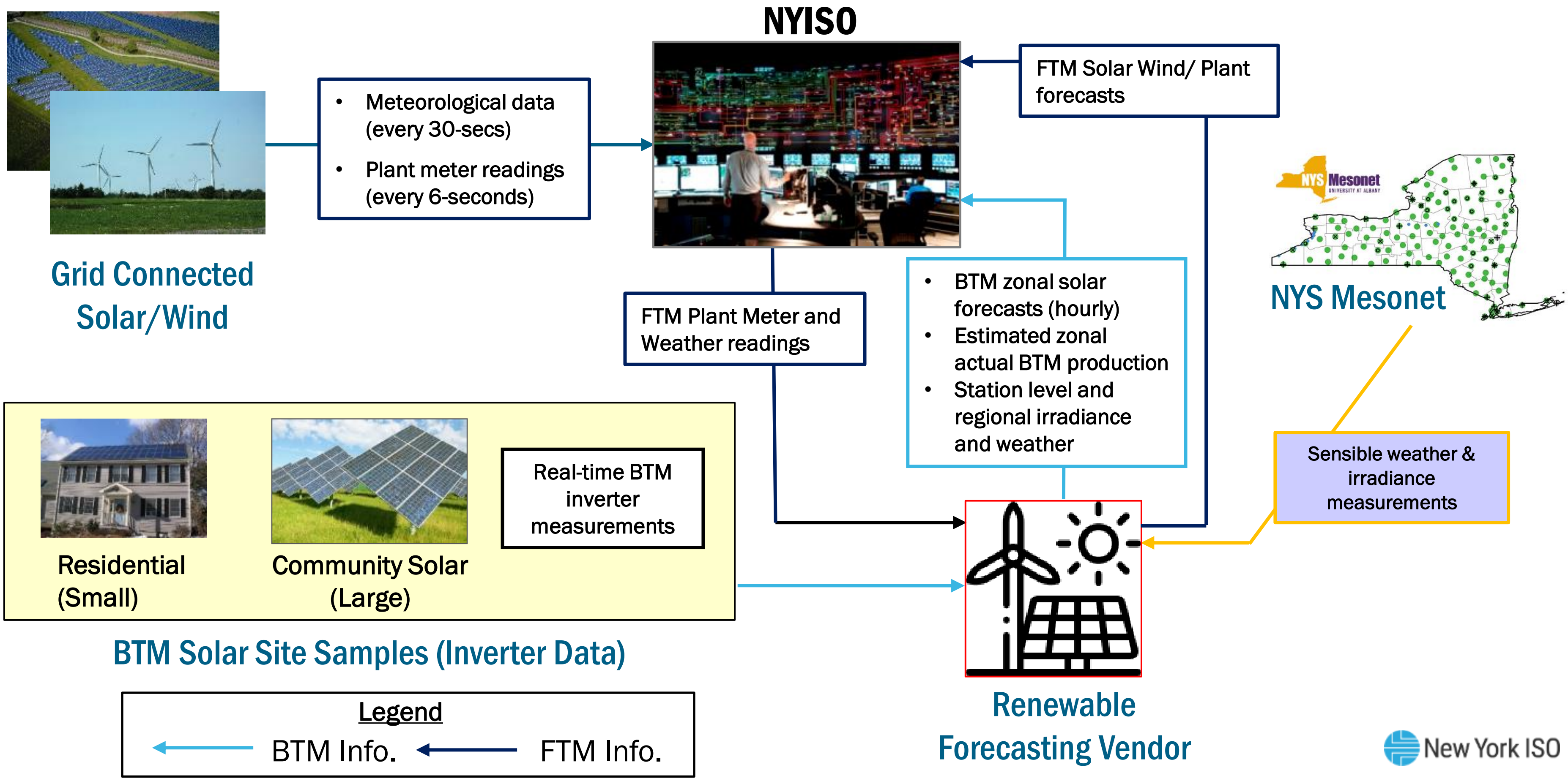
Real-Time Load Forecast System



New York ISO

Renewable Forecasting System

Renewable Forecasting System - Overview



New York ISO

NYISO BTM Solar Forecasting System

- The NYISO Behind-the-meter (BTM) Solar forecasting system was developed in concert with the growing number of solar installations across NY state (Operational launch occurred in 2017)
- Important to monitor and forecast solar systems that are not connected to the NY bulk power system because the BTM resources act to modify local loads fed by utility distribution networks (load forecast adjustment)
- Inverter data provides BTM Solar Photovoltaic (PV) generation data once per hour for about 10,000 sites to a renewable energy forecasting provider
  - Sample represents over 200,000 installed sites throughout the state, a sample of ~ 1,600 MW-DC installed capacity
  - Data are continuously sampled from the prior 24 hours and aggregated by county and size-bin
  - Sampling is stratified to capture the differences in performance between large (e.g., > 250 kW) and small sites (< 250 kW)

New York ISO

NYISO BTM Solar Forecasting System (Cont.)

- **Solar forecasting provider produces irradiance and solar MW forecasts 7-days ahead**
  - Actual irradiance measurements obtained from 25 NY State Mesonet monitoring sites
  - Estimated irradiance is derived from high resolution satellite imagery (Mesonet used to calibrate satellite)
  - Forecasts are created for each county, aggregated to 11 load zones, and delivered hourly at 15-minute intervals (B734 project is moving this to 15-minute updates)
- **BTM forecast and actual data are used as inputs into the NYISO real-time load forecasting system**
  - Day-ahead load forecast models (15 minutes-per-interval) forecast the total load (net system load + BTM PV generation) for 11 load zones
  - The BTM PV generation MWs are subtracted to obtain the (net) load forecast used for NYISO generator commitment & dispatch
  - Forecast archiving is done in a custom database (Load Forecast Data Repository [LFDR]) and analysis performed against data from that system

New York ISO

NYISO BTM Solar Forecasting System

BTM Solar Site Samples (Inverter Generation Data)

Residential & Small Commercial (Small)

Community Solar (Large)

Retrospective (prior day) and Real-time (last hour) BTM inverter measurements

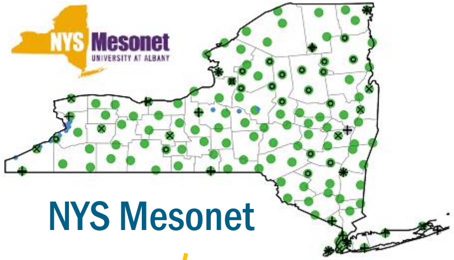
Feed is stratified by size into Large (> 250 kW DC) and Small (<= 250 kW DC) systems

NYISO

County and Zone capacity schedule updates (MW DC)

- BTM zonal solar generation forecasts (hourly)
- Estimated zonal BTM production (scaled from sampling/estimates)
- Mesonet station irradiance and weather (25 sites)

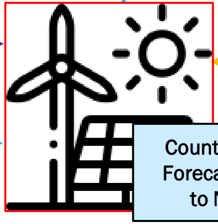
Per Unit Output (AC output relative to DC capacity)



NYS Mesonet

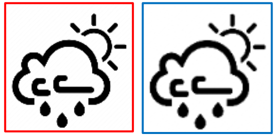
Sensible weather & irradiance measurements

Weather Forecasts & Actuals



County Level BTM PV Forecasts aggregated to NYISO Zones

Renewable Forecasting Vendor



Weather Forecasting Vendors

New York ISO

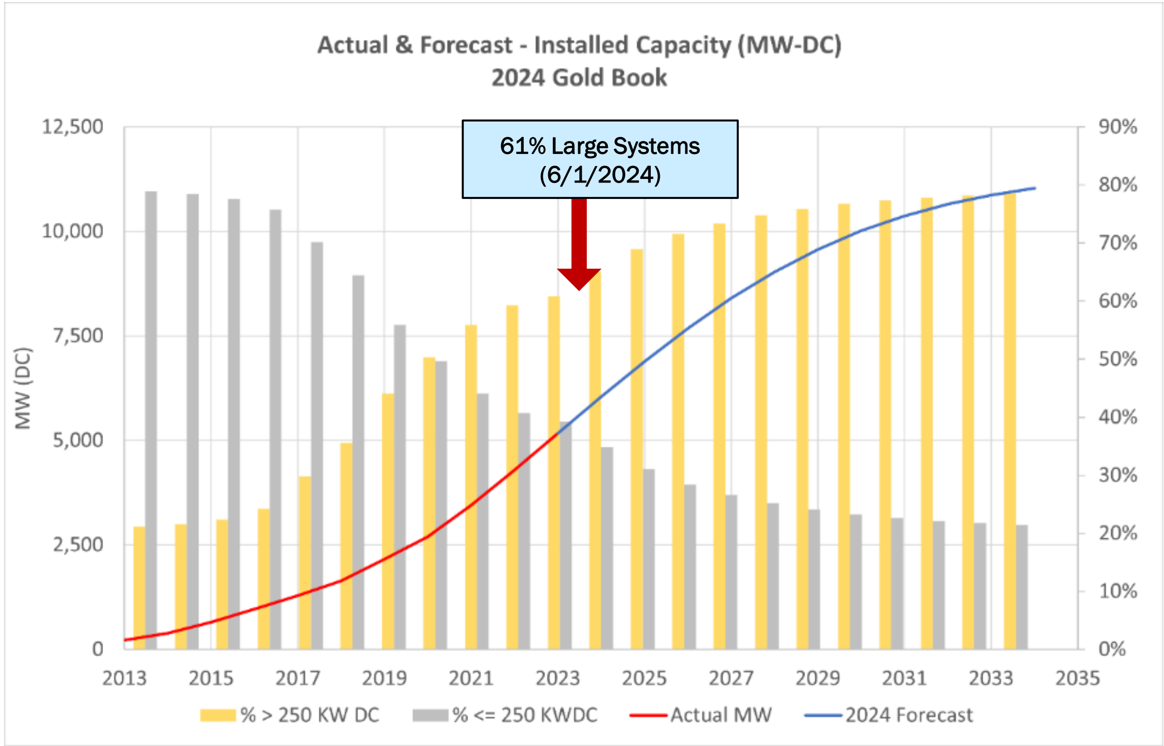
NYISO FTM Renewable Forecasts

- **Front-of-the-meter (FTM) forecasting was developed in concert with the growing number of wind installations across NY state (Operational launch occurred in 2006)**
- **<u>Most</u> grid connected resources participate in the NYISO wholesale market and are dispatchable**
- **NYISO telemeters site generation data, weather information, and select operational characteristics for each site (e.g., site orientation for solar)**
  - Current installed solar capacity is over 254.4 MW (AC) with over 10.7 GW planned in the NYISO queue
  - Solar forecasts come with risk products delivered via email (e.g., fog warnings, and snow on PV panel risk)
- **FTM forecasting provider (UL) produces irradiance and solar MW forecasts 7 days ahead**
  - Actual weather conditions obtained from the solar sites
  - Estimated irradiance is derived from high resolution satellite imagery (adjusted to Mesonet measurements) and used in real-time forecasting
  - Forecasts are created for each site, aggregated to the 11 load zones, and delivered at 15-minute intervals
- **FTM forecast and actual data are used as inputs into the NYISO marketplace (MIS) and EMS/BMS systems**

New York ISO

NYCA Solar Trends

BTM PV Installed Capacity Forecast



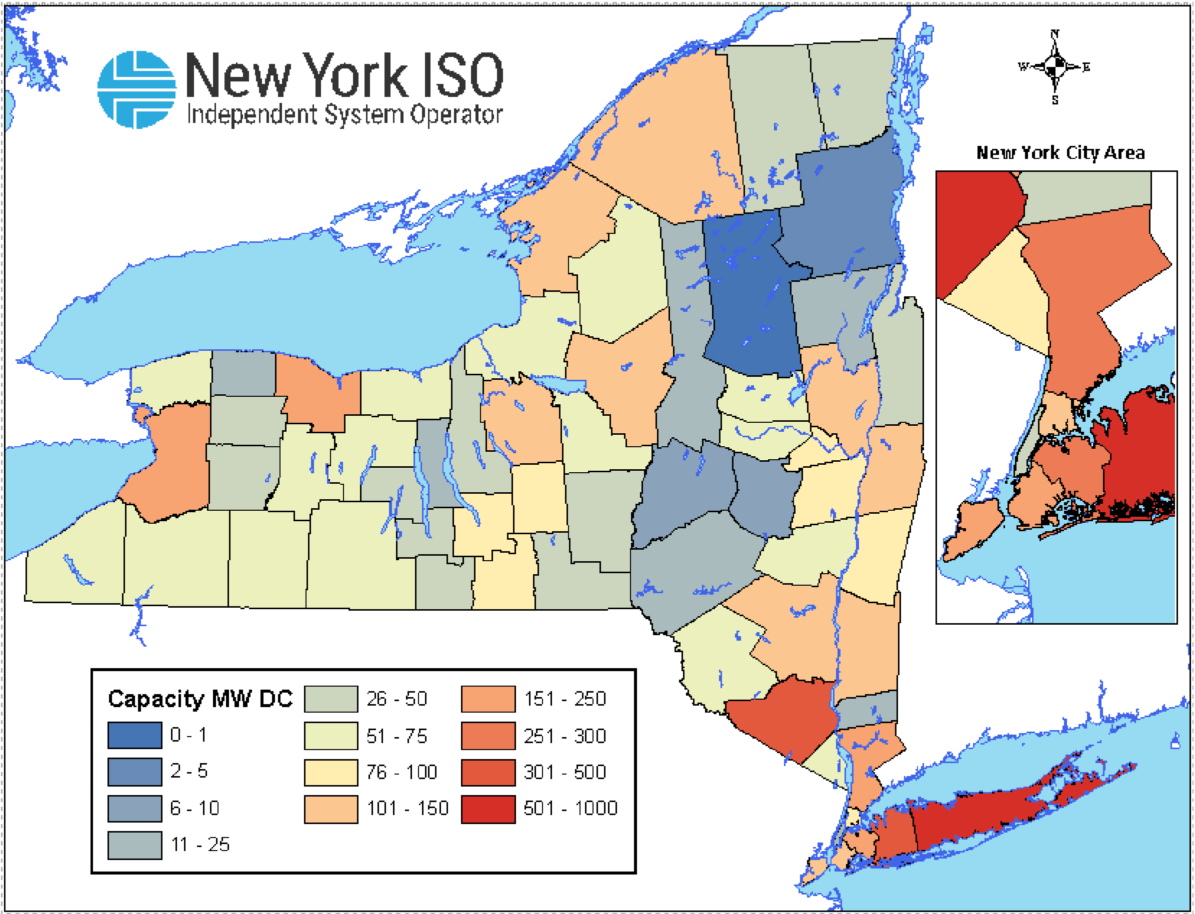
- All actual and forecast values represent the end of year BTM Solar installed capacities
- Forecast includes strong capacity growth through 2030
  - >75% of 10GW 2030 NYS goal exists between complete and current pipeline projects
- Continued growth expected for large (> 250 kW DC) distributed solar projects

New York ISO

BTM Solar Installed Capacity

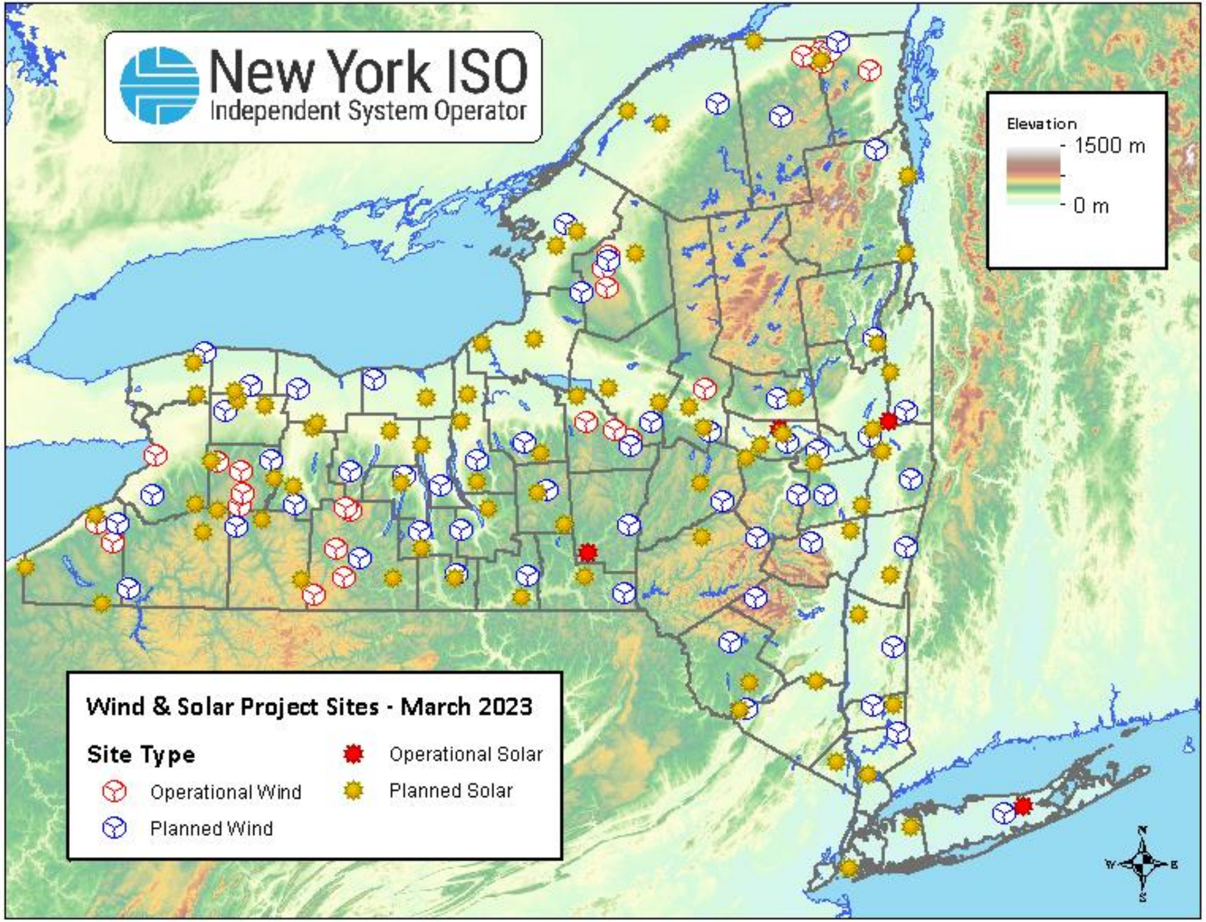
5,475 MW DC (Est.)

as of 6/1/2024



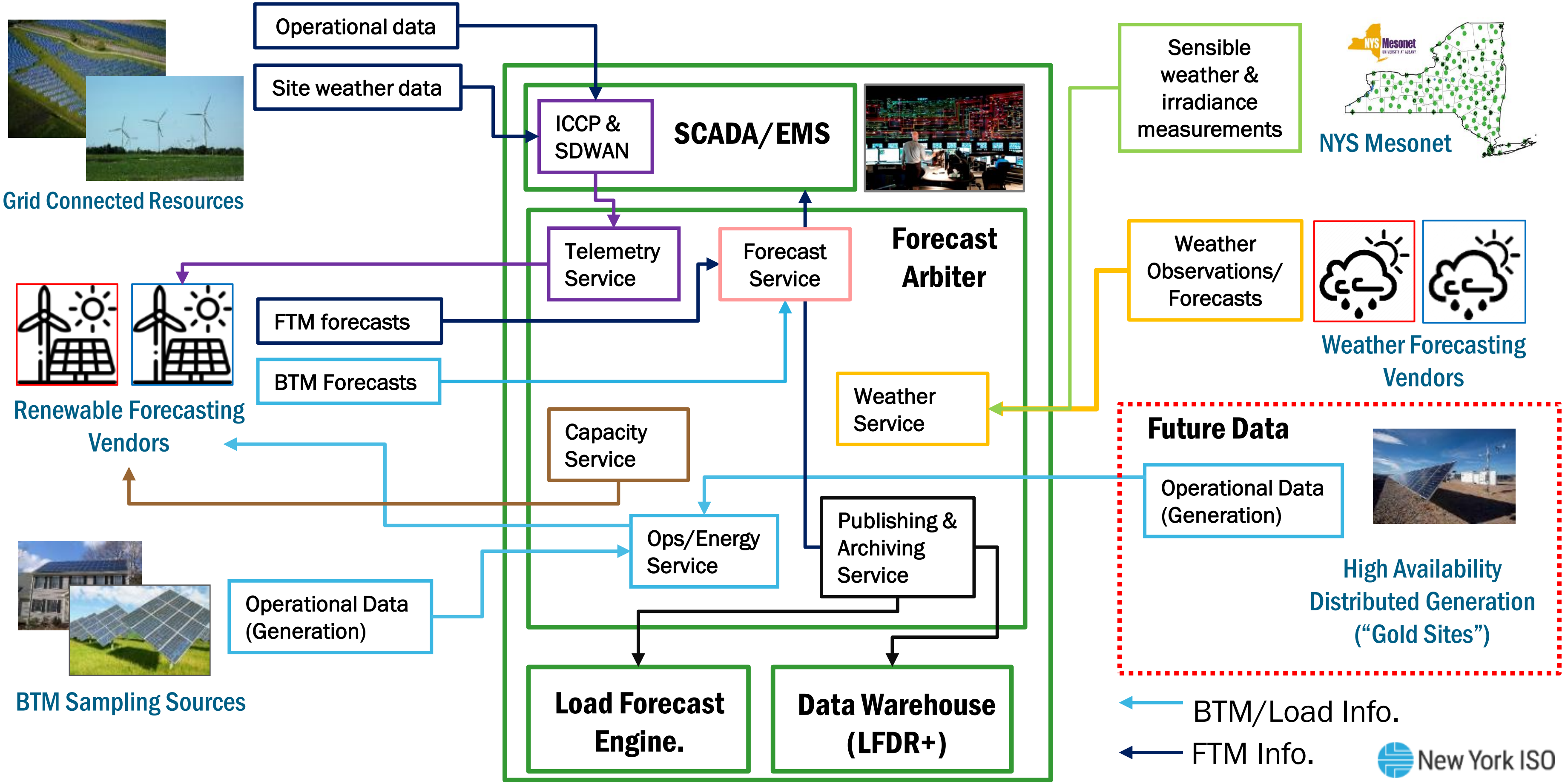
New York ISO

FTM Renewable Geographic Distribution



Future Development: BTM/FTM Integration

Forecasting Data Integration



Our Mission and Vision

Mission

Ensure power system reliability and competitive markets for New York in a clean energy future

Vision

Working together with stakeholders to build the cleanest, most reliable electric system in the nation

New York ISO

Q&A and Discussions

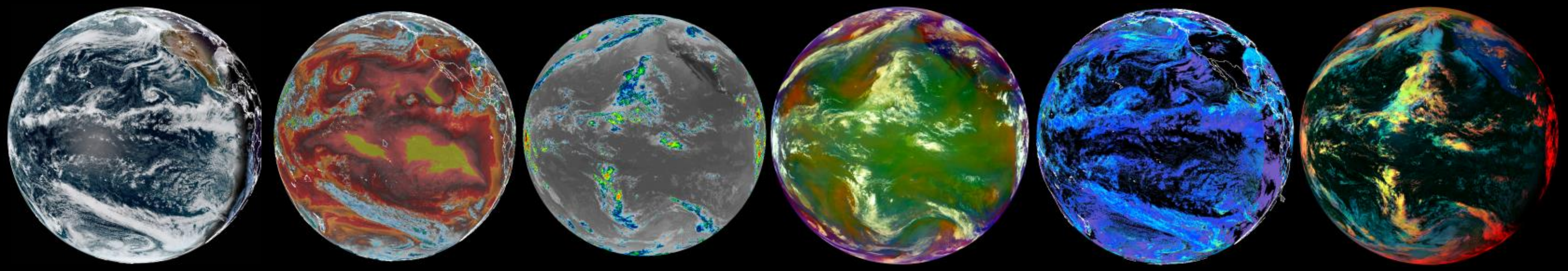
Previous solar forecasting prize winners

NIMBUS AI

Day-Ahead Probabilistic Irradiance Forecasting Prize

AMERICAN MADE SOLAR PRIZE

U.S. DEPARTMENT OF ENERGY



Nimbus AI GOES-17 multispectral profile

Nimbus AI Core Team

Geoff Galgon, PhD

CEO

Peter Sadowski, PhD

Chief Analytics Officer

Associate Professor

UH Computer Science

Giuseppe Torri, PhD

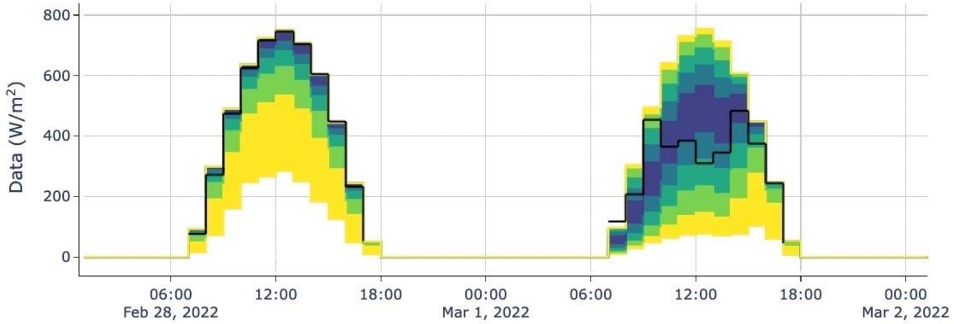
Chief Science Officer

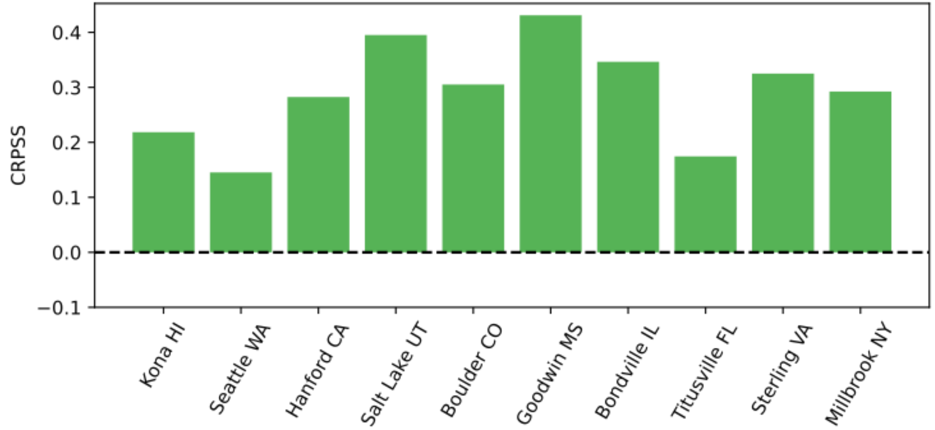
Associate Professor

UH Atmospheric Science

Forecasting Prize: Setting and Performance

- Setting: four-week evaluation period of day-ahead probabilistic forecasts at 10 US sites.
- Statistical downscaling approach performed much better than baseline:
  - Only competitor to beat baseline at every site
  - Lessons learned throughout the competition led to increased final model performance





Forecasting Prize: Lessons Learned

NWP (GFS/HRRR) variable inputs

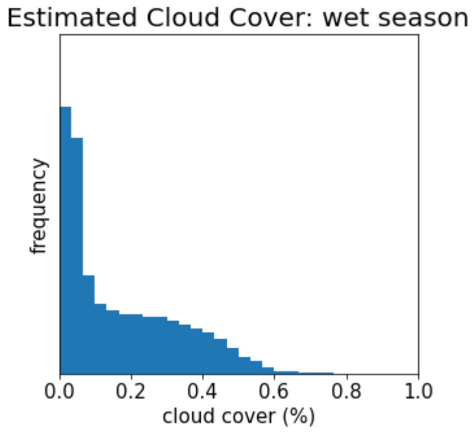
- GFS **input variable selection** is important.

Geography & Clear-Sky model inputs

- Clear-sky models under/over-estimate irradiance by as much as 10%.

Probabilistic forecasting

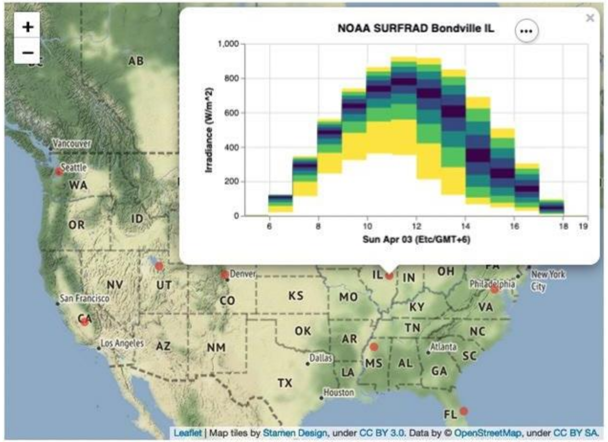
- Use CRPS or other **proper scoring** to discourage hedging
- Model densities should reflect spatiotemporal **structured uncertainty** (more later)
- Real dispersion characteristics **are not captured** by NWP ensembles



Current and Future (Solar) Plans

Leveraging irradiance forecasting methods

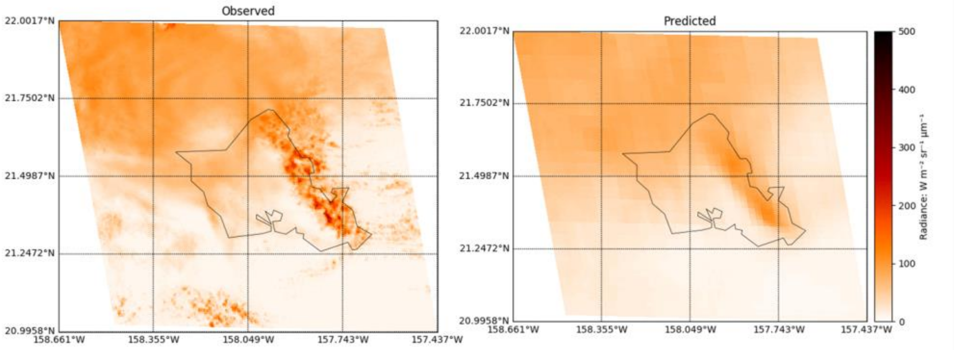
- Live API-based Hawaii commercial PV system (net load / PV production)
- Site-specific probability forecasts for other solar-dependent variables



Solar Forecasting Day-Ahead Dashboard: Forecasting Prize Sites

Diffusion models (generative AI)[1]

- Use diffusion models in forecasting joint probability distributions across a region of interest (substation/grid vs. individual sites).

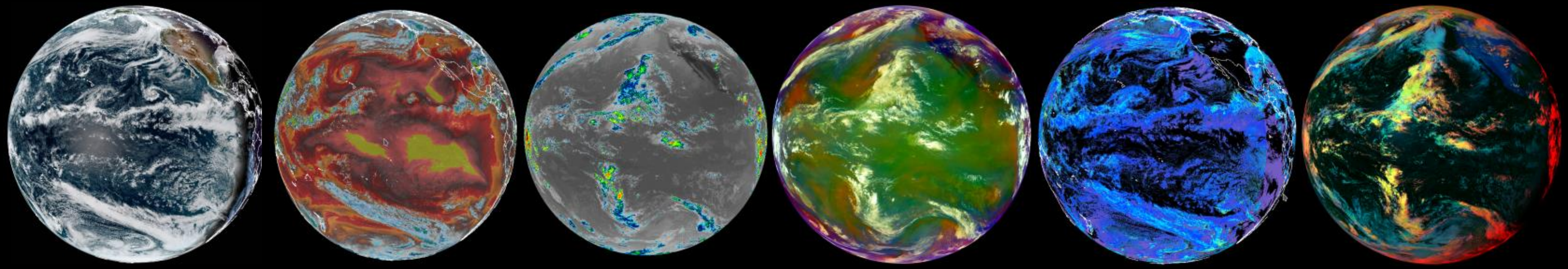


Observed vs. Nimbus AI 60-min 1st generation CNN nowcasts: Island of Oʻahu

[1] Hatanaka, Y. et al.(2023). *Diffusion Models for High-Resolution Solar Forecasts*. 10.48550/arXiv.2302.00170.

Thank you

Contact: geoff@nimbus.solar



Nimbus AI GOES-17 multispectral profile

DOE: Solar Forecasting Workshop

Zhimin Xi, CEO and Founder
Email: zxi@rautonomy.com
Reliable Autonomy LLC
https://rautonomy.com/

Winners

DOE selected three winners and three runners-up to receive cash prizes in the amounts of $200,000 (first place), $150,000 (second place) and $100,000 (third place). Runners-up will receive $50,000 each.

- **First Place:** Reliable Autonomy (Basking Ridge, NJ)
- **Second Place:** Shifted Energy (Honolulu, HI)
- **Third Place:** Teraton Partners HQ (San Francisco, CA)
- **Runner-up:** Leaptran (San Antonio, TX)
- **Runner-up:** Linear Intelligence LLC (Apex, NC)
- **Runner-up:** Innowatts Team (Houston, TX)

Our Forecasting Method

Hybrid Prediction Models:

•**Baseline Methods**: Includes methods like PeEn (Periodicity Ensemble) for initial predictions based on historical data.

•**Physics-based and Data-driven Models**: Integrates physics-based models and data-driven approaches to refine predictions. Combines these methods to leverage the strengths of both approaches.

Our Forecasting Method

Physics-based Machine Learning Model: We use an ensemble of regression trees (boosted trees) to model the relationship between input features and net load.

Parameter Optimization:
•**Bayesian Optimization**: Offers a feature to optimize key parameters (number of trees, learning rate, minimum leaves in a tree) using Bayesian optimization, aiming to enhance prediction accuracy.

Our Forecasting Method

Input Feature Preparation:

- **Meteorological Data**: The method utilizes meteorological features such as temperature, humidity, solar radiation, precipitation, wind speed, and cloud cover, etc. to make predictions.
- **Time-Based Features**: Additional features like time of day (hour) and day of the week are included to capture daily and weekly patterns in energy usage.
- **Historical Data**: Past net load data is used to train the model.
- **Feature Importance:** The importance of different predictor variables is calculated and visualized to understand their impact on the model.
- **Error Analysis:** Prediction errors are analyzed by hour of the day to identify patterns and improve model accuracy.

Our Forecasting Method

- **Bias Correction**: The method incorporates bias correction for weather forecasts, ensuring that predictions account for discrepancies between forecasted and actual weather conditions.

- **Uncertainty Handling**: Weather forecast uncertainty is considered by generating multiple samples of weather data, which are then used to produce a range of possible load forecasts.

➢ Leaptran’s Innovative Solar & Net Load Forecasting

Spinoff of Univ. of Texas at San Antonio (UTSA) in 2017

SBIR Phase I & II from DOE/USDA

Prize Winners from Both Solar Forecasting & Net Load Forecasting

Winning commercial contracts recently

DOE’s SETO: Solar Forecasting Workshop
July 9th-10th, 2024, Washington DC

leaptran™

Behind the Meter (BTM) Solar Penetration

Facts from Four Substations during Net Load Prize Competition

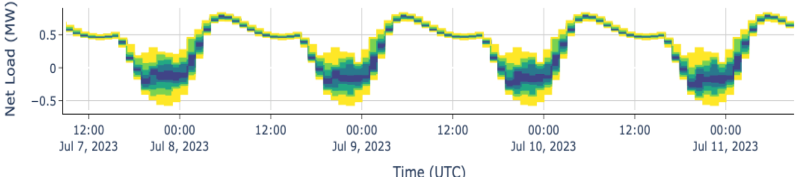
- Located in three climate zones
- Solar penetration from high to low

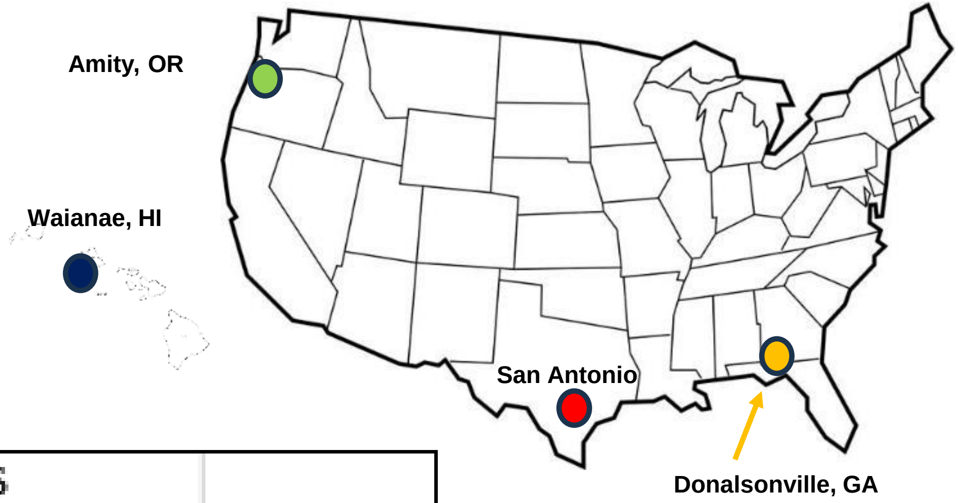
Locations	Waianae, HI	Donalsonville, GA	Amity, OR	San Antonio, TX
Solar Penetration (%)	166%	63%	35%	Unknown (<10%)
N. Peak to Peak (Low to High)	-0.59 to 0.82	-0.16 to 0.42	0.20 to 0.70	0.36 to 0.93
Remark (6/15-7/17/2023)	-load in everyday	-load in weekend	+load always	+load always

High BTM Solar Penetration – Net Load Forecasting Challenge

Multiple Hybrid Forecast Algorithms Developed for 4 Substations:

- Different ensemble regression and classification models are used case by case



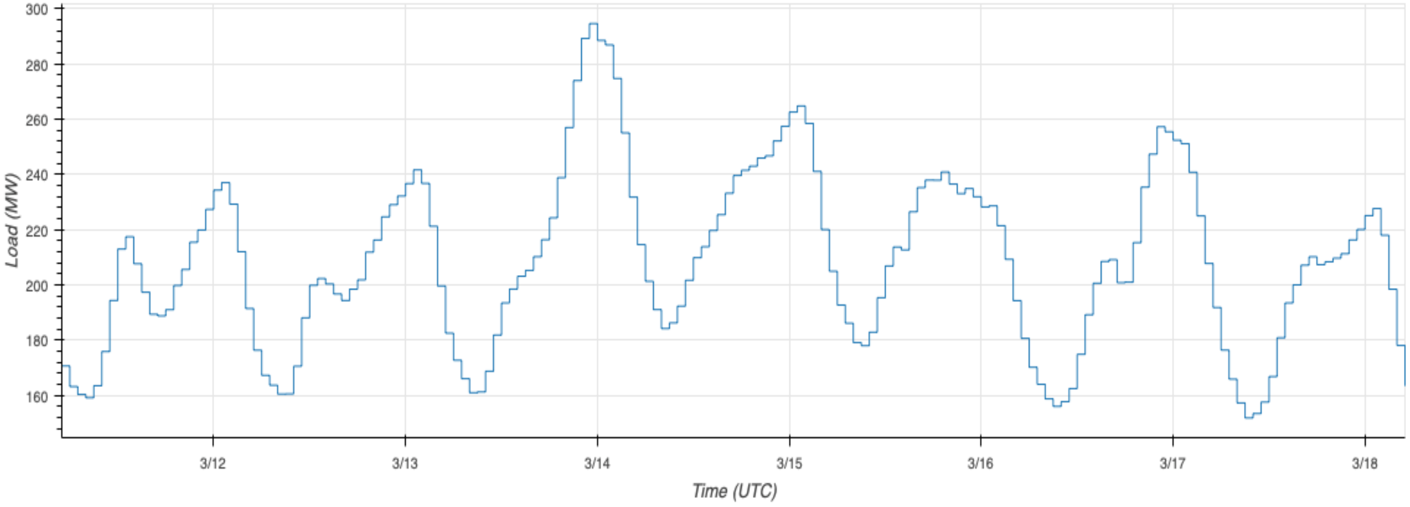


		CRPS		
Substation	State	Persistence	Leaptran	CRPSS
Donalsonville	GA	0.0487	0.0376	0.228
San Antonio	TX	0.0540	0.0307	0.432
Amity	OR	0.0430	0.0306	0.288
Waianae	HI	0.0831	0.0863	-0.039

High BTM Solar Penetration – Net Load Forecasting Challenge

Some Interesting Observations in a Texas Moderate Solar Penetration Network Load

- Spring season peak load ~300 MW
- 3/11/24 – 3/17/24 (Monday – Sunday) Net Load Profile



leaptran proprietary & confidential

THANK YOU!

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2024

Probabilistic Solar Forecasting for Rapidly Changing Weather Conditions

Sara Eftekharnejad, Ph.D.
Associate Professor

Department of Electrical Engineering and Computer Science
Syracuse University
Email: seftekha@syr.edu

Research Gaps Addressed

Dynamic Models for Spatio-Temporal Data

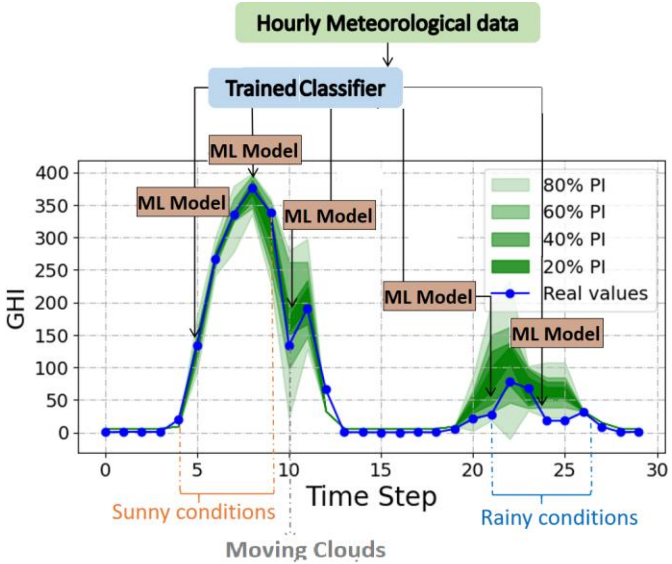
- Machine Learning-based Feature Extraction
- Statistical Modeling

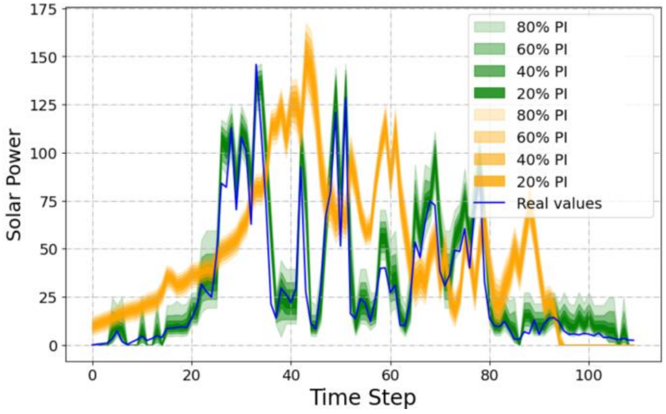
Enhancing Accuracy under Rapidly Changing Weather Conditions

Targeting Short-Term Operations

[1] Lyu, Cheng, and Sara Eftekharnejad. "Probabilistic Solar Generation Forecasting for Rapidly Changing Weather Conditions." IEEE Access (2024)

Forecast Performance





Baseline: N. Zhou, X. Xu, Z. Yan, and M. Shahidehpour, “Spatio-temporal probabilistic forecasting of photovoltaic power based on monotone broad learning system and copula theory,” IEEE Transactions on Sustainable Energy, vol. 13, no. 4, pp. 1874–1885, 2022.

Looking Forward

- Forecast with limited data
- Operations and planning models with uncertainties
- Grid resiliency
- A combined generation + failure probabilistic forecast

Solar forecasting to improve grid operation

Managing Risk in Power System Operations

Forecast Integration and Metrics Evaluated

ENERGY DELIVERY AND CUSTOMER SOLUTIONS

Aidan Tuohy
Director Transmission Operations and Planning
Contributions from Miguel Ortega Vazquez, David Larson, Armaan Ladak, Erik Ela

Forecasting is key for grid planning and operations

Decarbonization Strategies → Integrated Resource Planning → Resource Adequacy → Delivery System Planning → Real-Time Grid Operations

Better use of better forecasts can drive more efficient investment decisions and grid performance across timescales

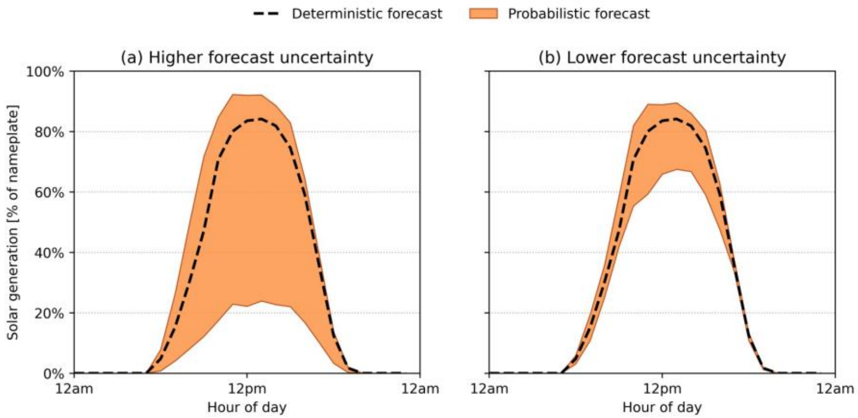
Increased Customer Opportunities

Increased Asset Utilization

Reduced Operating Costs

Reduced Reliability Risks

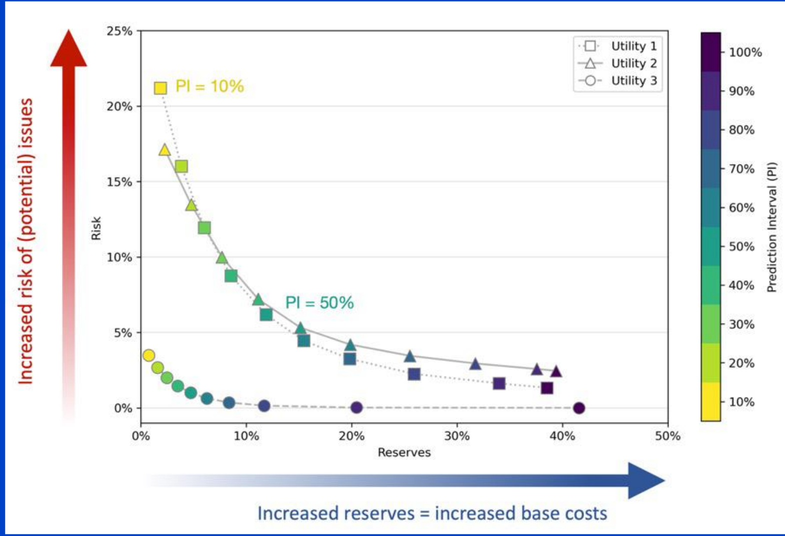
Recent DOE-funded Effort: Managing Uncertainty



Quantifying uncertainty in output of renewables allows us to better understand how we will operate the system

More: www.epri.com/optsun

Tools, methods, data to understand tradeoffs between risks and costs of operating system with high renewables



EPRI developing tools for ensuring sufficient reserves, while minimizing costs

EPRI

What's Next? Key R&D Needs

Need to develop and implement methods for fully integrating risk in operations

- Different sources of uncertainty and variability
- Different decisions to be made (look ahead time, spatial and temporal scales, planning vs ops)
- New sources of risk management – transmission, demand, storage
- Tools need to be demonstrated and integrated into EMS, MMS as well as appropriate planning tools

Metrics and tools to assess forecasts and identify opportunities for improvement

- Linkage to value of improved forecasts (reliability, economics)
- Data sharing and validation – need good underlying datasets to benchmark and understand uncertainty, for ops and long term planning, incl. resource adequacy
- Based on metrics, identify key areas for improvement (DER, new loads, extreme weather, etc.)

Considering Risk in Operations

What is Risk?

Risk is the *Expectation* of *Loss**

1. "**Expectation**" entails a probabilistic process for the likelihood of occurrence
2. "**Loss**" is the magnitude of damage or adverse outcome

- Then, in power system's operation ***risk is the theoretical mean or long-term average of reserve shortages!***

- **A fixed amount of reserve (e.g., "x" MW) *are not* *measures* of risk**
- **The expectation of undergoing events greater than "x" is the risk metric**

- To compute risk, we must compute the (1) probability of the events and (2) their associated magnitude

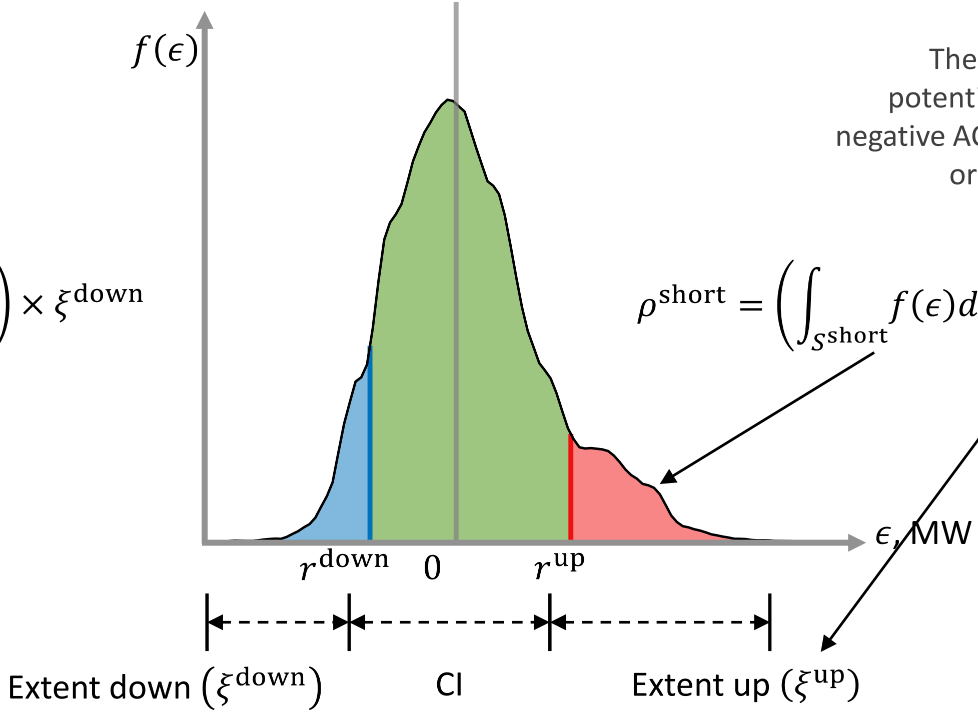
*M. H. DeGroot, Optimal Statistical Decisions. John Wiley & Sons, 2004.

Risk of Reserve Shortages

Risk is given as the expectation of loss (insufficient reserve), and is given as: $\rho = P \times \xi$

The system is long: potential for over-frequency and ACE or excessive curtailment of VRES

$$\rho^{\text{long}} = \left(\int_{S^{\text{long}}} f(\epsilon) d\epsilon\right) \times \xi^{\text{down}}$$



The system is short: potential under-frequency, negative ACE, reliability violations, or load shedding

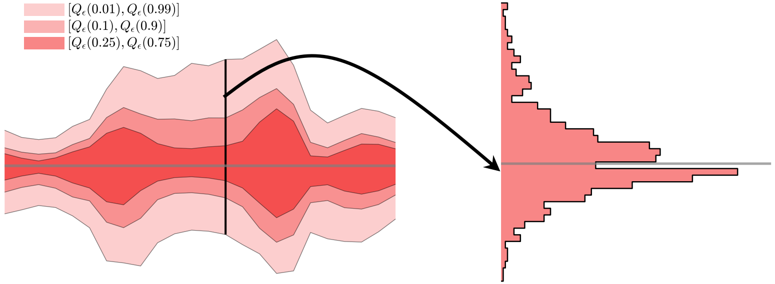
$$\rho^{\text{short}} = \left(\int_{S^{\text{short}}} f(\epsilon) d\epsilon\right) \times \xi^{\text{up}}$$

M. A. Ortega-Vazquez, N. Costilla-Enriquez, E. Ela, A. Tuohy, "Risk-Based Reserve Procurement," *2020 Conference on Probabilistic Methods Applied to Power Systems*, Liege, Belgium, Aug. 18-21, 2020.

T. R. Rockafellar and S. Uryasev, "Optimization of Conditional Value-at-Risk," *Journal or Risk*, Vol. 2, No. 3, pp. 21-41, Apr. 2000.

Tools need to use both Historical and Probabilistic Uncertainties

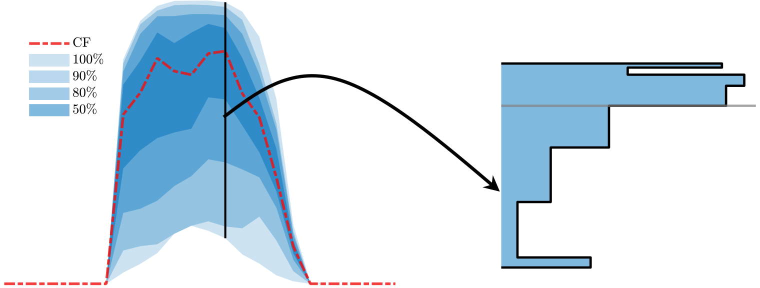
Distribution of historical deviations



It accounts the historical deviations in the system for net demand: It implicitly includes load, solar, and wind deviations

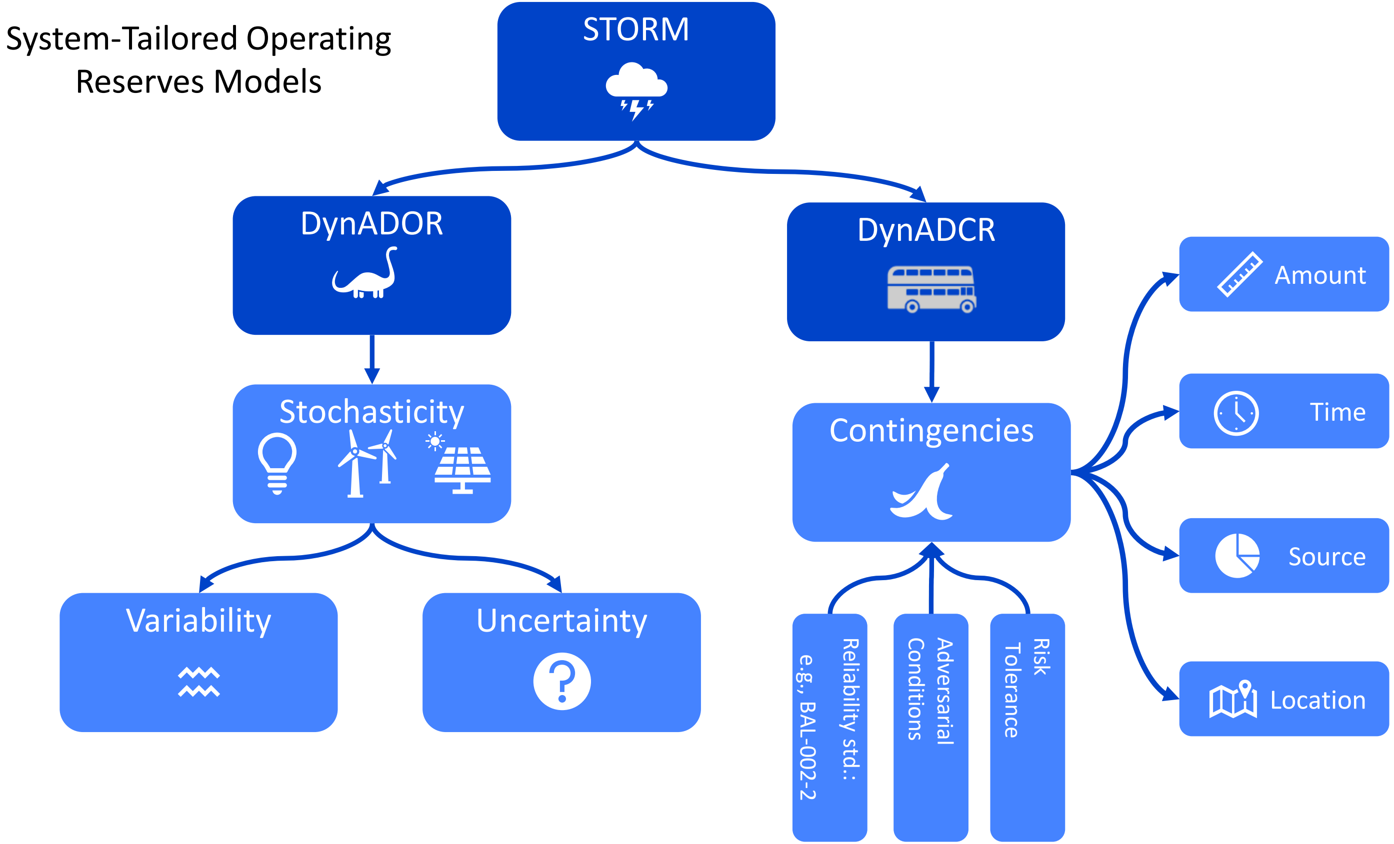
Probabilistic uncertainty for a solar probabilistic forecast

It provides a wealth of information that captures specific of unique characteristics of the day, e.g., expected clouds at a particular day hour



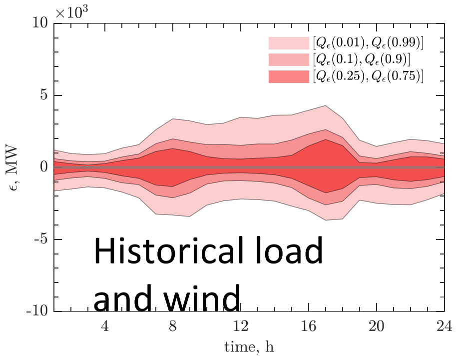
Need to integrate these independent sources of information in an unified framework

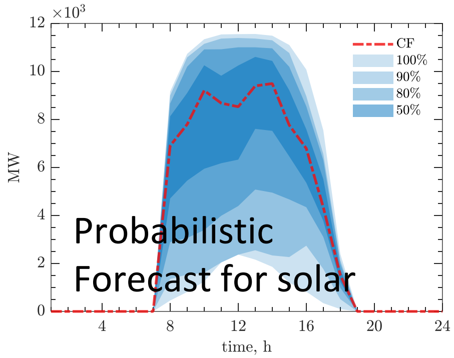
Tools to Parametrize Operating Reserves

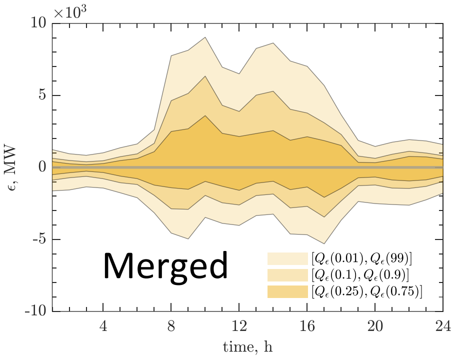


Combining uncertinty provides more insight (indicative)

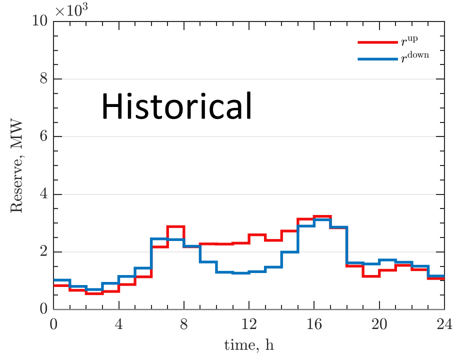
Uncertainties

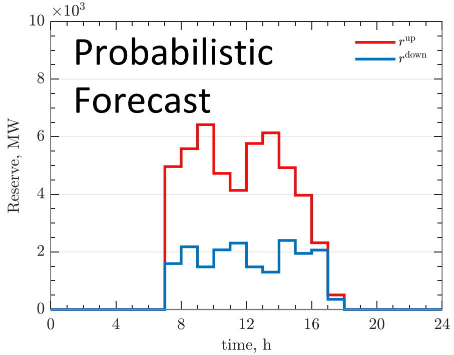


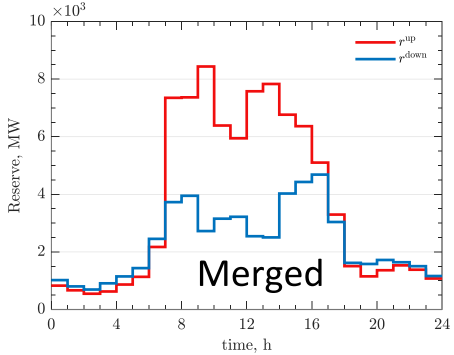




Reserves







Myopic to specific day characteristics

Unaware of historical deviations

Considering both historical and probabilistic deviations

Evaluating Performance

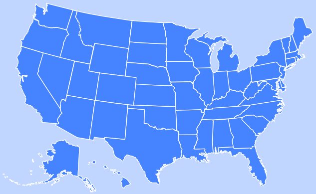
Evaluating Forecast Performance (Recent Project)

Caveats

- The day-ahead forecasts values reported in this study may not wholly reflect the forecasts used by operators in these regions because:
  - Operators may use other forecasts
  - Operators may update their forecasts closer to real-time
  - Forecast values reported from the EIA and ENTSO-E have quality issues which cannot be rectified

Report:
EPRI, Benchmarking Operational Forecasts: Review of Published Day-Ahead Operational Forecasts, 3002026990. November 2023

- ➤ Evaluate the **performance** of **day-ahead load forecasts** relative to one another
- ➤ Evaluate the **robustness** of the **day-ahead load forecast**
- ➤ Explore the consequences of forecast performance and robustness



eia

Opendata API v2

82 Facets

10 Regions

7 ISO/RTO

65 BAs + Utilities

entsoe
Transparency Platform

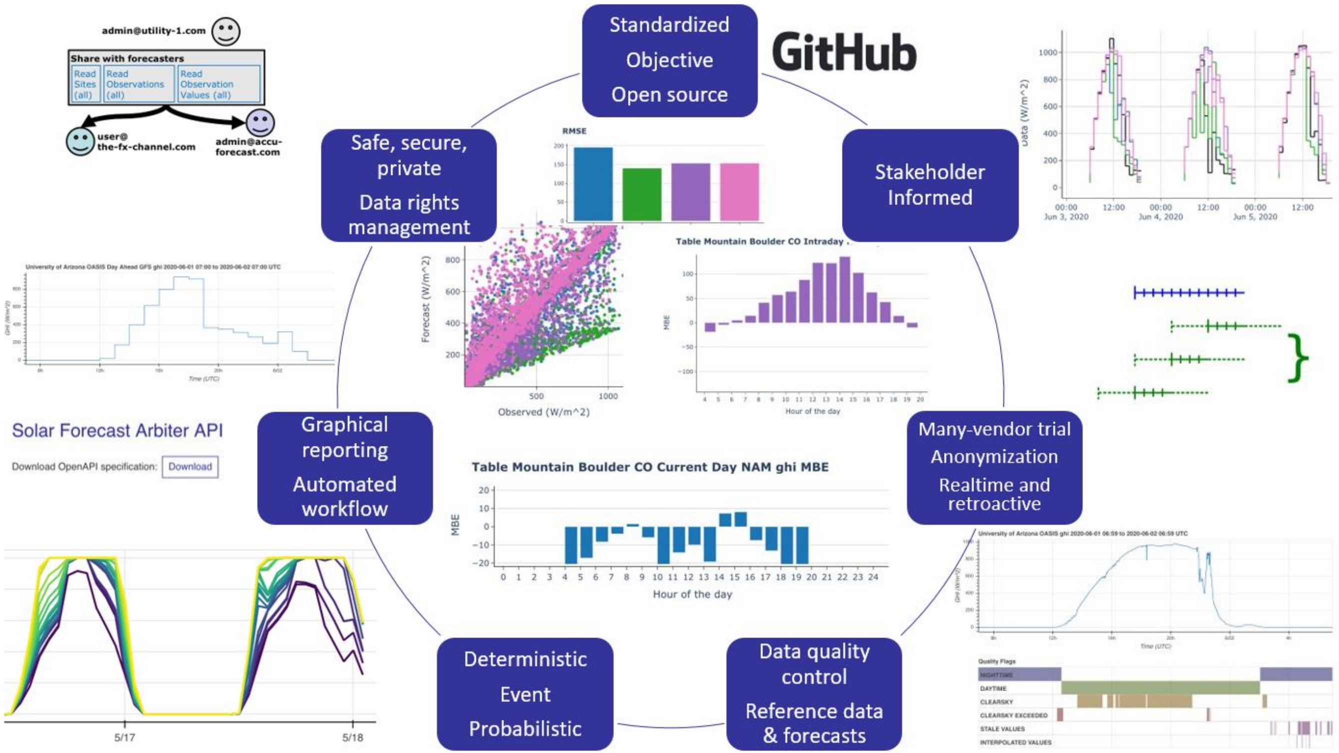
~1k+ Energy Identification Codes (EIC)

45 Countries

How well are day-ahead forecasts performing?

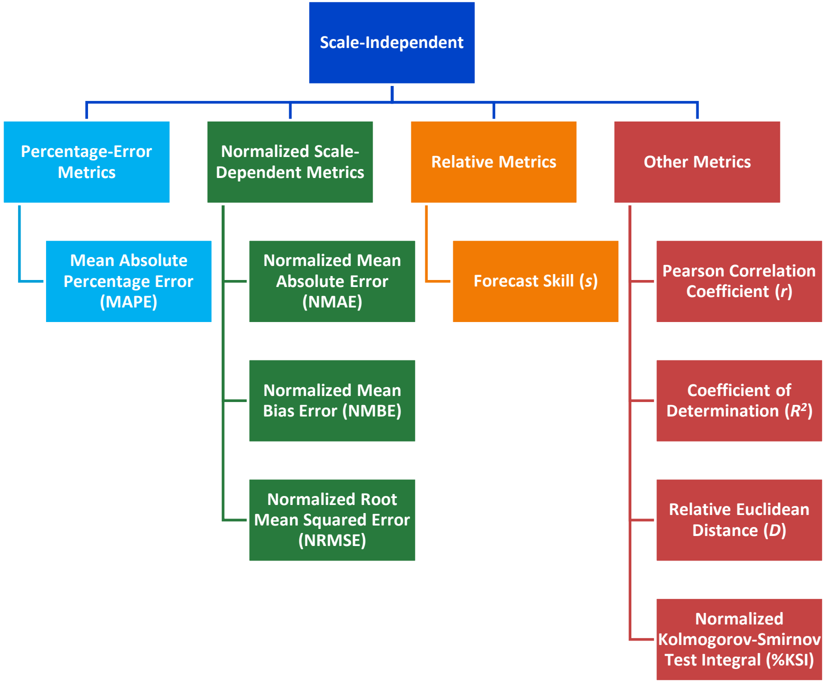
EPRI

Forecast Arbiter: https://forecastarbiter.epri.com/



Clear, transparent forecast evaluation tool

Usefulness of Metrics for Setting Benchmarks

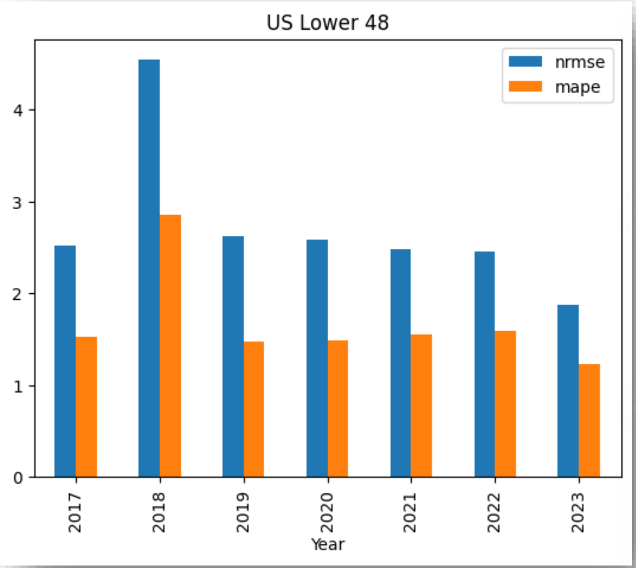


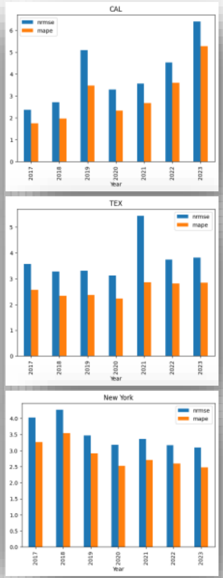
- **MAPE** and **NMAE** consistently yielded the exact same results, due to the scaling factor used in NMAE.
- **NRMSE** and **NMBE** were both particularly important: NRMSE indicated the same trends as MAPE while deviating in datasets with significant outliers, while NMBE was most useful when paired with an error magnitude metric like NRMSE/MAPE to interpret the error and its bias.
- Due to limitations of available reference forecasts, **Forecast skill** was not thoroughly investigated.
- The **Pearson Correlation Coefficient** does not have the requisite resolution to differentiate forecasts with <5% MAPE.
- The **Coefficient of Determination** has similar problems to Pearson's, although less severe since it is more sensitive.
- **Relative Euclidean Distance's** combination of a bias error component with a correlation error component and a percent variance error made it difficult to interpret,
- **%KSI** was by far the most sensitive metric and was most useful as an indicator for large differences in the observation and forecast distributions, which could then be explored by plotting.

No shortage to choose from… but which are *useful*?

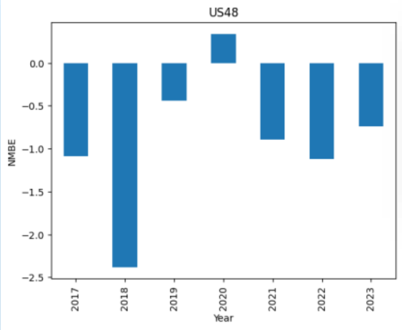
Error Metrics and Year - US

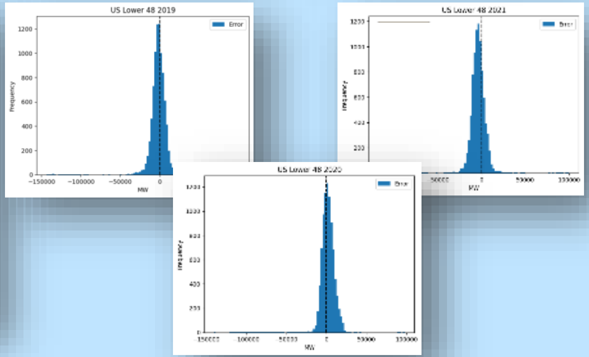
- General trends
  - **NRMSE/MAPE:** No consistent change in forecast performance
  - **2021 Winter Storm:** NRMSE/MAPE spiked in 2021 for Texas, and is more clearly shown by NRMSE
  - **California:** Increase might be partially due to BTM resource increases





- COVID-19
  - **MBE:** The US's tendency to under-forecast was flipped in 2020





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TOGETHER...SHAPING THE FUTURE OF ENERGY®

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m

Southern Company R&D: Solar Forecasting

William B. Hobbs, PE

Southern Company R&D

DOE Solar Forecasting Workshop, July 10, 2024

Outline

- EPRI Forecasting Trial
- Probabilistic Solar Forecasting
- Net Load
  - Independence of solar and load forecast errors?
  - Weather-to-load models
- Flexible Solar

Conclusions

DOE-funded Forecast Arbiter is great

- more metrics needed?

More work needed in probabilistic solar forecasting (we’re doing some)

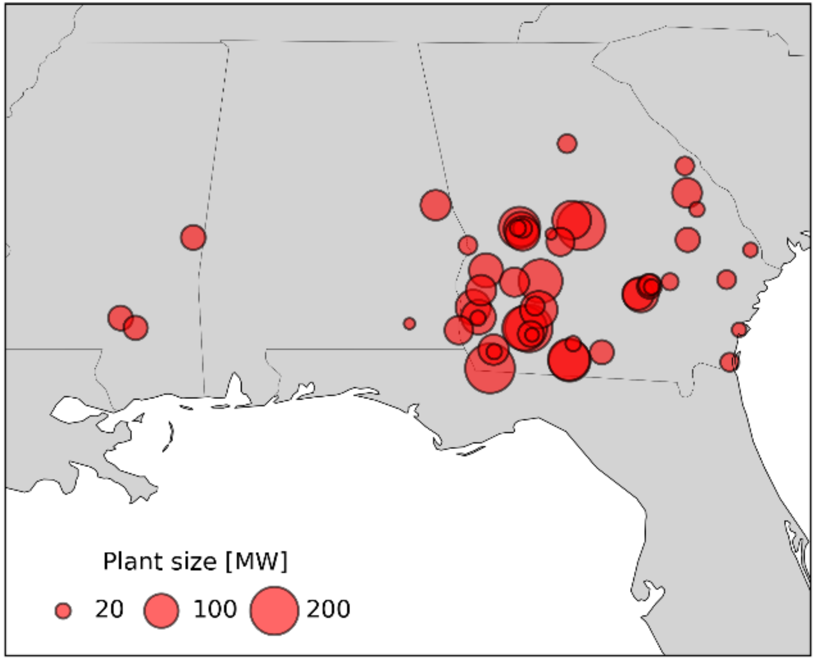
Work (funding?) needed here!

Upcoming work, some needs

Open production cost models to benchmark these things, understand sensitivity

Solar Fleet

- About 4 GW in Southern Company's Balancing Area, ~40 GW peak load
- Additional ~10 GW anticipated by 2035 *in Georgia alone*



Plants ≥ 10 MW

Forecast Arbiter Trial

Benchmarking Utility-Scale PV Power Forecasts in the Southeast US using the Forecast Arbiter

Orals – Area 10: Irradiance and PV Power Forecasting

Friday, June 14, 2024

David P. Larson, EPRI, <DLarson@epri.com>

William B. Hobbs, Southern Company

Brent Duncan, Southern Company

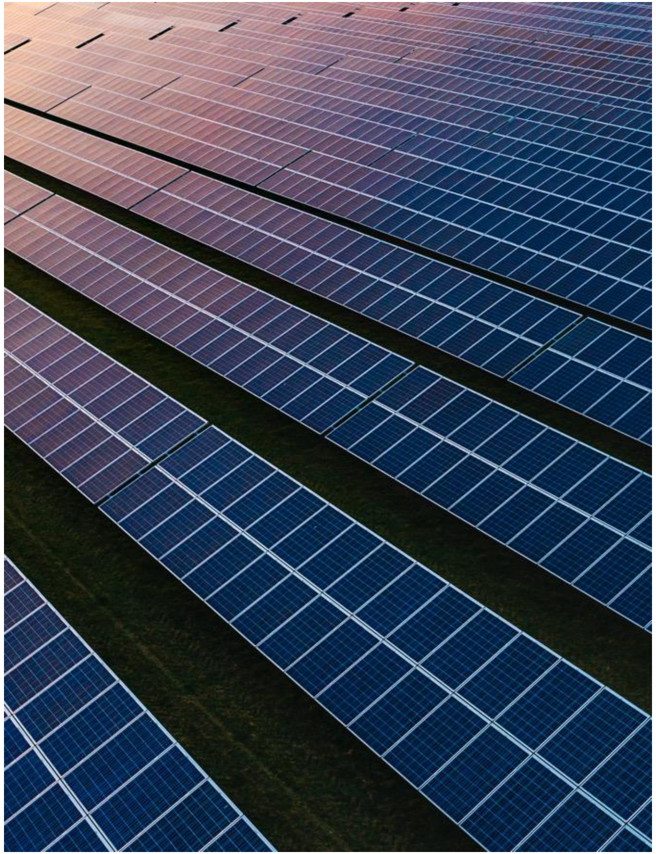
[PRESENTED AT IEEE PVSC 2024, this is an abridged version]

in X f

www.epri.com

Forecast Trial Setup

- **Deterministic power forecasts**
- **4 utility-scale PV plants** in the Southeast US
- **5 forecast schedules**
  - day-ahead (hourly) down to real-time (5-min)
- **9 forecasters** (anonymized commercial forecast vendors)



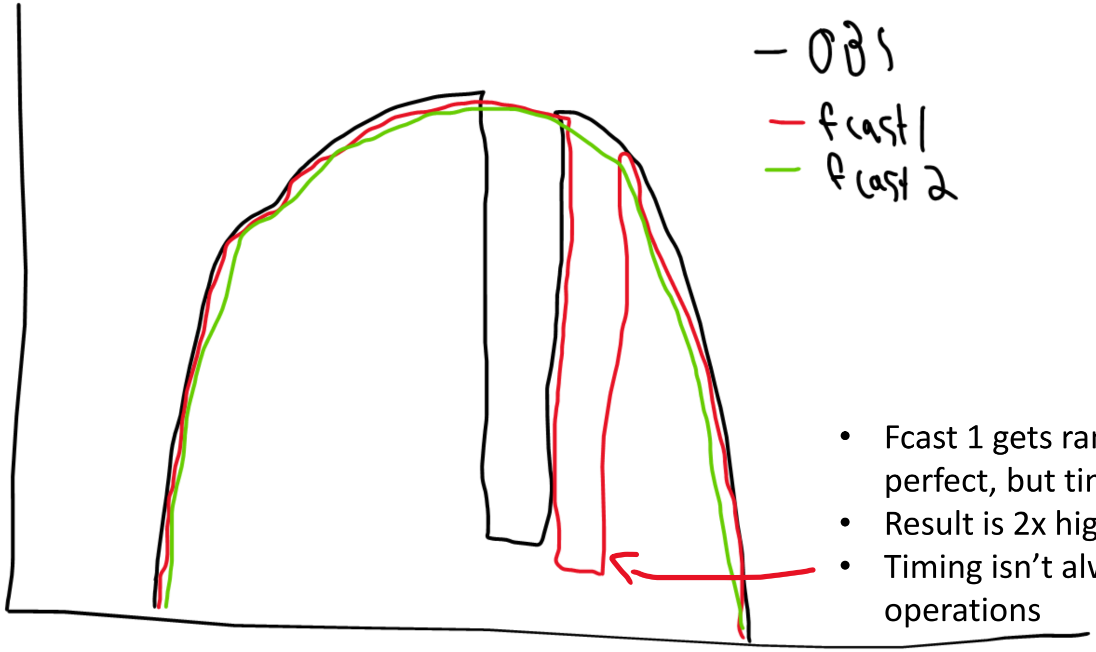
Key takeaways from this trial:

- Solar power forecasting is a **mature technology**, available from many commercial vendors
- Top forecasters can achieve **similar forecast errors**
- The same conditions are **challenging for all forecasters**
- **Sub-hourly resolution** forecasts continue to be difficult
- **Forecast Arbiter** enables multi-vendor, anonymized forecast trials
- (Will's opinion) **New ramp metrics** could be useful for future evaluations, but need work

Post-trial ideas
(Will’s slides, not EPRI results…)

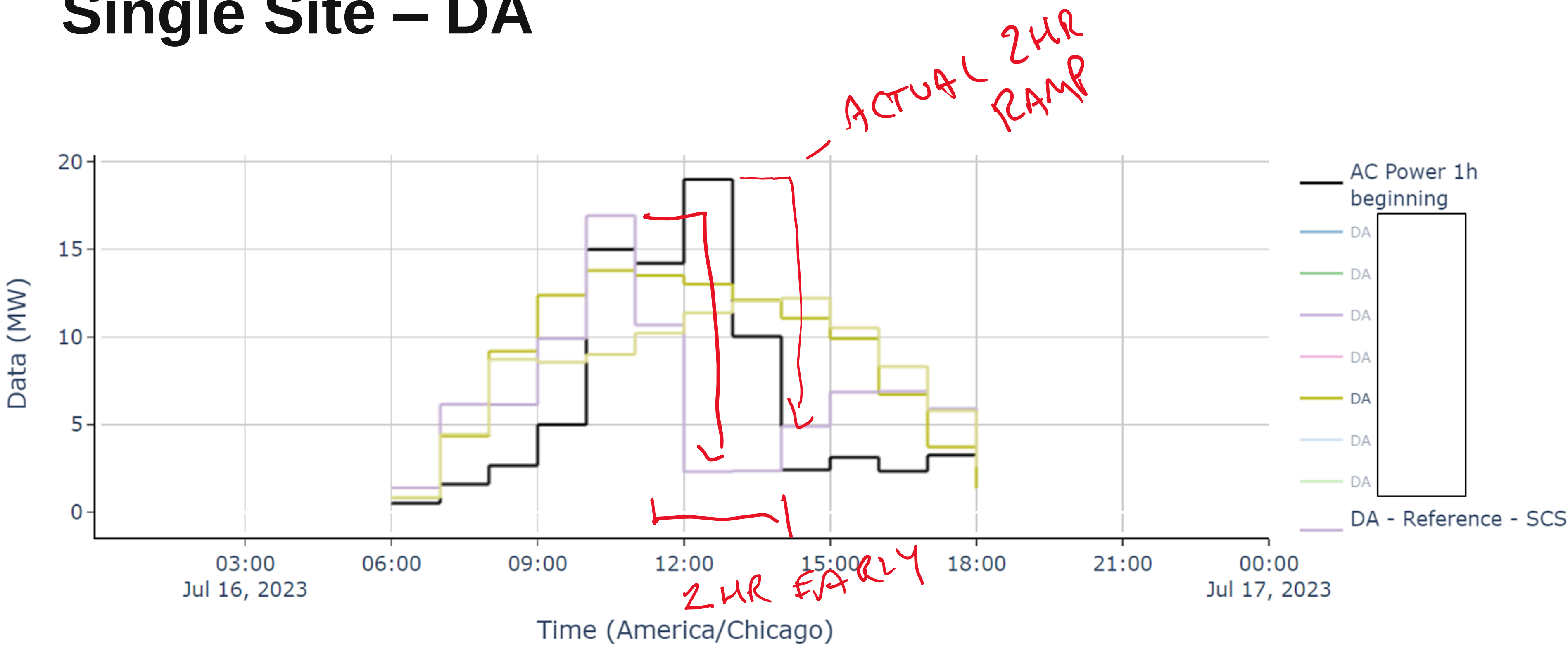
Forecast Error Metrics

- Normalized Mean Absolute Error (NMAE) run hourly for DA penalizes large errors, so better forecasts are "smooth"



- Fcast 1 gets ramp magnitude and direction perfect, but timing is off
- Result is 2x higher NMAE
- Timing isn't always critical in real operations

Single Site – DA



DRAFT ramp metric

- General ideas are:
  - downward ramps in solar are worse than upward ramps
  - exact timing isn't critical
- On a 5-hr rolling interval (current hour, 2 before, 2 after), calculate the largest 2-hr downward ramp
  - For each forecast, calculate NMAE of 5-hr rolling largest 2-hr down-ramp (excluding ramps smaller than 1% of nameplate)

Worse by standard metric, better with ramps

Forecaster	DA NMAE, hourly power	5-hr max down ramp (NMAE)
Reference	15.1%	14.6%
Pearl	11.8%	15.3%
Sapphire	12.1%	15.9%

Probabilistic Solar Forecasting

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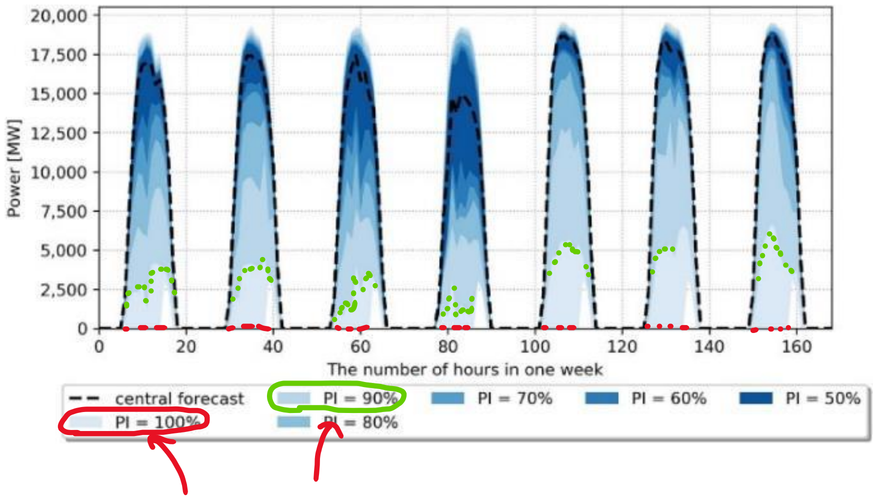
Motivation

- Lots of good deterministic forecasts are available
- None are perfect
- Grid operators have increasing need for uncertainty information
- Most probabilistic forecasts focus on single sites
- Errors across sites are not independent → can’t simply combine site-level probabilistic forecasts

EPRI OPTSUN Project

- DOE Solar Forecasting II project
- Found that probabilistic forecasts might improve reliability, but only marginal impact on costs (see paper [1], recorded presentation [2])
- Discovered after project ended: Possible mistake in forecasts may have led to too much uncertainty
  - **better forecast might show much higher value**



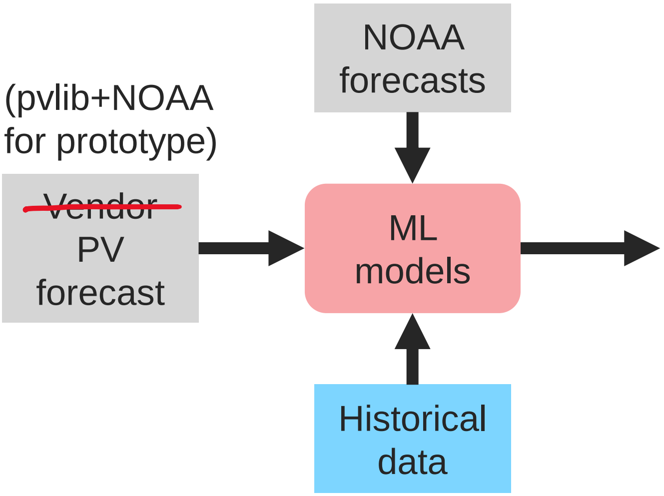
PI 100 and PI 90 lower bounds look too low

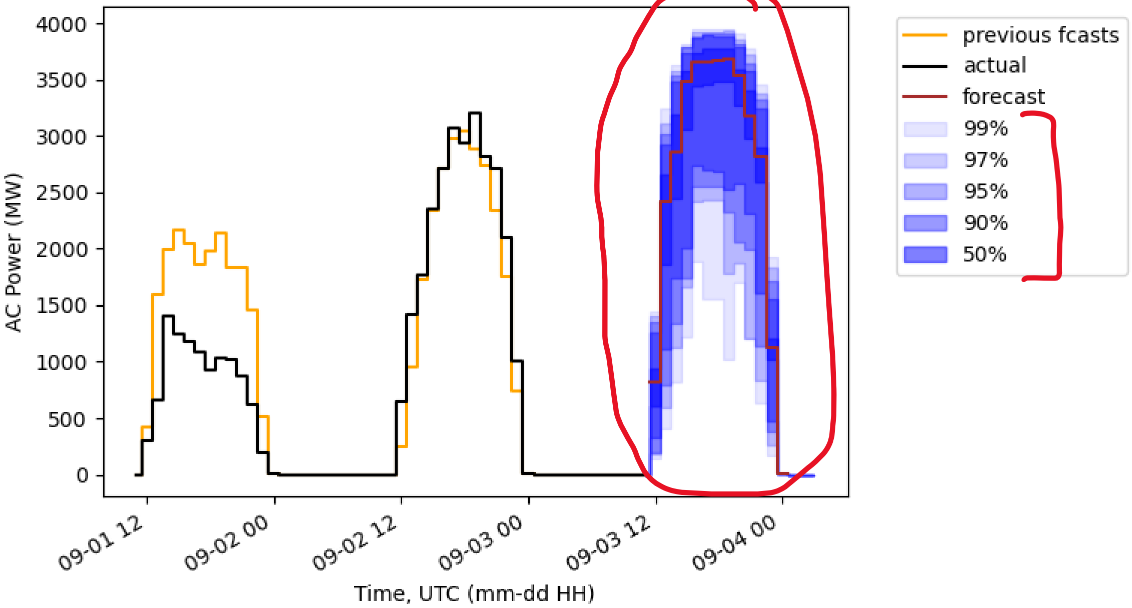
[1] Wang, Q., Tuohy, A., Ortega-Vazquez, M., Bello, M., Ela, E., Kirk-Davidoff, D., Hobbs, W.B., Ault, D.J. and Philbrick, R., 2023. Quantifying the value of probabilistic forecasting for power system operation planning. *Applied Energy* (https://doi.org/10.1016/j.apenergy.2023.121254)

[2] W. Hobbs, "Probabilistic Methods in Operations," ESIG 2022 Spring Technical Workshop (Presentation) (https://www.youtube.com/watch?v=1aO4kOoR2nc&t=1370s, https://www.esig.energy/event/2022-spring-technical-workshop/)

New in-house R&D

- Open-source tool to produce probabilistic forecast from an existing deterministic forecast (e.g., vendor)
- Focus on day-ahead for now



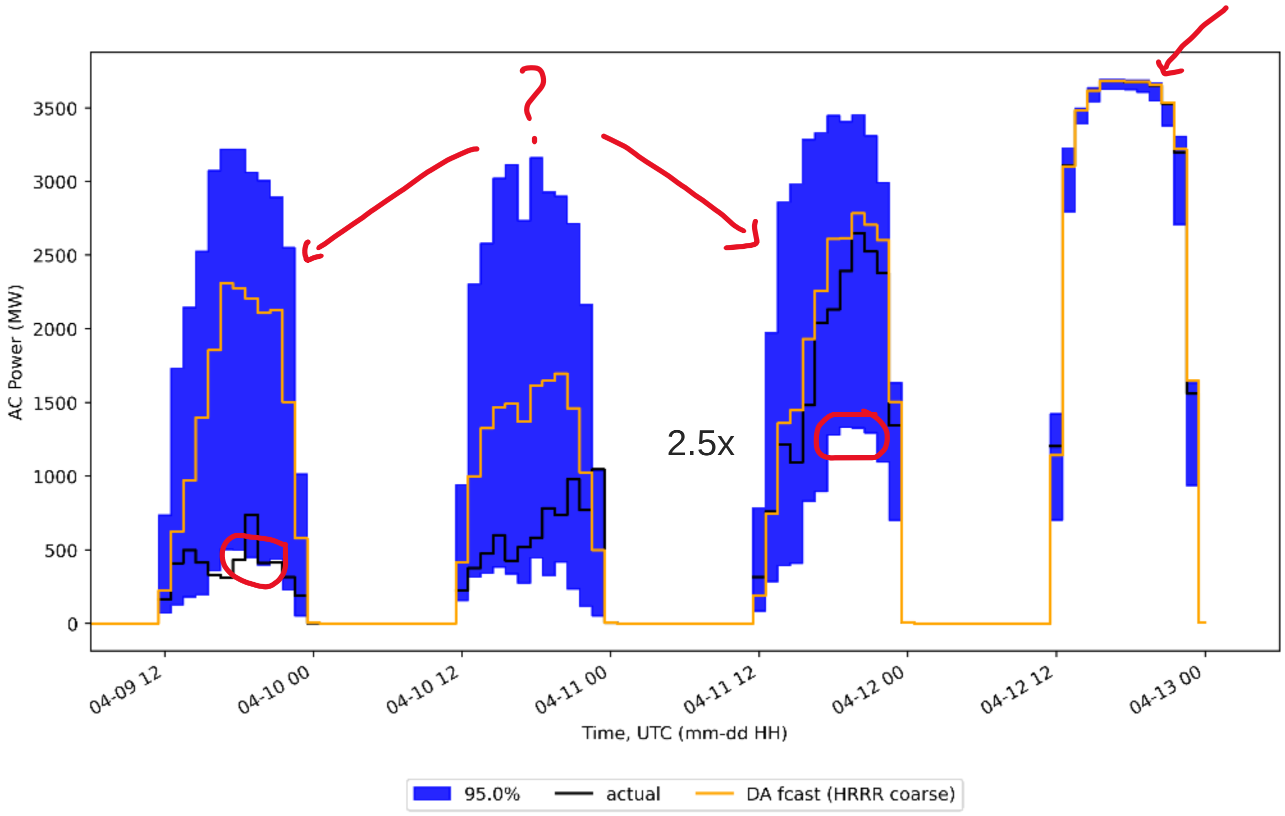


Tools and data

- All in python, open-source (and free) tools
- pvlib for weather-to-power (forecast and synthetic actuals)
- Herbie to retrieve NOAA NWPs from AWS
  - A portion of this work used code generously provided by Brian Blaylock's Herbie python package (Version 2024.3.1) (https://doi.org/10.5281/zenodo.4567540)

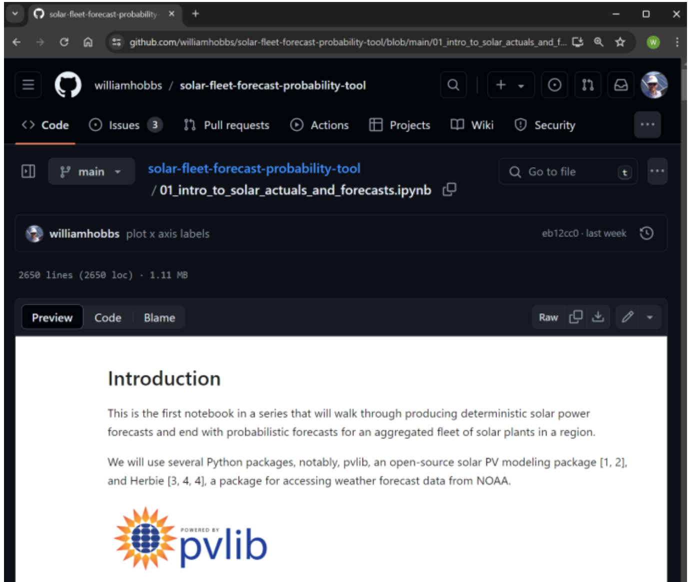
Important side note: historically, accessing NWPs has been way too hard. Tools like Herbie need more attention and support from our industry.

Sample Results



Available Code

- github.com/williamhobbs/solar-fleet-forecast-probability-tool
- BSD-3-Clause License
- Python, with Jupyter Notebooks to run everything yourself
- **Please let me know if you use it!**



Next steps

- Retrain using more representative forecasts (reforecasts from a vendor)
- Explore additional ML “features”
- Feedback/iterate with operations team
- (tentative) benchmark against SLAC approach
- **Re-evaluate value in production cost models?**

Net Load

Probabilistic Net Load Forecasting

- Operators dispatch to *net* of load and solar (and wind)
- Load and solar are influenced by the same weather – **forecast errors might not be independent** [1, 2]
- Most studies I see assume they **are independent**, e.g., ARPA-E PERFORM [3] (usually because of practical limitations, I think…)

[1] Li et al., "A copula enhanced convolution for uncertainty aggregation", 2020, DOI: 10.1109/ISGT45199.2020.9087644
[2] Beichter et al., "Net load forecasting using different aggregation levels", 2022, DOI: 10.1186/s42162-022-00213-8
[3] https://github.com/PERFORM-Forecasts/documentation

Industry Needs

- **A key industry need:**
  - Explore the relationship between load and solar forecast errors
    - (for different regions/climates/aggregations)
  - Answer question: *are load and solar forecast errors independent*?
- **An intermediate need:**
  - Open weather-to-load models:
    - Bottom-up
    - Trained from historical data
  - Reference production cost models (open-source, e.g., in PyPSA?)
- Assuming errors are *not* fully independent:
  - Research is needed in regional probabilistic net load forecasting
  - Current NWP ensembles are under-disbursed [1], so this could be challenging

Useful in lots of applications that currently "re-invent the wheel", can't be compared. We need *pvlib for load* (or EnergyPlus for regional grids)

[1] Wang et al., "An archived dataset from the ECMWF ensemble prediction system for probabilistic solar power forecasting," 2022, https://doi.org/10.1016/j.solener.2022.10.062

Flexible Solar

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Solar on AGC

- "Flexible" solar = easily curtailable solar
- Flexible solar will be curtailed less than traditional solar [1]
- Flexible solar can carry its own reserves, **but with some error** [2]
- Grid operators may need to forecast this error
  - It is tied to solar resource variability [3]
  - Will be explored in NREL OPTIMA project (CORRECT), but likely room for more R&D here

[1] Q. Wang; W. Hobbs; A. Tuohy; M. Bello; D. Ault. Evaluating Potential Benefits of Flexible Solar Power Generation in the Southern Company System. IEEE JPV, 2022. 10.1109/JPHOTOV.2021.3126118.
[2] W. Hobbs, D. Ault, V. Gevorgian, G. Saraswat, "Accuracy of Potential High Limit Estimation for Solar Plants in the Southeast US." IEEE PVSC 2022.
[3]. M. Gostein, W. Hobbs, "Exploring Distributed PV Power Measurements for Real-Time Potential Power Estimation in Utility-Scale PV Plants." IEEE PVSC 2023. https://dx.doi.org/10.36227/techrxiv.23262056.v1.

Questions?

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github.com/williamhobbs/solar-fleet-forecast-probability-tool

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NYSolarCast: Utility-Scale and Distributed Solar Power Forecasting in New York State

DOE Solar Forecasting Workshop • 10 Jul 2024 • Washington, DC

Jared A. Lee[1], Susan Dettling[1], Julia Pearson[1], Thomas Brummet[1], and David P. Larson[2]

[1] *Research Applications Laboratory, NSF National Center for Atmospheric Research*
[2] *EPRI*

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Published Article & Github Repository

- Article describing the NYSolarCast system published in *Solar Energy* in March 2024
- https://doi.org/10.1016/j.solener.2024.112462
- Github public repository: https://github.com/NCAR/nysolarcast_delivery

Solar Energy 272 (2024) 112462

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journal homepage: www.elsevier.com/locate/solener

ELSEVIER

NYSolarCast: A solar power forecasting system for New York State

Jared A. Lee[a,*], Susan M. Dettling[a], Julia Pearson[a], Thomas Brummet[a], David P. Larson[b]

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Mesonet
Distributed PV
Utility PV

ABSTRACT

Solar energy generation capacity will need to be greatly increased to meet aggressive clean energy targets by New York State (NYS), which are 70% renewable energy (RE) generation by 2030, and 100% by 2040. Because solar energy is a variable, weather-driven resource, accurate forecasts of solar energy generation both in nowcast (intra-day) and day-ahead time horizons are necessary for electric utilities and independent system operators, as they maintain grid stability and maximize RE use.

Meeting this need for NYS, a gridded, open-source solar power forecasting system called NYSolarCast was developed (https://github.com/ncar/NYSolarCast_delivery). NYSolarCast makes 15-min resolution predictions of global horizontal irradiance (GHI) on a 3-km grid covering all of NYS, which are then used to estimate solar power generation both for select utility-scale PV plants (15-min resolution) and for zone-aggregated distributed PV (1-h resolution). The statewide GHI forecasts are made by applying the StatCast statistical forecasting model, which is trained on over two years of GHI observations from pyranometers at all 126 NYS Mesonet stations and gridded numerical weather prediction forecasts from both the Weather Research and Forecasting model tuned for solar applications (WRF-Solar®) and NOAA's operational High-Resolution Rapid Refresh (HRRR) model. Forecasts are made at each NYS Mesonet site and then blended outward into the rest of the grid. This paper gives an overview of NYSolarCast performance for intra-day (0–6-h) GHI and power forecasts during a one-year period.

Motivation

- New York State (NYS) Clean Energy Standard
  - 70% renewable energy (RE) generation by 2030
  - 100% RE generation by 2040
- Much more solar energy must be deployed across NYS
  - Highly variable, weather-driven resource
  - Challenge for grid balancing & stability
- Accurate forecasting is increasingly critical for electric utilities and independent system operators like NYISO
  - Nowcast/intra-day forecasts
  - Day-ahead forecasts
  - Utility-scale photovoltaic (UPV) plants
  - Distributed PV (DPV) sites
- Multi-phase project to build a solar power forecasting system for NYS
  - Funded by NYSERDA & NYPA
  - Team: EPRI, BNL, NSF NCAR, U of Albany

Image: Department of Energy, PV Magazine

NEW YORK STATE OF OPPORTUNITY. | NY Power Authority

NEW YORK STATE OF OPPORTUNITY. | NYSERDA

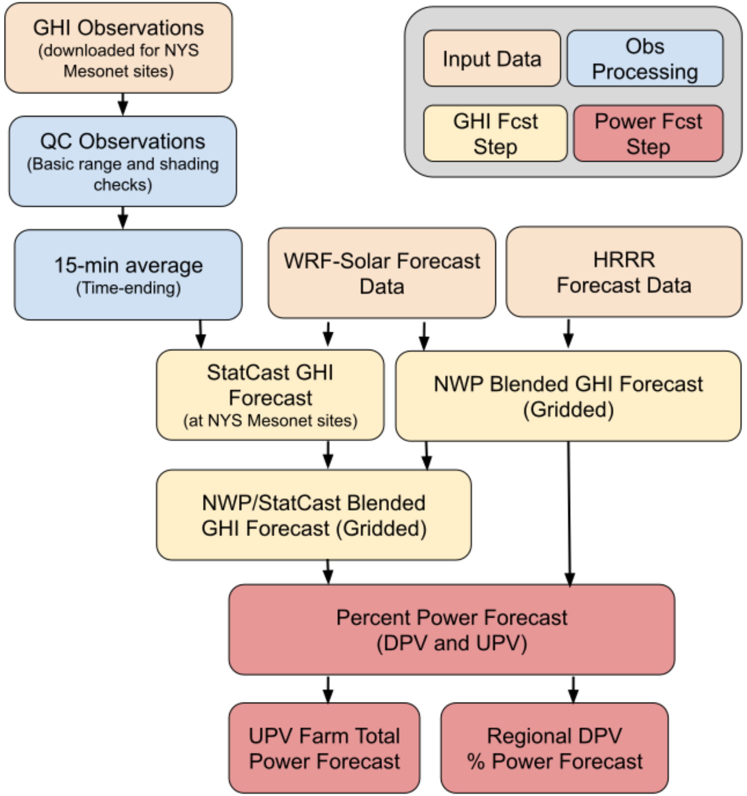
EPRI | ELECTRIC POWER RESEARCH INSTITUTE

Brookhaven National Laboratory

NSF | NCAR Operated by UCAR

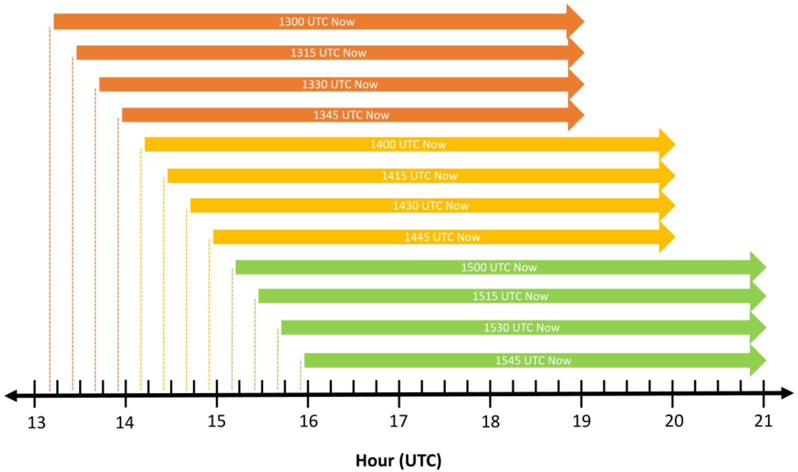
UNIVERSITY AT ALBANY State University of New York

NYSolarCast System Design & Schedule

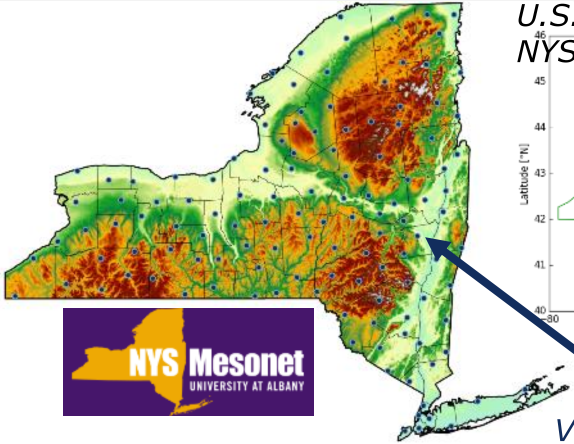


- Intra-day
  - Forecasts issued every 15 min 1115–1900 UTC
  - 15-min frequency for GHI and UPV forecasts
  - 1-h averages for DPV forecasts
- Day-ahead
  - Forecasts issued once daily at 0600 UTC

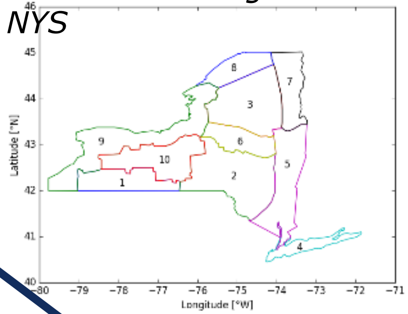
NYSolarCast Intra-Day Forecast Simulation Schedule



New York State Mesonet (NYSM)



U.S. Climate Regions in NYS



Voorheesville NYSM site:

CNR4 Pyranometer

LI-200R Pyranometer

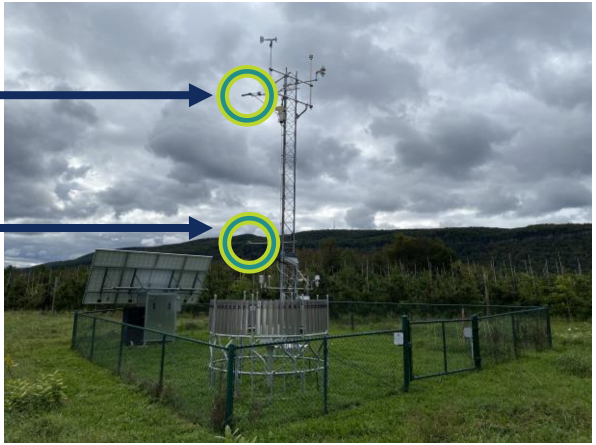


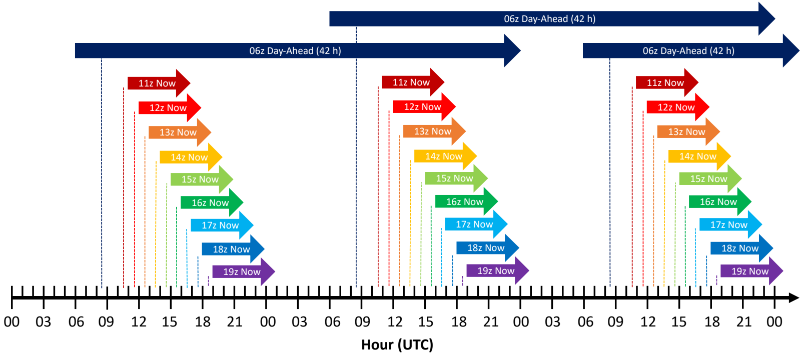
Photo by Jared Lee

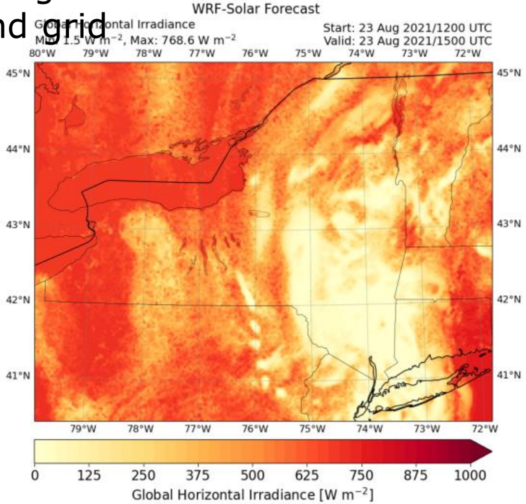
- Historical and real-time data from all 126 Standard NYSM stations, 1 Jan 2018–31 Aug 2022
  - All atmospheric data, incl. GHI, temperature, wind, humidity, etc.
  - Averaged into 15-min time-ending values for use in NYSolarCast
  - LI-COR LI-200R and LI-200RX pyranometers
- Instances of shaded or snow/ice-covered pyranometers were found, confirmed by U Albany, and excluded from training and validation datasets
- LI-COR pyranometers at the Standard sites can have bias/calibration issues, but these are not uniform network-wide
  - NYSM team is working to address this issue
  - Occasional updates to calibrations
  - Sensors periodically replaced
- 17 of these Standard Network sites are also NYSM Flux Network sites with high-quality Kipp & Zonen CNR4 pyranometers

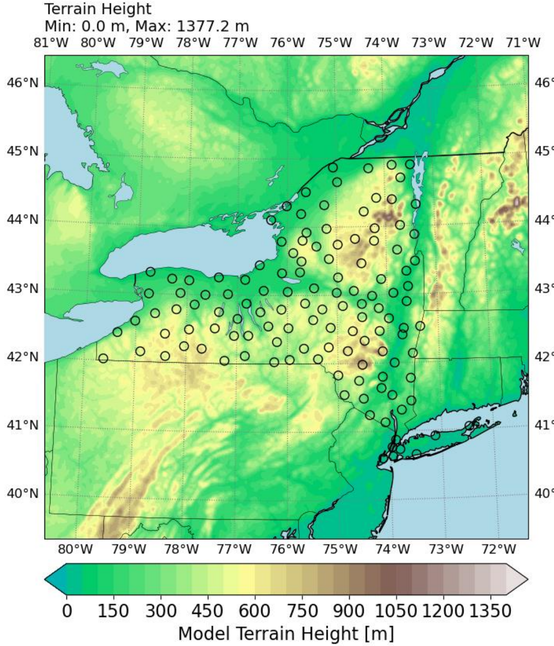
WRF-Solar & HRRR

- Extended history of WRF-Solar® reforecasts over NYS for training for machine learning models
  - 15 Jul 2018 – 31 Aug 2022, using WRF v4.2
  - **Intra-day**: Out to 6 h, initialized hourly 11z–19z from 2-h old HRRR
  - **Day-ahead**: Out to 42 h, initialized once daily at 06z from 06z HRRR
  - Several valuable 2-D solar diagnostics in standard output
  - 15-min, 3-km gridded output for both Nowcast & Day-ahead cycles
- Operational HRRR also downloaded and re-gridded to WRF-Solar grid to provide a blended NWP background grid

NYSolarCast WRF-Solar Daily Simulation Schedule





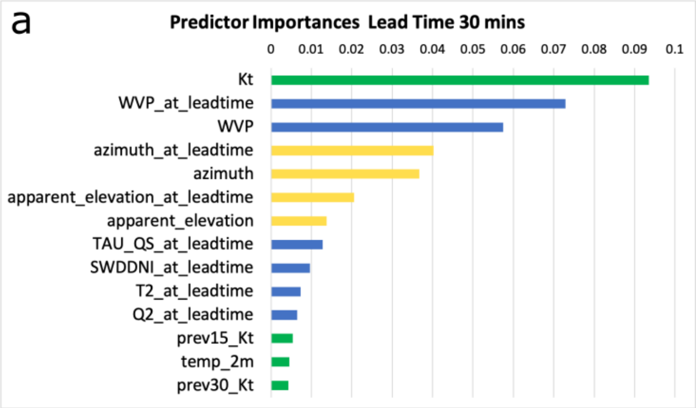


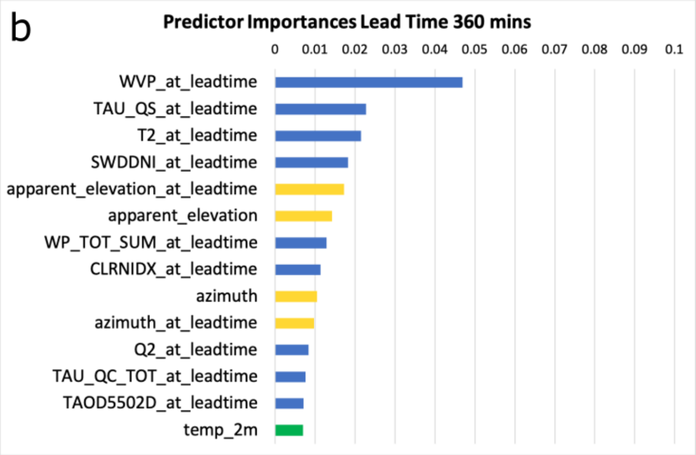
Above: WRF-Solar domain (265x265) with NYS Mesonet stations included

Left: Sample WRF-Solar GHI forecast

StatCast: Blending NWP Models and GHI Observations from NYSM

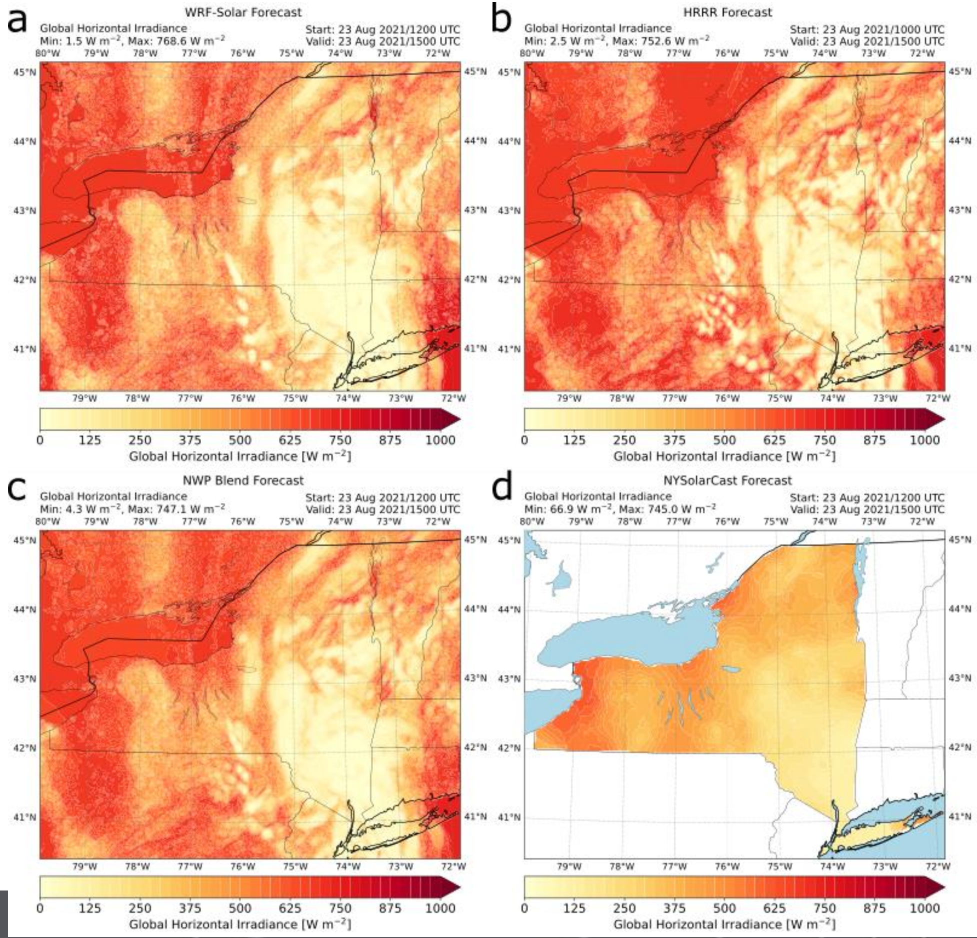
- StatCast is a statistical forecasting model developed by NCAR, and has been applied to wind/solar forecasting previously
- StatCast uses the Cubist machine learning (ML) algorithm
  - Rule-based decision trees
  - Separate model for each lead time
  - Single model for all of NYS
- Cubist predictand: Clearness index (Kt)
  - Removes strong diurnal trend in GHI
  - Can easily be converted back to GHI
- Cubist predictors for each lead time model include:
  - WRF-Solar variables
  - Past 45 min of observed Kt at NYSM sites
  - Known solar angles
- Training period: 15 Jul 2018–30 Apr 2021
- Validation period: 1 May 2021–30 Apr 2022





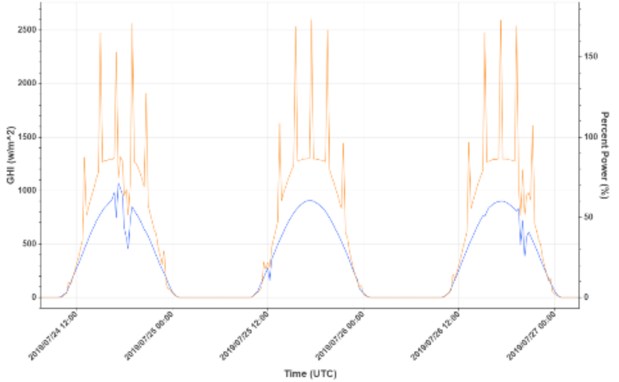
Blending StatCast & NWP

- NYSM sites mapped to WRF-Solar grid points
- Kt is converted back to GHI at NYSM sites
- Initial radius of influence (ROI) of 40 km
- Each grid point in NYS is a weighted average of forecast GHI, with weights inversely proportional to distance to nearest NYSM site ("intermediate product")
- WRF-Solar (panel a) & HRRR (panel b) are blended together as a background forecast (currently a 50/50 blend, panel c)
- StatCast blends intermediate product with NWP blended GHI to generate **final gridded GHI product (panel d)**
- StatCast weights (linear in between these points):
  - 100% at 0 km, 90% at 30 km, 0% at 40 km from nearest NYSM site
  - 100% from 0–3 h, 50% from 5.5–6 h

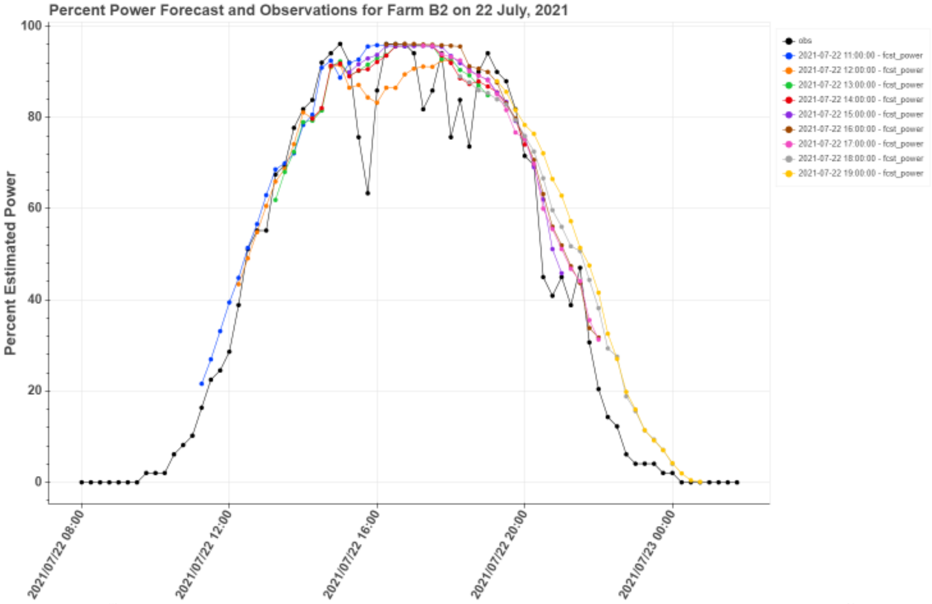


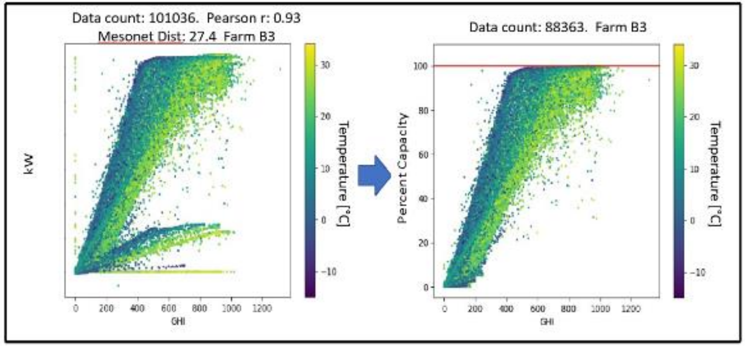
Percent Power Forecasts — UPV Farms

- Power production (in kW) and GHI data from several PV farms in NYS on monthly basis
  - Provider A: 4 farms, training data to Apr 2021
  - Provider B: 6 farms, training data to Apr 2021
  - Varying start dates, varying QC issues
  - Some farms are curtailed daily, some aren't
- Rescaled to % capacity, set to P99.9 of obs
- Cubist used to generate % power models from GHI forecasts every 15 min at 15-min res.



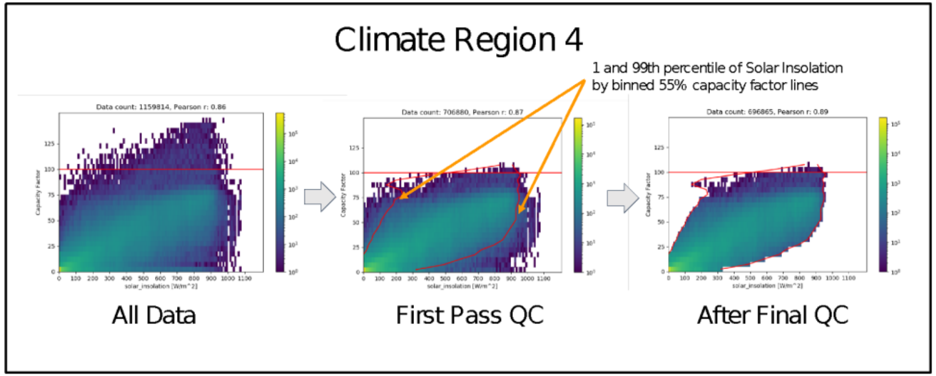
GHI and % power output for one PV farm.
Real data is often messy and QC is crucial!

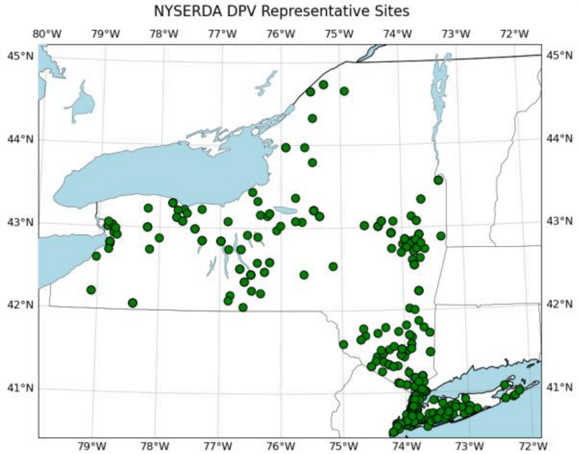




Percent Power Forecasts — DPV Sites

- NYSERDA has a database of over 101,000 DPV installations (nameplate capacity, lat, lon, ZIP)
- NYSERDA has 1-hourly DPV production data from almost 500 "representative sites"
  - Start/end dates & data quality vary by site
  - Training 1 Jan 2018–1 Apr 2020 when available
  - Most of these sites are within 10–15 km of the nearest NYSM station, all within 30 km
- NYSM obs (GHI, 2-m T, 2-m RH) converted to 1-hourly time-ending averages





The 436 NYSERDA DPV representative sites that were not completely rejected by QC

- Single statewide distributed % power Cubist model
  - U.S. Climate Regions in NYS is a variable for Cubist
- The data is messy—additional QC beyond NYSERDA's QC is needed, e.g.:
  - Pearson r of capacity factor (CF) & GHI < 0.75?
  - P99 CF > 100% or < 50% of nameplate capacity?
  - GHI > 1200 W/m^2? CF > 150%?
  - CF = 0 and GHI > 240 W/m^2 (20% of 1200 W/m^2)?
  - GHI and CF both 0 or missing/NaN values for either?

DPV Forecast Aggregation

- % power forecasts produced for every grid point in NYS
- For each distributed PV site, % power at nearest grid point multiplied by nameplate capacity
- All sites’ forecasted total power then aggregated regionally
- NYSolarCast currently configured to aggregate by regional (3-digit) ZIP code
- Could also use NYISO load zones, counties, or other useful regions of interest
- NYSolarCast framework is flexible for any aggregation — simply assign each grid point to a zone/region in a config file
- Note: Unresolved large mismatches of total DPV capacity in NYISO load zones between NYISO & NYSERDA databases

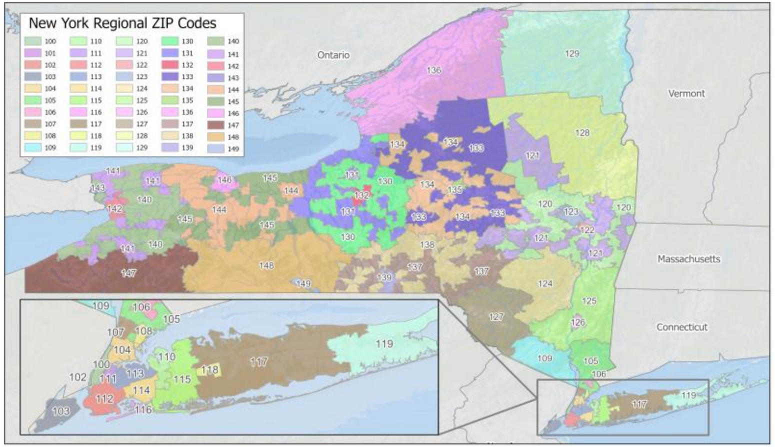
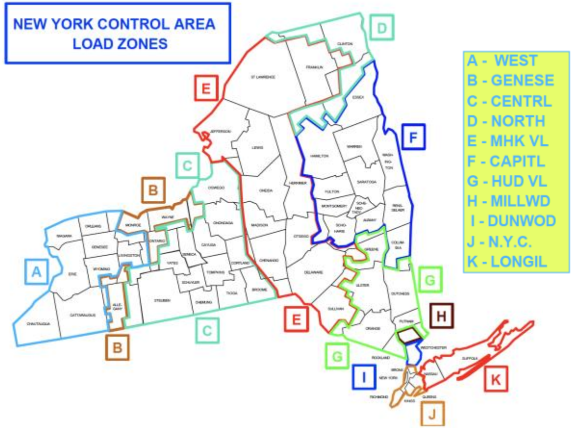
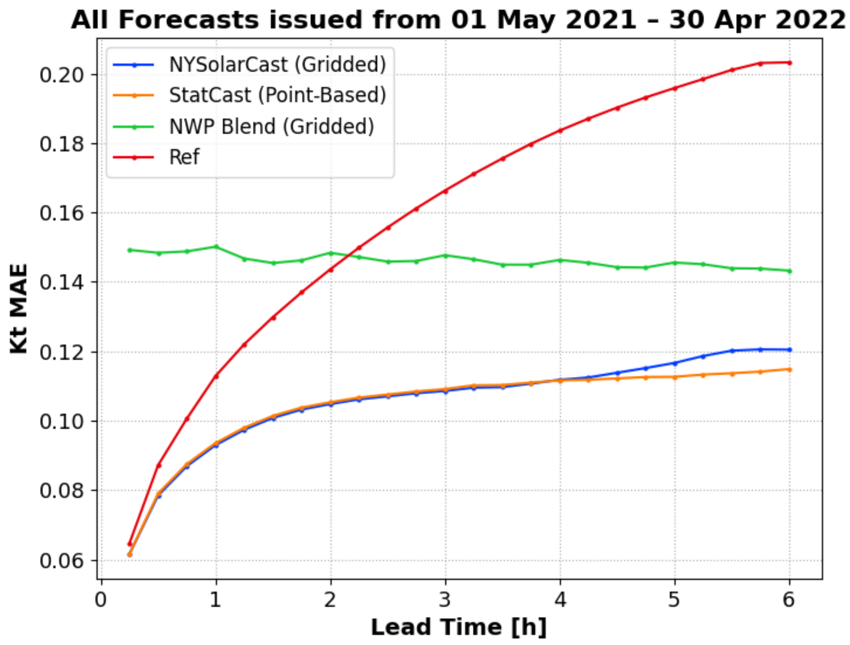


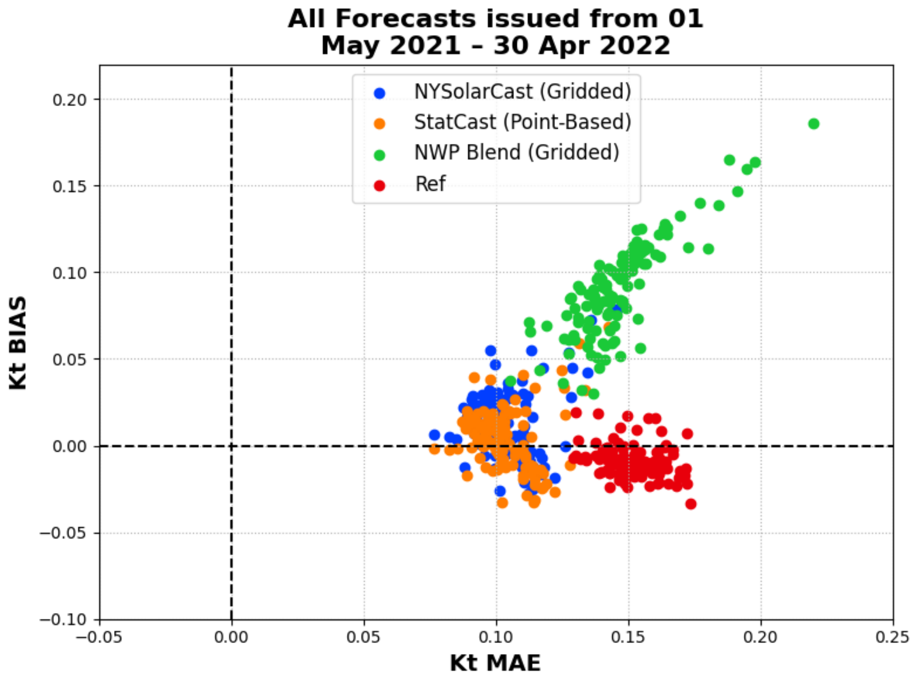
Image: Jennifer Boehnert (NCAR)



Source: NYISO

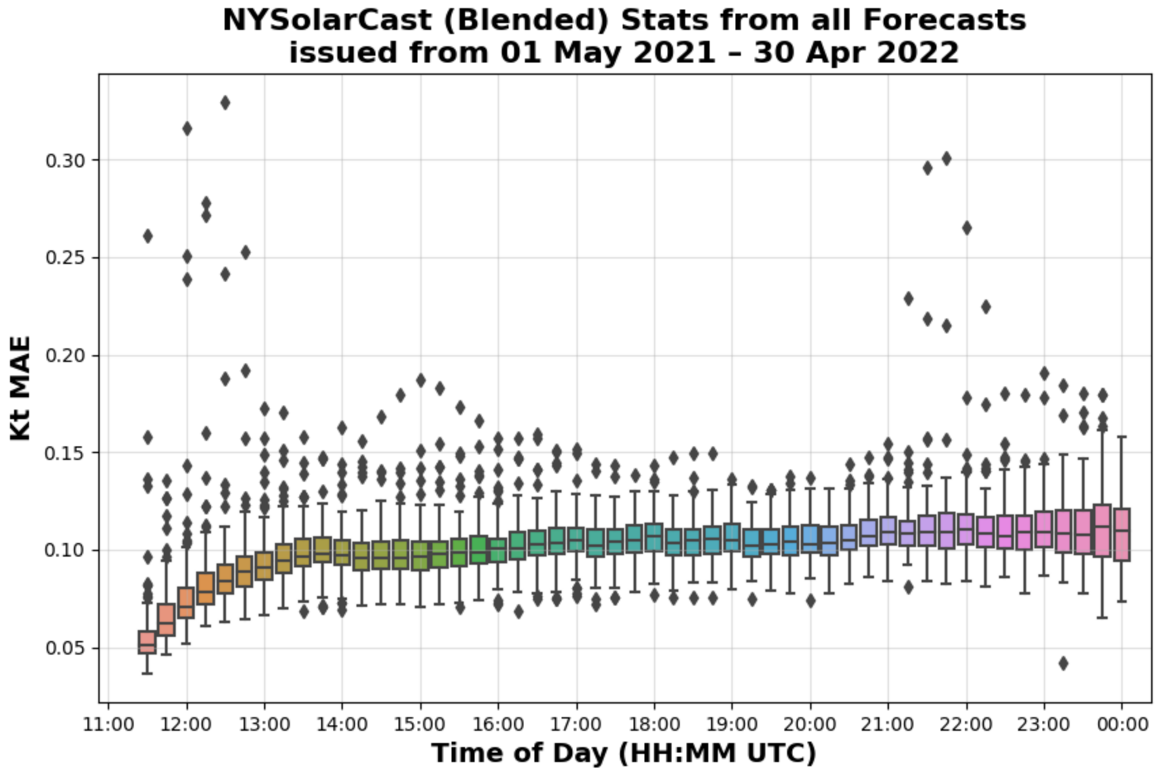
Kt Validation at NYSM Sites





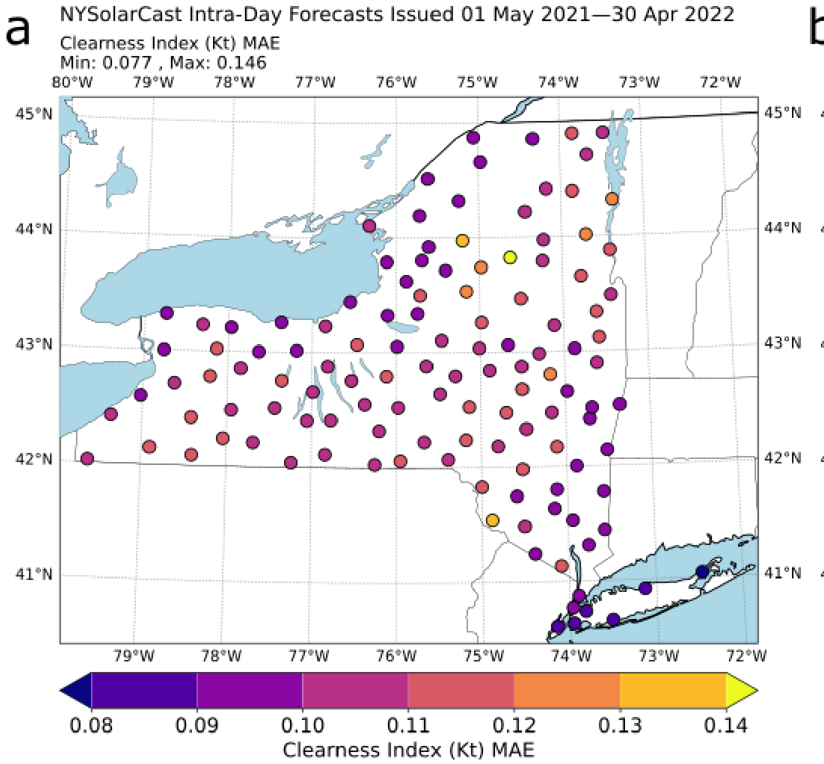
- NYSolarCast & StatCast identical at NYSM for first 3.5 h, then NYSolarCast relaxes toward NWP Blend
- NYSolarCast better MAE than smart persistence and NWP Blend at all lead times and nearly all sites
- NWP Blend better MAE than smart persistence after 2 h, and slowly declines with lead time

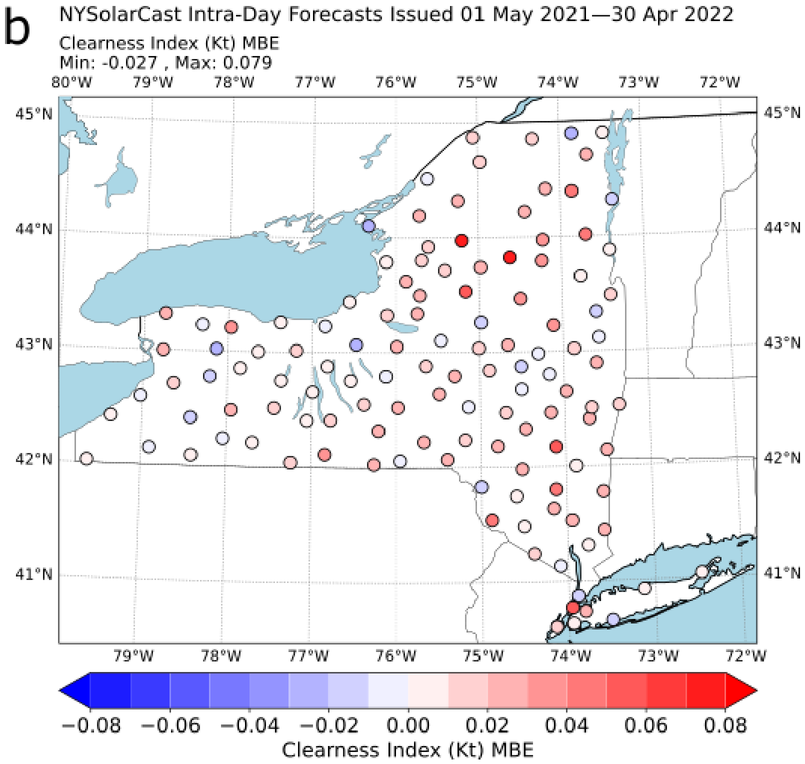
Kt Validation at NYSM Sites



- Kt MAE fairly consistent at most sites at all times of day
- A few outlier sites with high MAE in early morning and late afternoon (additional shading issues??)

Kt Validation at NYSM Sites



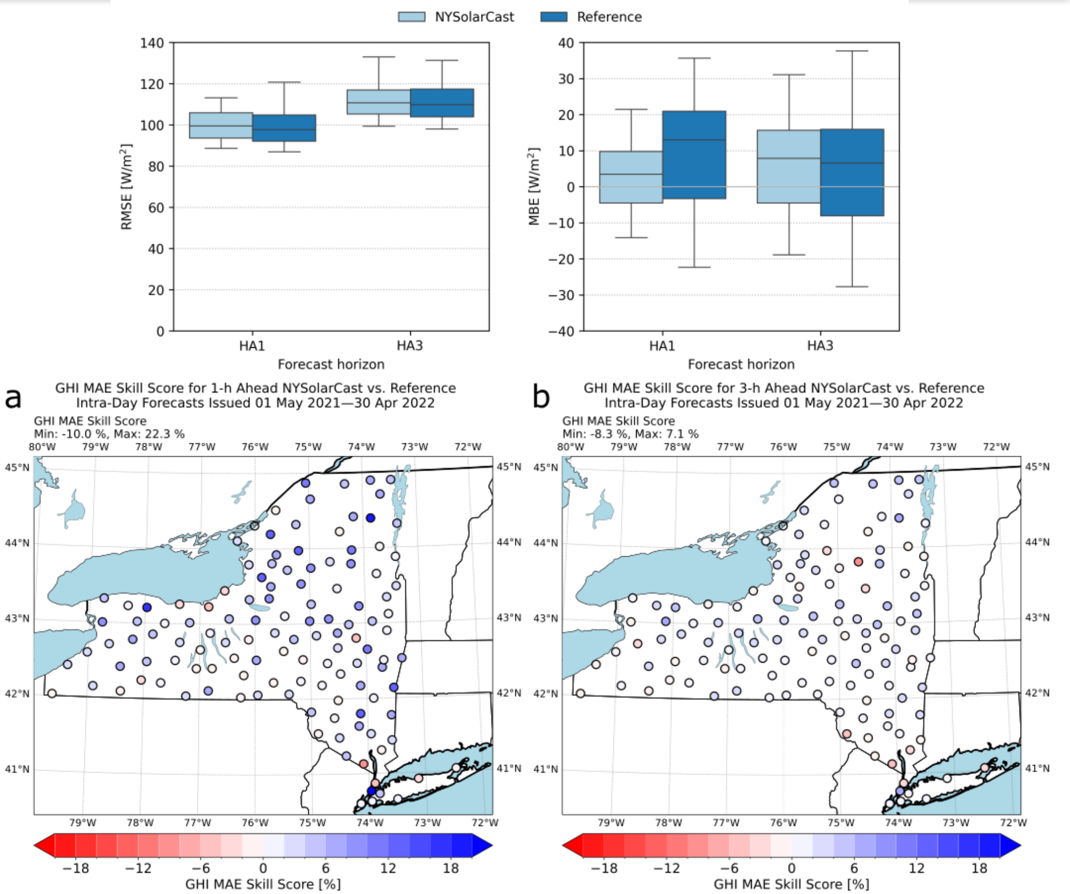


- Highest MAE mostly in Adirondacks, Upper Hudson Valley
- Possible additional snow/shading impacts at some sites?

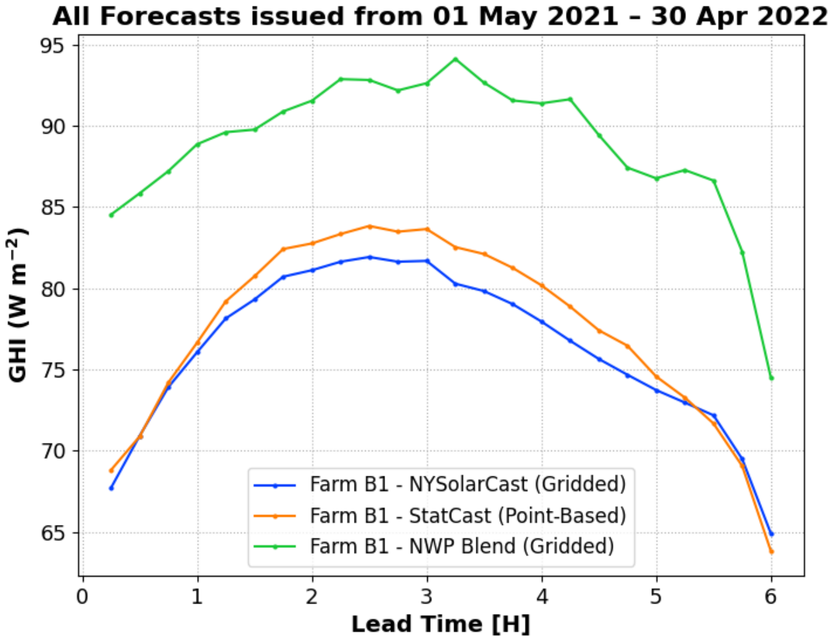
- Near-zero Kt MBE at most sites
- Highest MBE sites mostly correspond with highest MAE

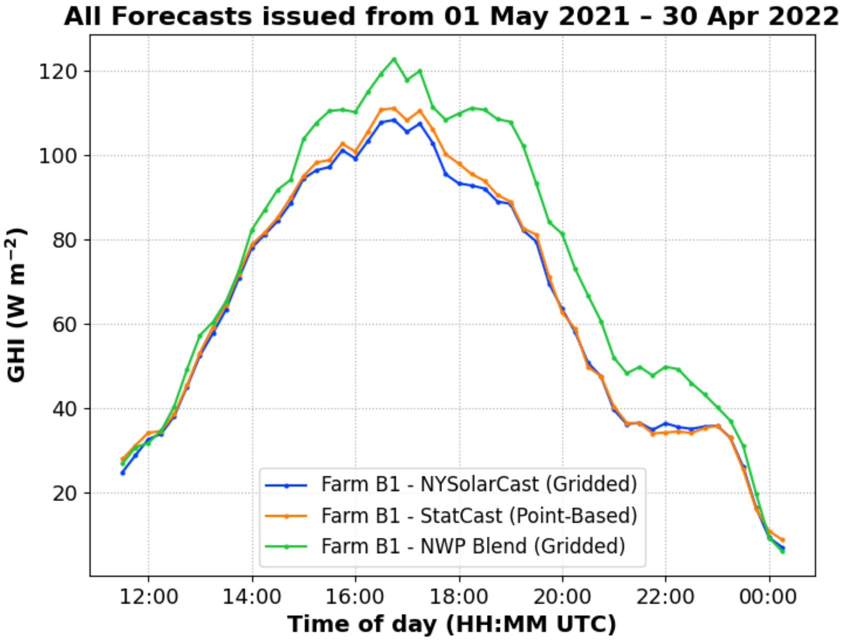
GHI Validation at NYSM Sites — Comparison with Reference Forecast

- Compared NYSolarCast GHI forecasts at NYSM sites with a commercially available “off-the-shelf” forecast model as a reference
  - Reference forecast was in 30-min averages, so resampled NYSolarCast from 15-min instantaneous to 30-min averages
  - Forecast schedules only lined up to allow comparisons at lead times of 1 and 3 h (HA1 and HA3)
- Similar GHI RMSE at both lead times
- Improved GHI MBE at HA1 for NYSolarCast, also reduced spread
- GHI MAE skill score shows NYSolarCast is better at most sites at HA1, smaller differences at HA3



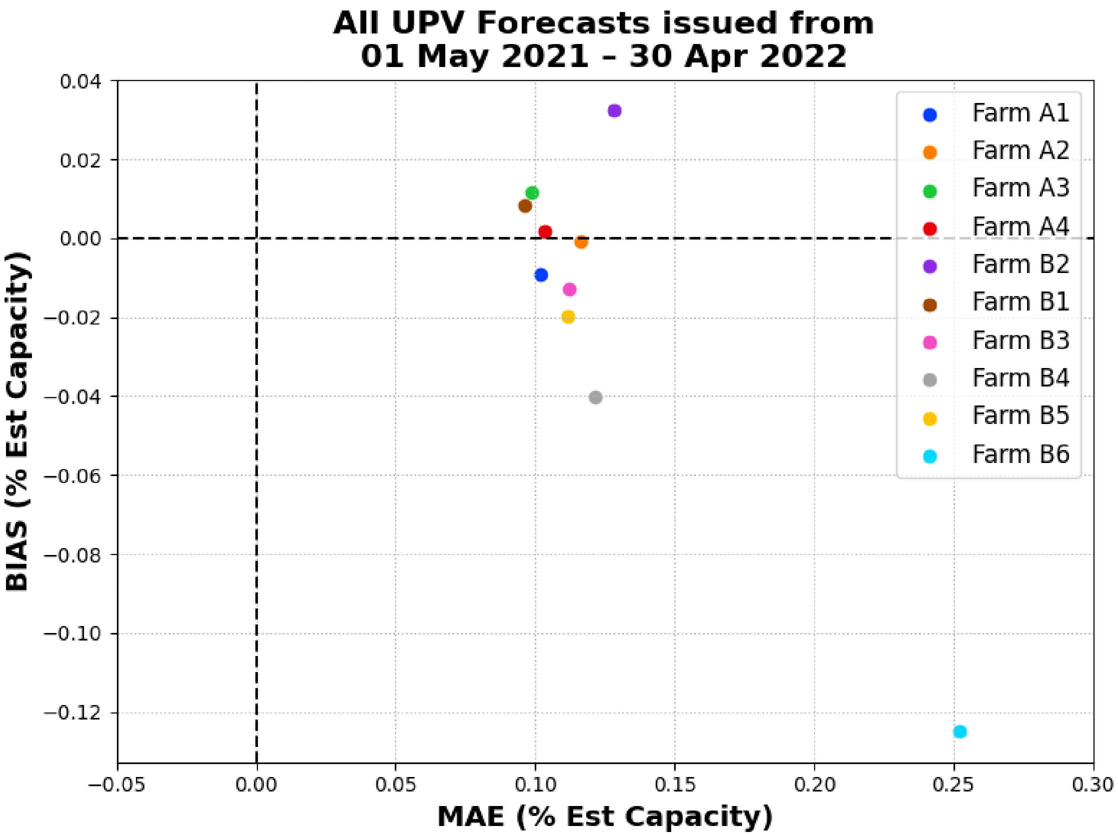
GHI Validation at UPV Sites





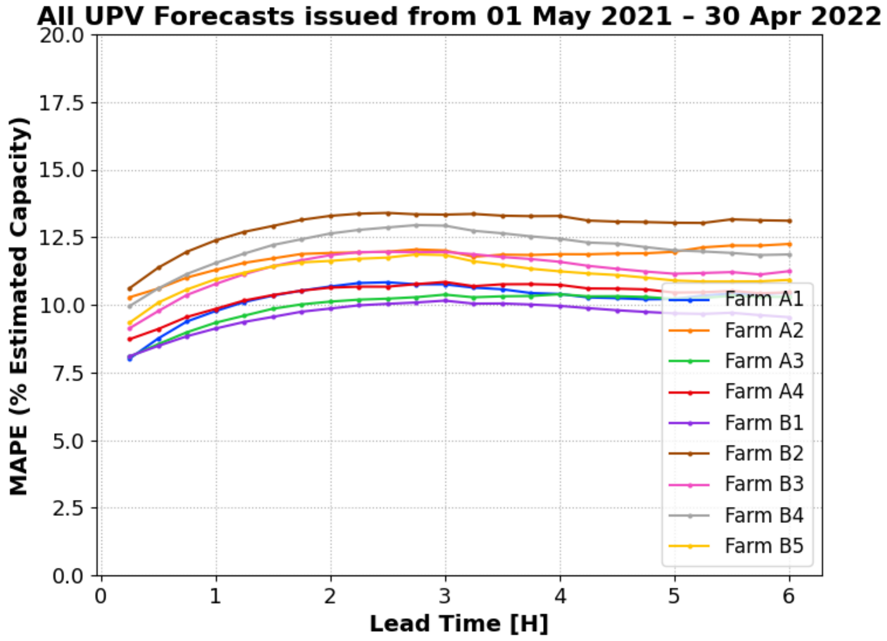
- **NYSolarCast GHI at the UPV farm is nearly always better than the StatCast GHI at the nearest NYSM site**
- If real-time obs from UPV farms are unavailable, NYSolarCast still adds value using nearby weather stations
- The forecast would be even better with access to real-time UPV farm obs (GHI, temperature, power)

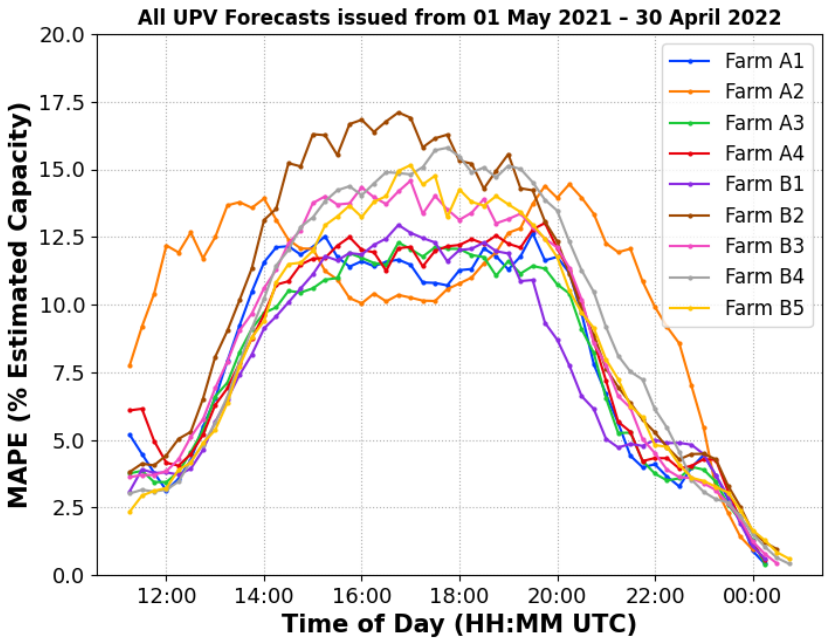
Power Validation at UPV Farms



- 7 of 10 farms have both an MPE of -2 to +2% and MAPE of 9–12%
- Farm B6 excluded from future plots
- Farm B6 outlier status attributed to much shorter training period than other farms and several months of missing data during this 1-year validation period

Power Validation at UPV Farms

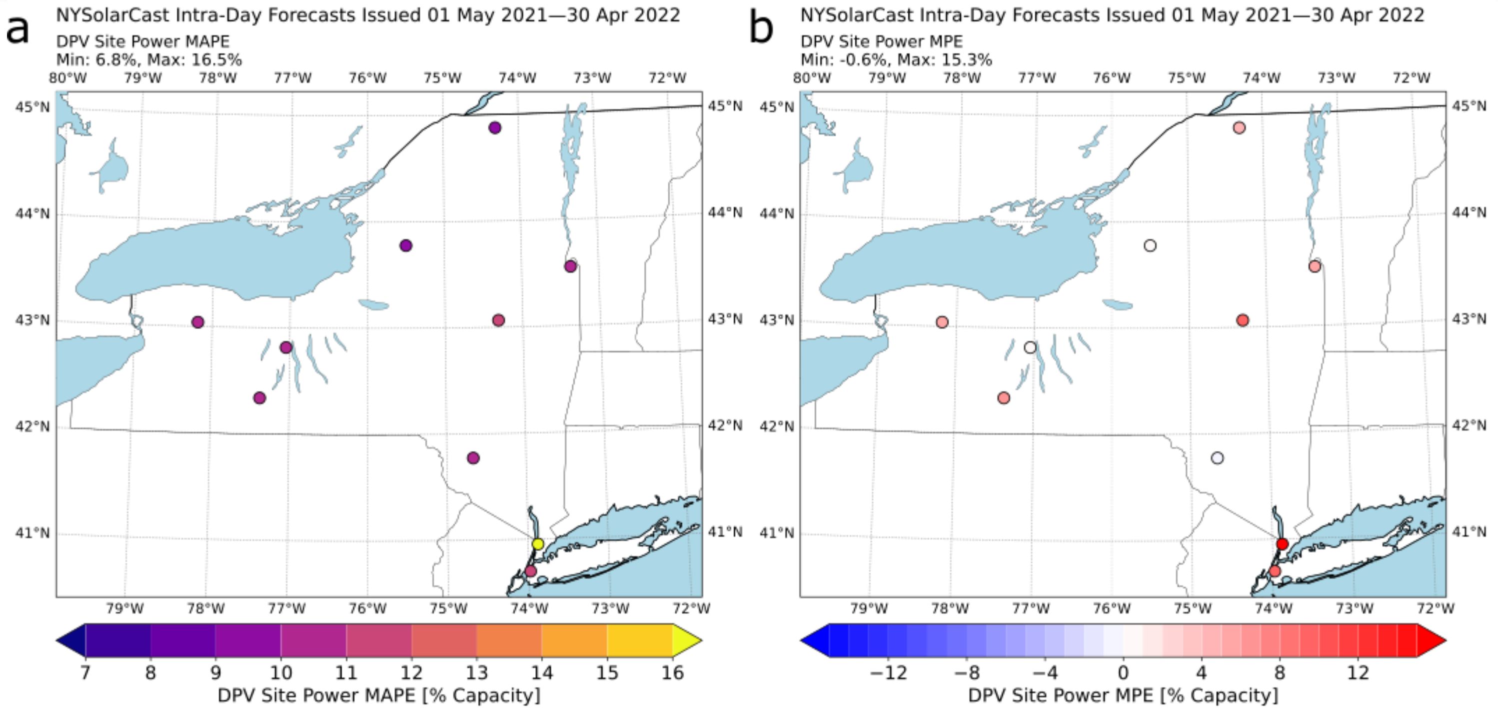




- Power MAPE for all UPV farms fairly constant as a function of lead time, between 8–13%
- Levels off after ~3 hours

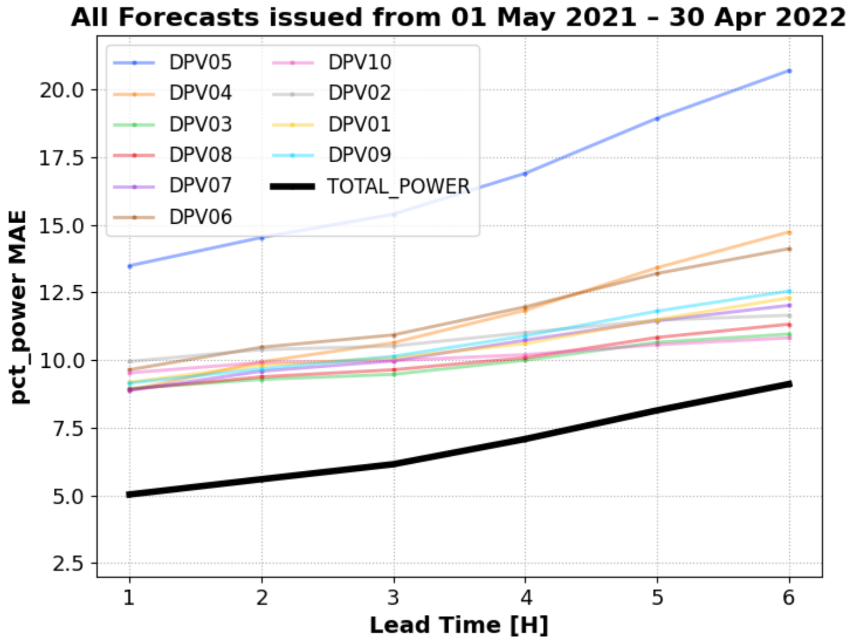
- Power MAPE for most UPV farms generally follows the diurnal GHI curve
- Farm A1, Farm A2, and Farm A4 all exhibit mid-day dip; production data indicates they are likely overbuilt

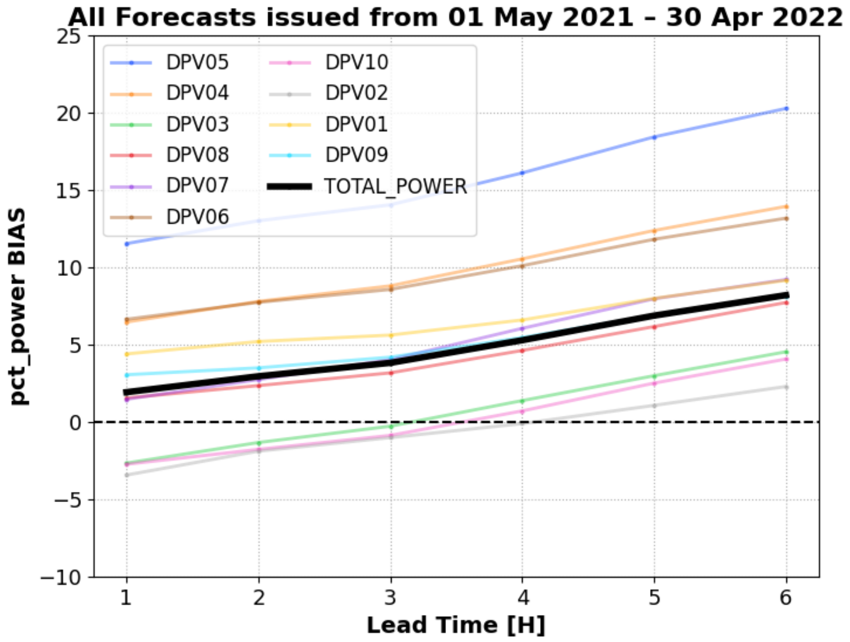
Power Validation at DPV Sites



- These 10 DPV sites have a range of sizes (783 kW–2.90 MW), tilt angles (10°–30°), and azimuth angles (141°–200°)
- 9 of the 10 sites have overall MAPE 6.8%–11.6%, and overall MPE –0.6% to 9.8%
- One outlier site just north of NYC has MAPE 16.5% and MPE 15.3% — data averaging/DST issues??

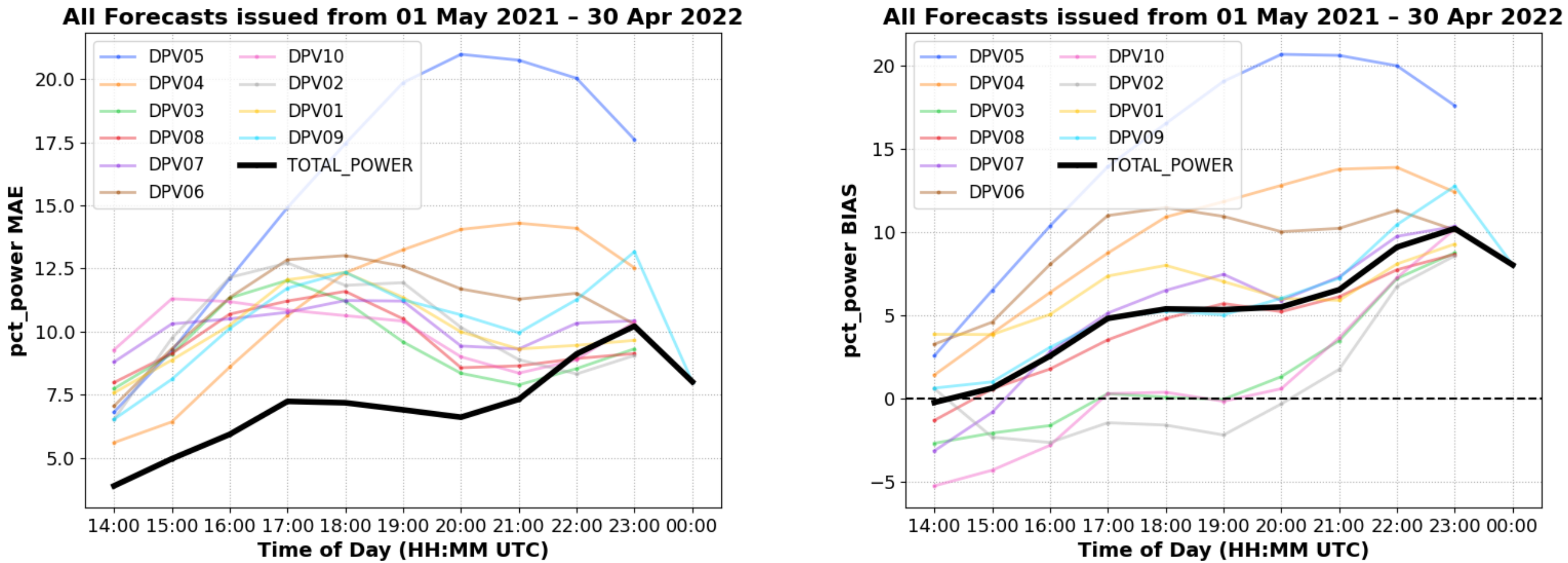
Power Validation at DPV Sites





- Aggregating these 10 sites across NYS together yields a lower MAE than any individual site, generally smaller MBE
- Aggregation over regions helps "cancel out" some of these differences in tilt & azimuth angle, shading, etc.

Power Validation at DPV Sites



- Aggregating these 10 sites across NYS together yields a lower MAE than any individual site, generally smaller MBE
- Aggregation over regions helps “cancel out” some of these differences in tilt & azimuth angle, shading, etc.

Summary

- We developed NYSolarCast to predict solar power in NYS — applicable in other areas!
  - Entirely open source software framework (https://github.com/NCAR/NYSolarCast_delivery)
  - Predicts GHI on a 3-km grid across NYS every 15 min out to 6 h, and at 06 UTC daily for day-ahead
  - Predicts 15-min % power capacity at select utility-scale PV farms
  - Predicts 1-hourly % power capacity for distributed PV aggregated to regions
- Real-time NYS Mesonet data is critical to NYSolarCast system, especially in the absence of real-time data from UPV farms or DPV sites
- NYSolarCast beats both smart persistence & NWP blend at all intra-day lead & valid times
  - A few sites with larger errors may have additional shading or snow cover issues not flagged in QC
- NYSolarCast compares favorably with reference commercial GHI forecast at 1 & 3-h leads
- NYSolarCast GHI at UPV farms is nearly always better than StatCast GHI at nearest NYS Mesonet station
  - Especially valuable when real-time data from UPV farms is not available
- Most UPV farms with MPE –2% to +2%, MAPE 9–12% over 1-year validation period
- NYSolarCast aggregated DPV MAPE < 10%, MBE < 7% for all times of day but late PM
- Article published in Solar Energy (https://doi.org/10.1016/j.solener.2024.112462)

Thanks for listening!

Photos: ©2019 Jared Lee, Shagaya Renewable Energy Park, Kuwait

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Questions? Interested in using/expanding/improving NYSolarCast? Please email me!

Distributed Energy Resource Forecasting

July 10th, 2024

Presented to: Solar Energy Technology Office (SETO) -Workshop on Solar Forecasting

Mack W Knobbe

Sr. Mgr, Grid Tech Innovation

SOUTHERN CALIFORNIA EDISON®

Energy for What's Ahead℠

Southern California Edison (SCE) is one of the nation's largest electric utilities

15 MILLION RESIDENTS

5 MILLION CUSTOMER ACCOUNTS

50,000 SQUARE-MILE SERVICE AREA

1.4 MILLION POWER POLES

724,000 TRANSFORMERS

1,360 MW ENERGY STORAGE CONTRACTS

3,500 MILES OF OVERHEAD POWER LINES REPLACED WITH INSULATED WIRE

118,000 MILES OF OVERHEAD DISTRIBUTION & TRANSMISSION LINES

6,090 POLES UPGRADED TO FIRE-RESISTANT

SCE VISION FOR DECARBONIZATION AND AN ADVANCED GRID DRIVES FORWARD THROUGH SUCCESSIVE EFFORTS

California's climate-change goals include a 40% reduction in absolute greenhouse gas (GHG) emissions from 1990 levels by 2030, and 80% by 2050, as well as net-zero GHG emissions economy-wide by 2045

SCE is required by law to meet the following retail sales requirements for the power it delivers to customers:

- ✓ By 2020 – **33%** of power from Renewables Portfolio Standard (RPS)-eligible resources *(requirement met)*
- ❑ By 2030 – **60%** of power from RPS-eligible resources
- ❑ By 2045 – **100%** carbon-free power

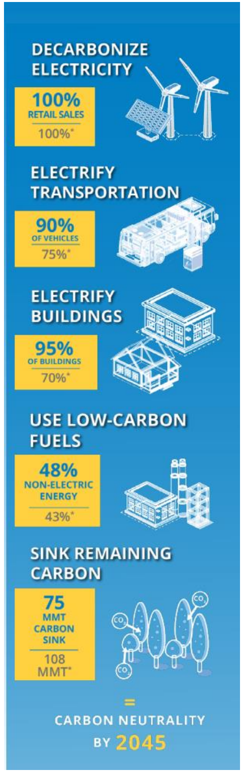
SCE has published several whitepapers outlining the cross-sector collaboration required for achieving carbon neutrality:

Pathway 2045 (2019)
SCE's 2019 data-driven analysis of the steps that California must take to meet the 2045 goals to clean our electric grid and reach carbon neutrality

Reimagining the Grid (2020)
An assessment of the grid changes needed to support GHG reduction goals, while adapting to evolving customer (EV, DERs) and climate-change driven needs.

Mind the Gap (2021)
An assessment of policy changes and additions needed to ensure California meets its GHG emissions reductions targets by 2030 in anticipation of its goal to decarbonize by 2045.

Countdown to 2045 (2023)
A data-driven analysis of the steps that California must take to meet 2045 goals, which identified 5 key actions for affordably achieving carbon neutrality

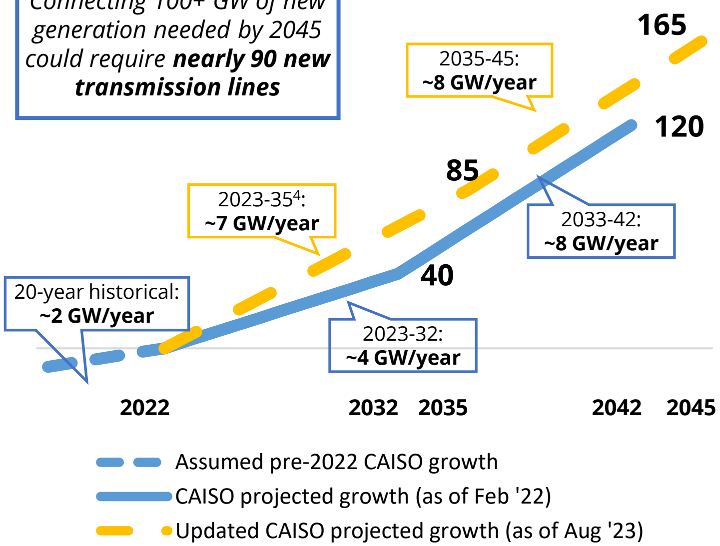


Countdown 2045: Grid Expansion Estimates

TRANSMISSION

New CAISO transmission capacity needed

*Connecting 100+ GW of new generation needed by 2045 could require **nearly 90 new transmission lines***



DISTRIBUTION

SCE distribution projects needed

	Planned in next 10 years (2023-2032)	Incremental for *Countdown* (2033-2045)
New substations[1]	~10	~75
Substation expansions[1]	~45	~300
New circuits[1]	~130	~1300

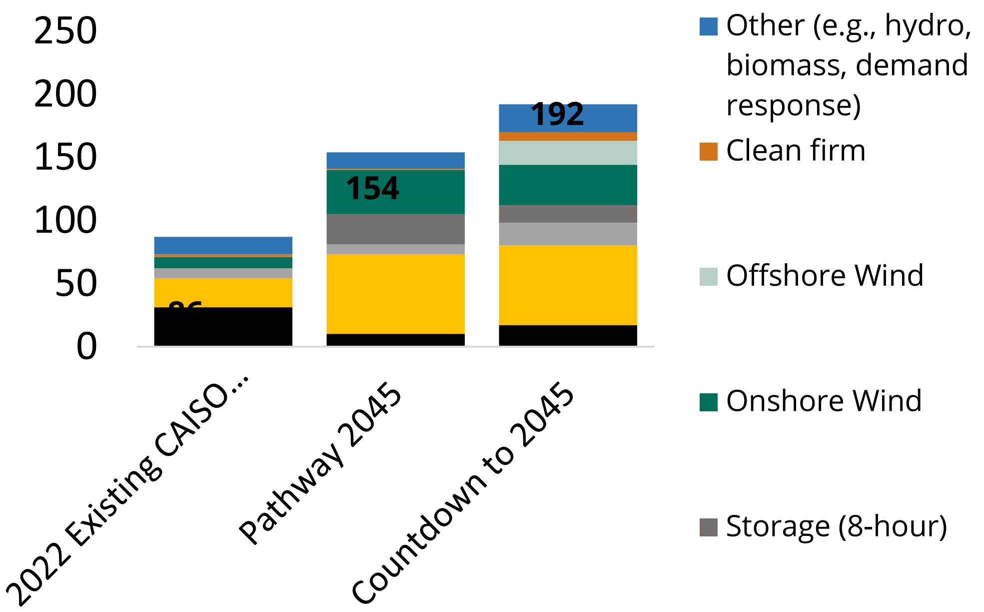
SCE Distribution in 2045…

- **~25% larger distribution system**
- ~90% average circuit utilization
- Many service transformers and wires upgraded

The Need for Forecasting & Managing DER

- Variable Renewable Energy (VRE) will need to be **forecasted** and **managed** to ensure generation and load are balanced on the distribution & transmission network
- >100GW of new resources needed from now to 2045, with biggest capacity growth **Solar**: **Expected to increase from 23 GW to 63 GW**
- **Nearly half the solar capacity** (31 GW) is BTM, representing **around 50 TWH** per year. Because of the magnitude, any error in forecasting is a significant opportunity in terms of energy value and operations
- Inaccurate forecasts can lead to reliability issues or incur significant costs for SCE to secure energy contracts within a short period of time
- Inaccurate forecasts can lead to canceled maintenance operations. SCE has ~100,000 yearly switching operations with a 2% cancellation rate. Customers require a 2 weeks notice, so any cancellation is a significant to operations.

Supply resources (installed capacity in GW)



Grid Management System (GMS)

Operational Forecasting (2 months, or less) Short Term Forecasting Engine (STFE)

Findings from this material were also published in *J. Schoene, M. Humayun, J. Ponnaya, A. Johnson, J. Ang, and A. Manella, "Operational Forecasting – Use Cases and Implementation Challenges," Southern California Edison, 2024.*

Energy for What's Ahead®

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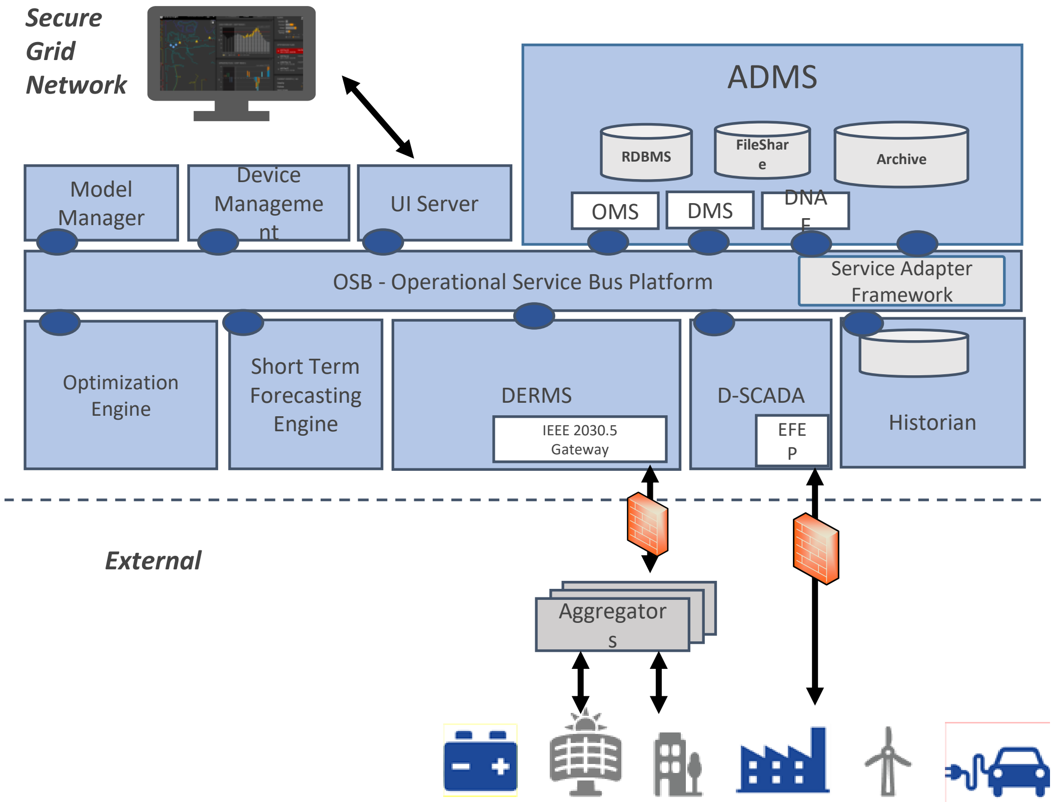
SCE's Grid Management System (GMS)



- GMS is a system of systems that provides integrated grid management functions and one plane of glass for distribution operations.
- GMS enables **model driven** operations will enable greater utilization of the electric grid while enabling much needed operational flexibility.
  - Allow SCE to run the grid closer to operating limits.
  - New model driven analytics that enable greater grid flexibility and shift towards active grid management.

Grid Management Capabilities Roadmap

2021	2022	2023	2024	2025+
D-SCADA Upgrade	Extensible FEP	Distribution State Estimation	Adaptive Protection Analytics	Day Ahead Planning
	IEEE 2030.5	Advanced Distribution Analysis Apps	Look-Ahead Analysis	Multi Interval Optimization
	DER Provisioning	Advanced Distribution Control Apps	High Impedance Faults	Adv Microgrid Orchestration
	DER Registration & Enrollment	FLISR	Adv. ADMS Enhancements	Demand Response Integration
	Microservice-based T&D Architecture	Enhanced Outage Management	Resource Scheduler	Sub-Transmission Level Outages
	Operational Service Bus	Storm Assist	Single-interval Optimization	
	Network Connectivity Analytic	AMI Pre-Filtering Engine	DER Forecasting	
		Mobile Outage Management	Net & True Load Forecasts	
		Consolidated Distr. Operations UI/UX Exp.	Device Management	

- **Distribution Optimization**
- **DER Orchestration**
- **Outage Response**
- **Mobile Operations**
- **Data Fabric, Analytics & Device Mgmt.**
- **End use-cases using forecast engine**

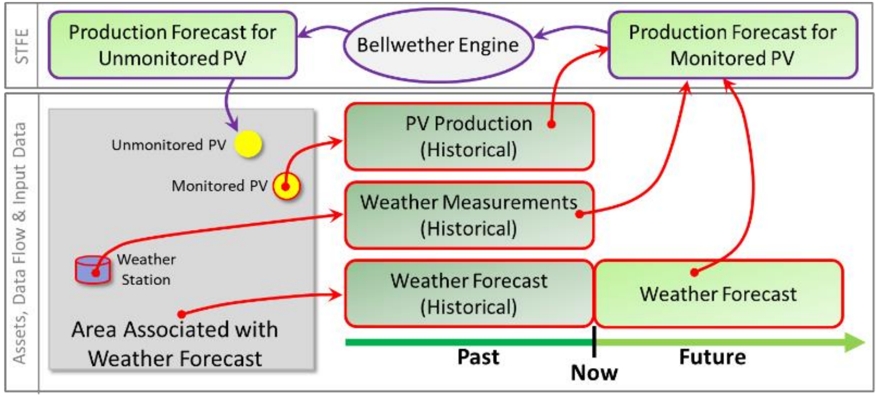
SCE's Short-Term Forecasting Engine (STFE)

No w 48-hrs 2- weeks 2- months

Short ***Intermediate*** ***Long-Range***

- **STFE provides information of real-time system generation and demand conditions** so Grid Operators can take informed actions toward proactively preventing or mitigating adverse system conditions, thereby ensuring system reliability.
- Forecasting unmonitored PV: STFE's Bellwether Methodology forecasts production of each unmonitored PV by associating it with a monitored PV of similar size and location. First value of STFE's 5-minute time series production forecast used as an estimate of each unmonitored PVs real-time production.

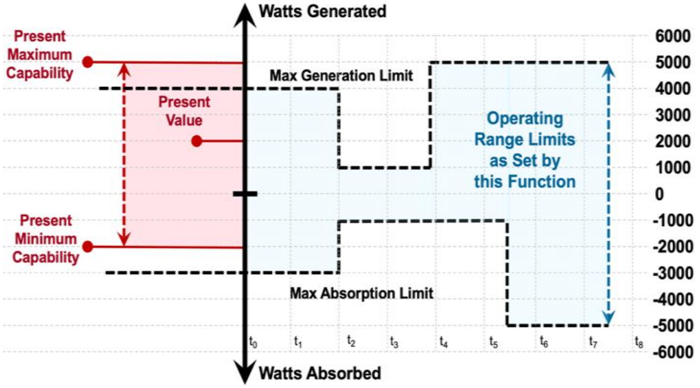
•**Short-term Forecast:** now to 48-hrs ahead at 5-minute intervals (updated every 15-minutes)
•**Intermediate range:** 48 hours to 2-weeks ahead at 1-hr resolution (updated hourly)
•**Long Range Forecast:** 2-weeks to 2 months ahead providing daily peak generation (updated hourly)



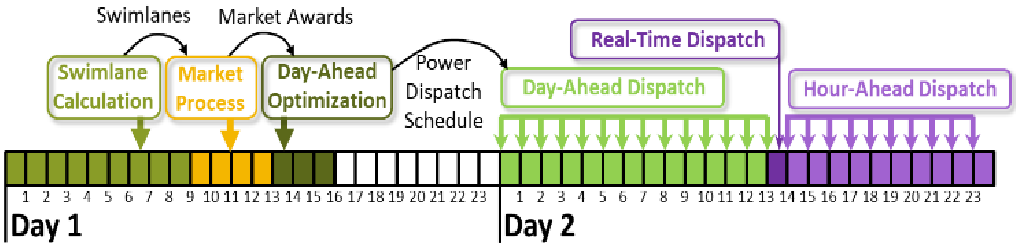
Economic Optimization Engine (OE)

STFE provides day-ahead forecasts and, if needed, intraday hour-ahead forecasts to OE that facilitates DER participation in the wholesale market by informing market awards for the day ahead.

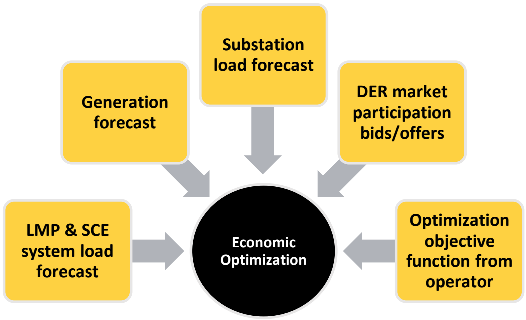
- **Day 1**: (1) **OE calculates operating limits for market-participating DERs** to inform market awards for the next day using STFE's day-ahead forecasts. (2) DERs bid into the wholesale market and receive awards accounting for DER operating limits. (3) OE calculates schedules for the non-market DERS.
- **Day 2**: (4) **schedules for all DERs are dispatched.** (5) Intraday optimization may create a new operating schedule to relieve actual or STFE projected constraint violations in the presence of changes not anticipated when the operating schedule was created on the prior day.



Swimlane calculation *determines the active/reactive power envelope customer DER can import/export within to ensure thermal/voltage constraints are maintained.*



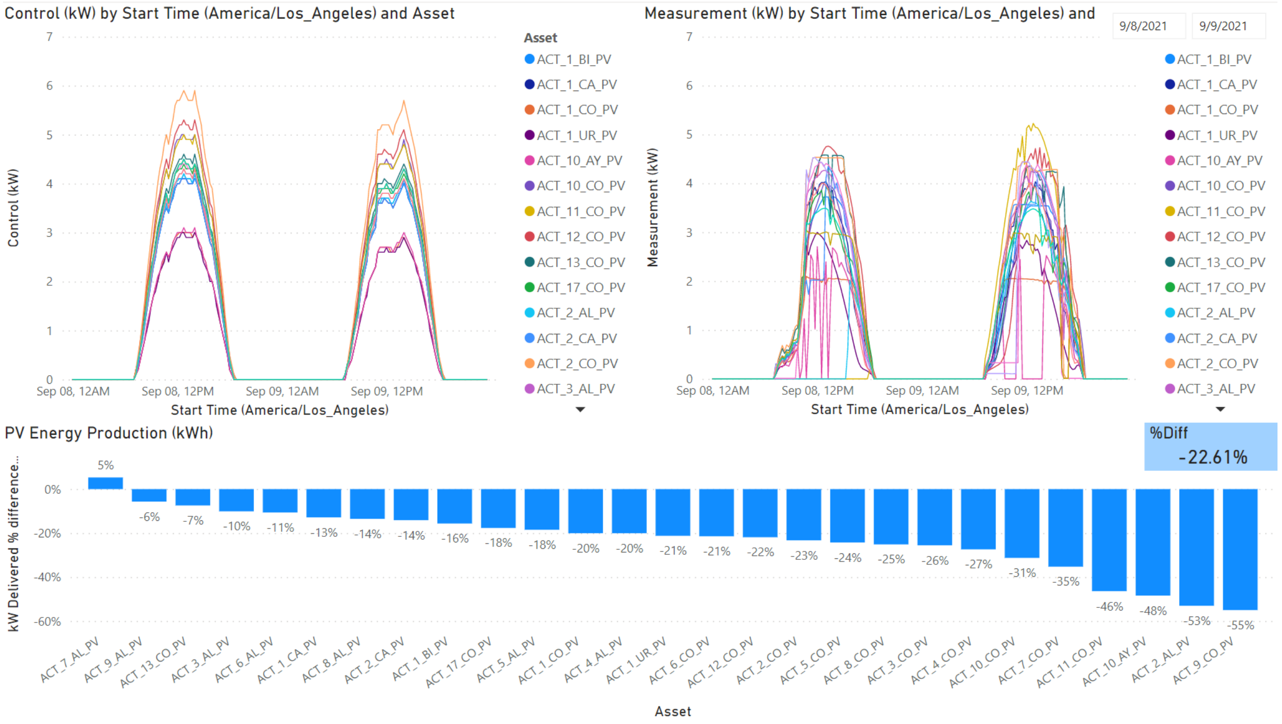
Economic Optimization Process



Data inputs to the Economic Optimization Process

Inaccuracies in Forecasting Photovoltaic (PV) from Field Trial

- Forecasts don't necessarily reflect actual output of DER
  - Actual PV generation profiles more complex with cloud coverage
  - Occasional dips in PV output caused by failure in calculating DER dispatches (OPF failures)
- Cost of Inaccuracies:
  - Mismatch in committed vs actual generation impact grid reliability
    - Rotating outages if there's insufficient supply
    - High cost of electricity to customers
  - 20% inaccuracy in forecasting could cost SCE's customers millions annually in additional energy procured
- Cost to DER owners:
  - Opportunity cost
  - Discourages market participation
  - Delays break-even point of customer return on investment for their DER

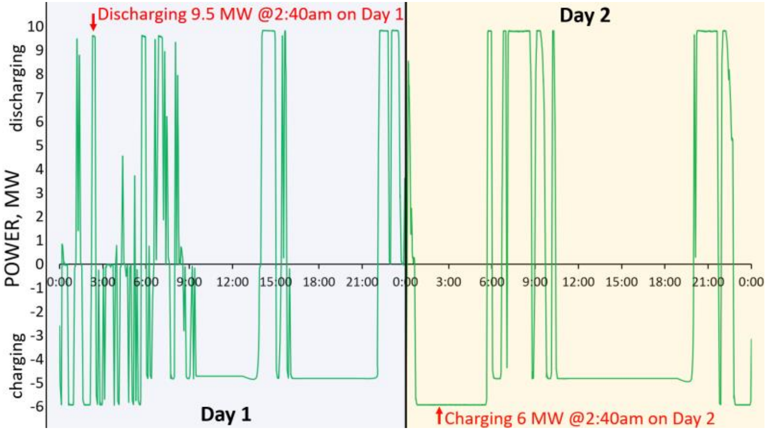


Photovoltaic Forecasting Inaccuracies *are illustrated in this dashboard where the forecasted (left) versus the measured (right) output of the residential PVs had a 22% average discrepancy throughout the day. Data from retrieved from SCE's, DOE and CEC funded,* ***EASE project***

Department of Energy Award #: DE-EE0008004
California Energy Commission Contract #: EPC-17-024

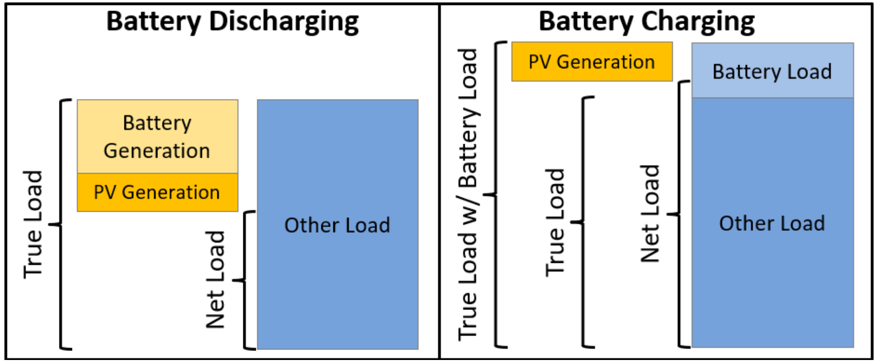
Inaccuracies caused by Battery Energy Systems (BESS)

STFE currently does not forecast **BESS** behavior, but it needs to account for it when training its load algorithm and applying it to forecast load. Notably, it is particularly difficult to predict **BESS** that are (1) customer-owned and controlled, (2) available as reserve capacity and may dispatch on short notice and (3) used for frequency control to manage fast load and generation variations.



Charging/Discharging of a large distribution-connected BESS

STFE results are compromised by unpredictable **BESS** behavior can cause large forecast errors. A provision that can be put in place to avoid or mitigate violations quickly is the re-computation of the forecast triggered by updated **BESS** profiles or by a violation, both necessitating circuit-level sensors that can provide this information in real-time. After re-computation, the applications are re-run with the corrected **STFE** results.



Interplay between BESS behavior, load, and PV generation

Challenges Impacting Forecasts and Optimization Results

SCE's Grid Management System put in place the systems to manage DER and prepare the grid for 2045.

SCE will be validating its forecasting and DERMS optimization systems in pilot evaluations in 2026 to ensure they can reliably and efficiently actively manage DER and other grid assets.

The models are only as good as the inputs. Grid operation will need accurate forecast at the short, intermediate and long-term ranges.

The rapid expansion of the grid and generation sources will increase the importance of accurate forecasting to maintain affordability and reliability.

Variance of Customer DER: Inaccuracies in committed vs actual dispatches due to variances in inverter products and accounting for uncontrollable customer DER

Weather services: Inaccuracy/absence of weather forecasts from weather services

Communication Issues: latency, aggregate network reliability at customer sites

Data historization: trade-off between cost and data resolution

Data quality: missing data, errors, time synchronization issues

Circuit model inaccuracy: impacts ability to effectively balance load/generation and conduct operational short-term demand planning

Usability: user interface design to provide enough customizability without sacrificing ease-of use for forecast advisors

Q&A and Discussions