Energy+Environmental Economics

Dynamic Reserve Calculation with E3's RESERVE Model

Energy Systems Integration Group: Meteorology and Market Design for Grid Services Workshop

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Denver, Colorado

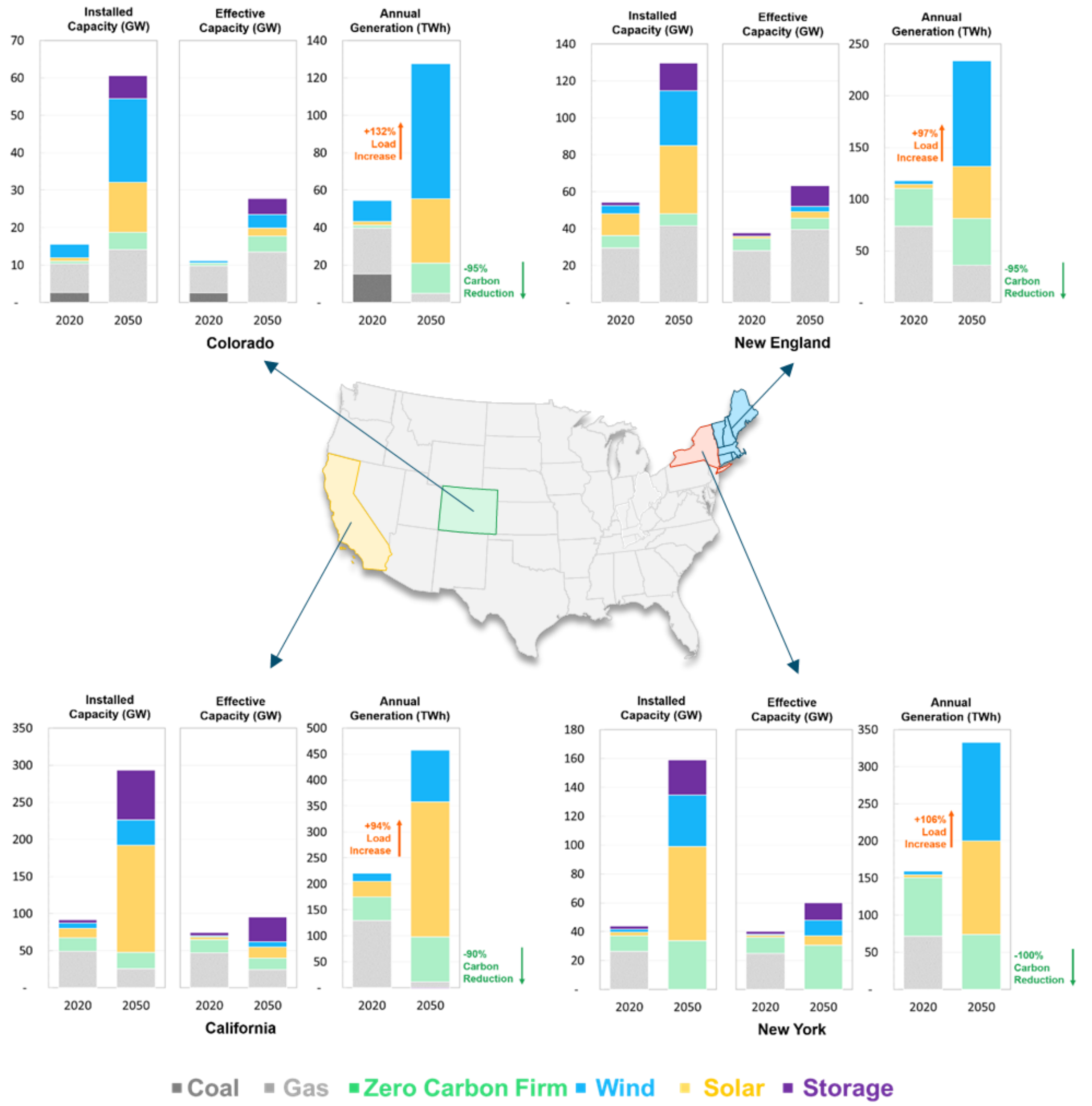
Arne Olson, Senior Partner

Decarbonization imperatives will lead to massive increases in wind and solar generation

+ Wind and solar are the lowest-cost sources of carbon-free energy in every region of the United States

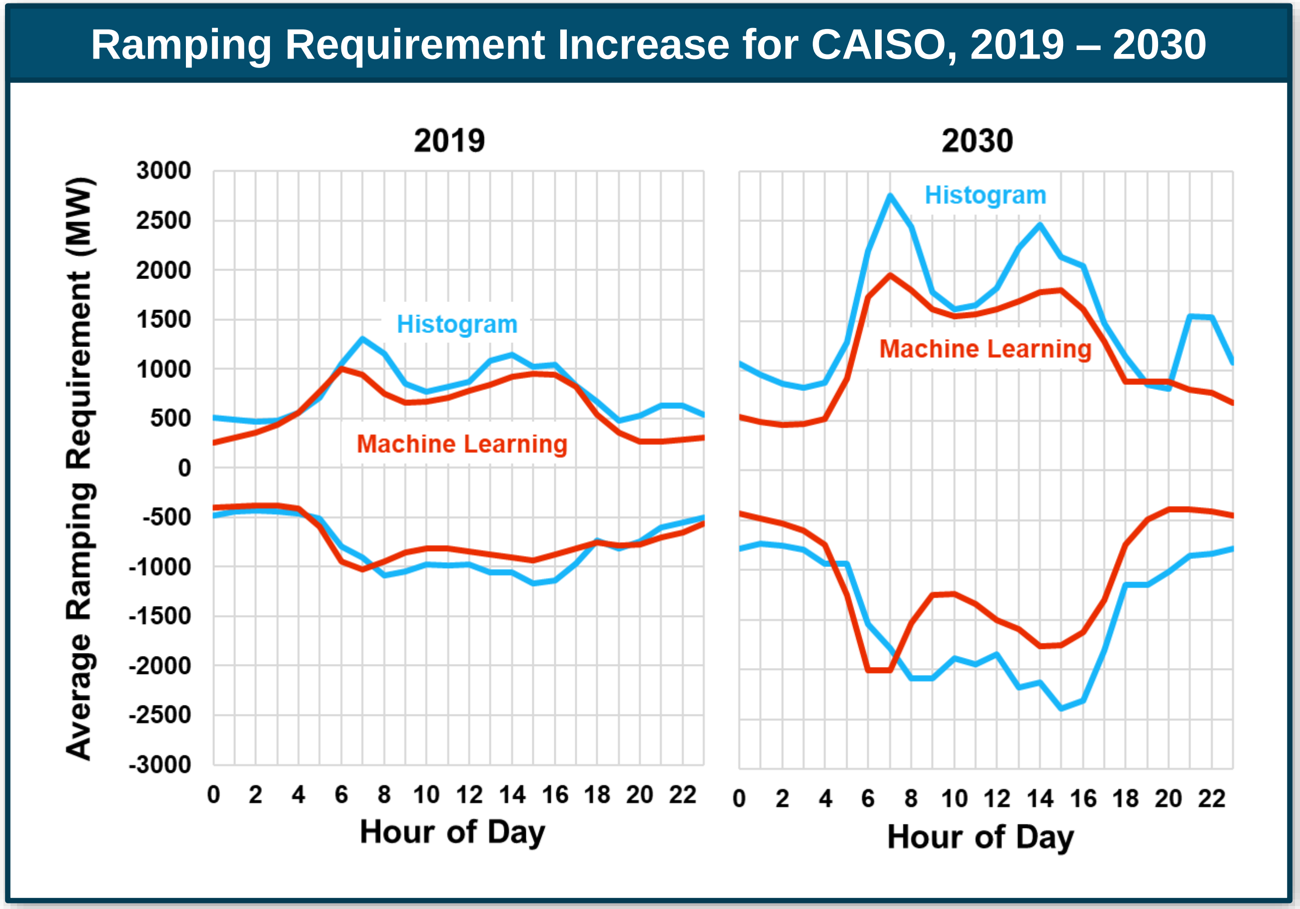
+ Electric loads may increase by 50-100% due to electrification, requiring more clean electricity

+ Massively increased reliance on weather-dependent resources will require much more intelligent and dynamic operating procedures



Need for grid services will grow with higher penetrations of wind and solar generation

- Grid operators have always balanced variability and uncertainty in demand and supply using ancillary services
- The need for grid services will grow as wind and solar increase due to increased variability and forecast errors
- The need for grid services will also become more dynamic as grid conditions change with the weather

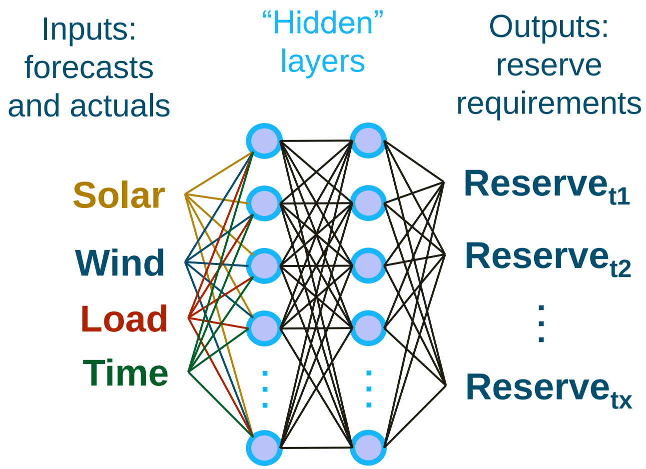


Source: E3, Predicting Reserve Needs Using Machine Learning, project partially funded with grant from ARPA-E

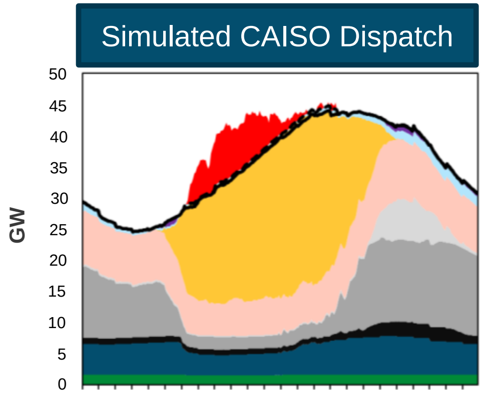
CHANGING WHAT'S POSSIBLE

E3 received a grant from ARPA-E to develop a machine-learning model for dynamic operating reserve calculation

Machine learning generates reserve needs using artificial neural network



PLEXOS production simulation of CAISO system validates operability



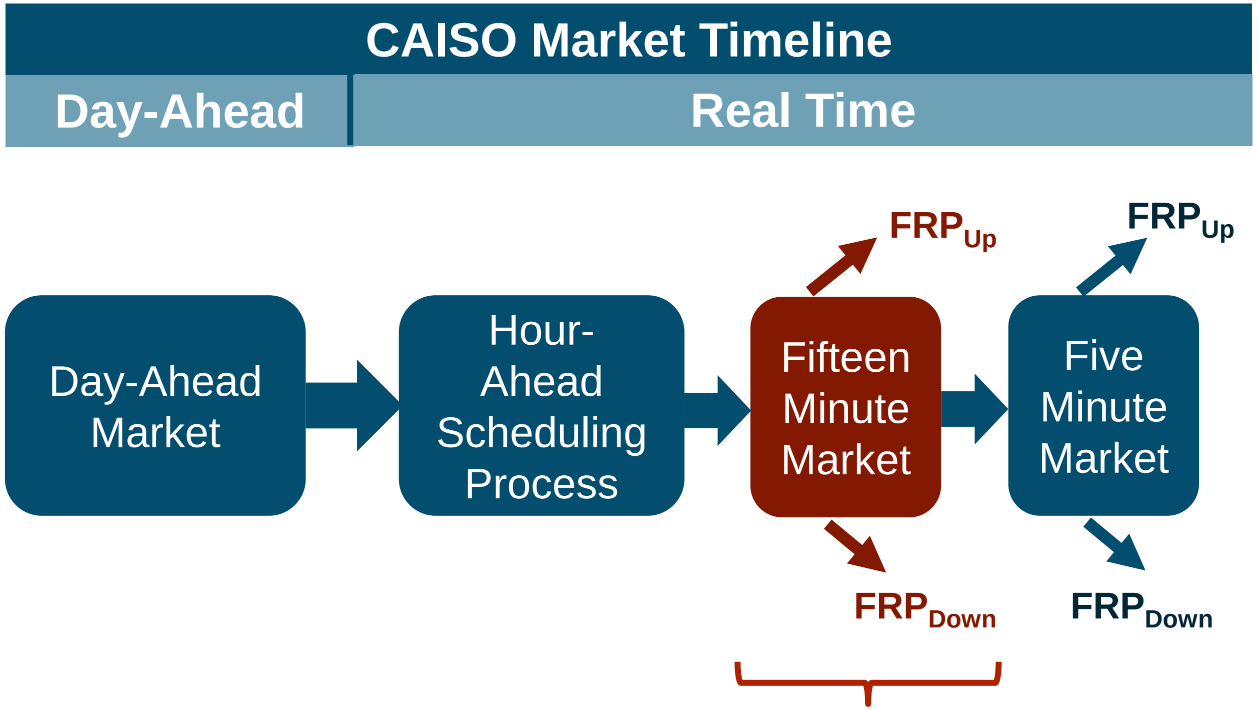
Summary and CAISO Comparison

- Compare machine learning reserves to CAISO current practice
- Estimate cost, GHG and curtailment savings

+ **E3 Team:** Adrian Au + Charles Gulian + Saamrat Kasina + Jimmy Nelson + Patrick O’Neill + Arne Olson + John Stevens + Yuchi Sun + Vignesh Venugopal + Mengyao Yuan
+ **ARPA-E PERFORM program provided grant funding**
+ **CAISO was our industry partner**

ARPA-E study focused on CAISO Flexible Ramping Product (FRP) as a proof-of-concept

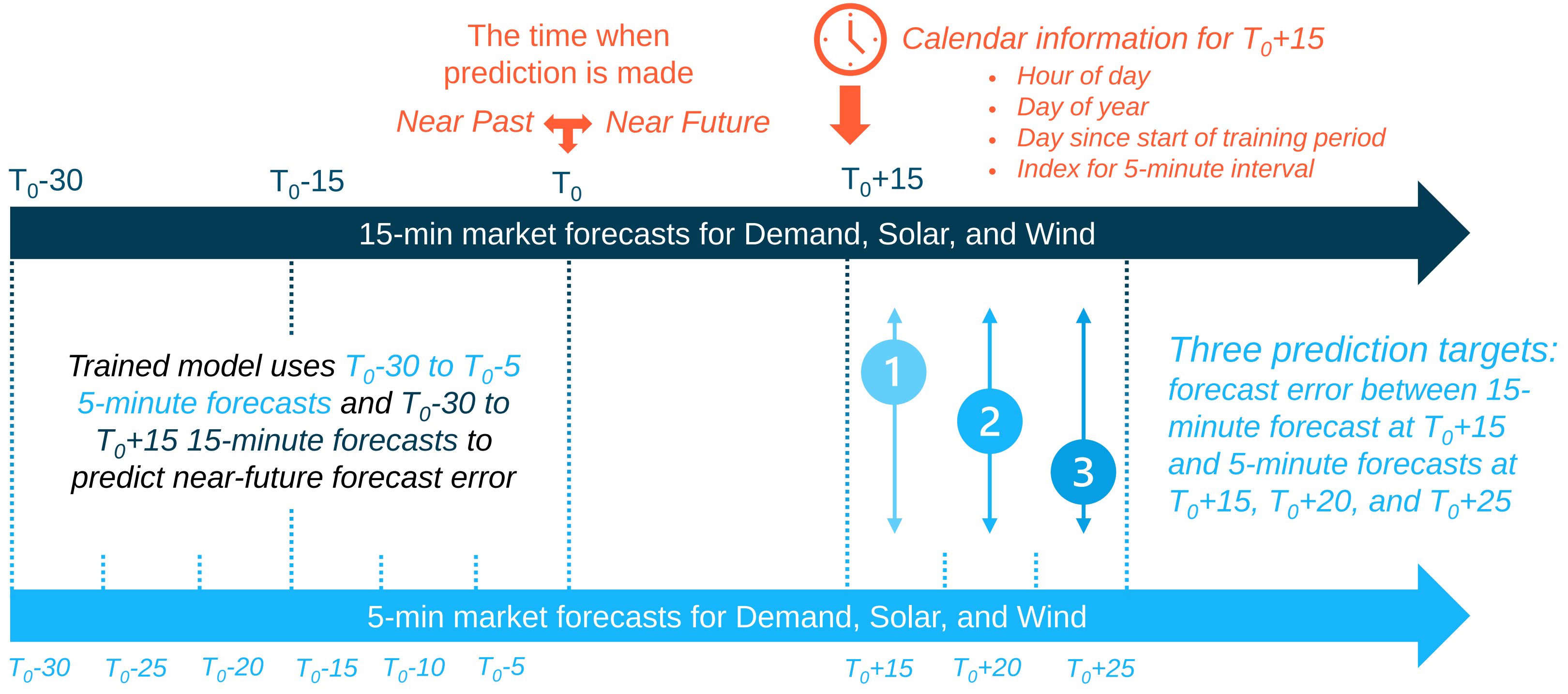
- **FRP is a 15-minute reserve product implemented in CAISO's Energy Imbalance Market**
  - Ensures each participating BAA has sufficient flexibility for the EIM to clear
  - FRP is a requirement for EIM participation but is not a cleared market product
- **Machine learning model can provide additional benefits if extended to other timeframes:**
  - Day ahead market, 5-minute market, Regulation (sub 5-min)



Our project calculates 15-minute Flexible Ramping Product (FRP) Up and Down requirements
The goal of 15-minute FRP is to reserve enough flexibility for successful 5-minute market operation

RESERVE Machine learning model inputs

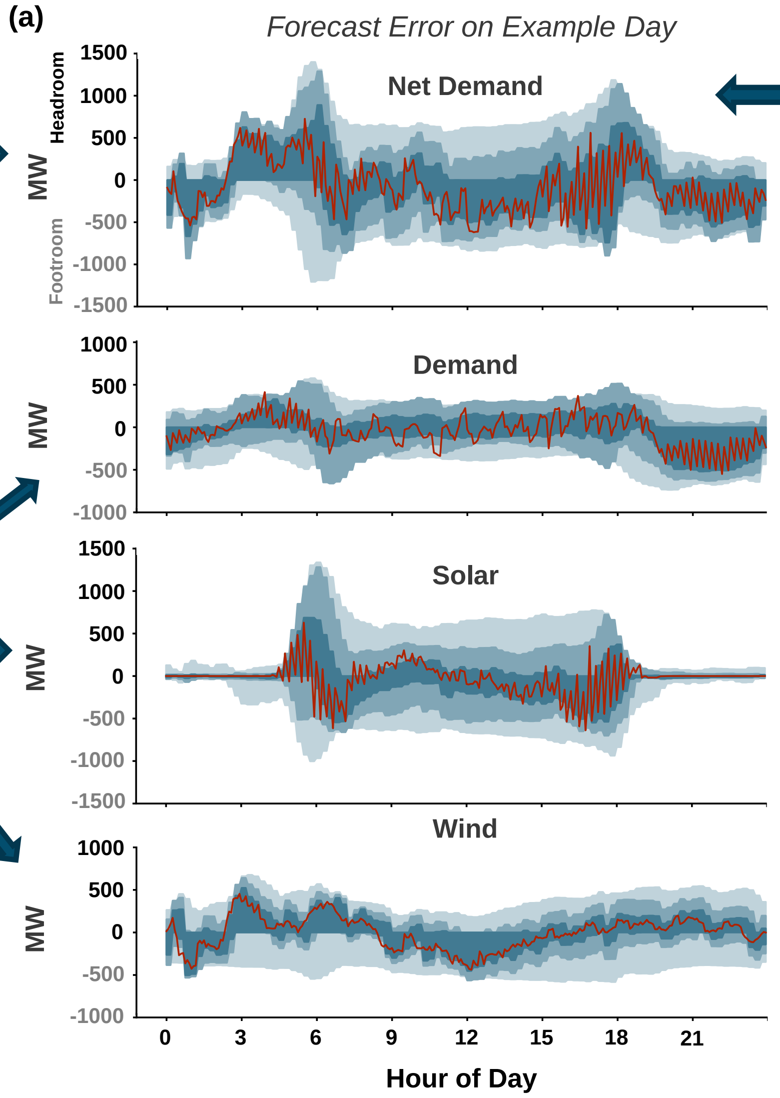
- **RESERVE takes in load, wind and solar forecasts and assembles them into a composite net load forecast error distribution using an artificial neural network**



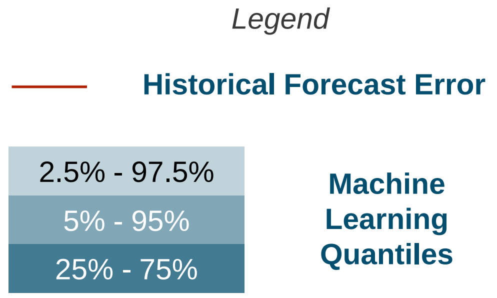
Example day machine learning model timeseries show ability of machine learning to predict forecast error

Net load forecast error…

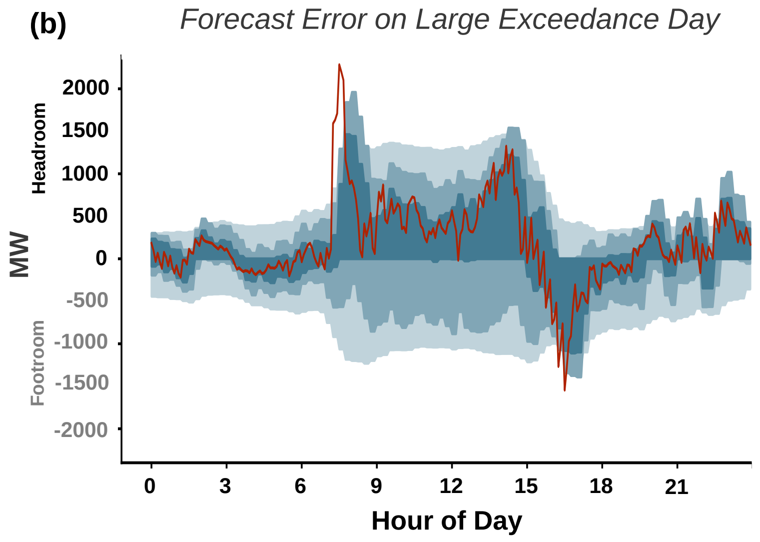
is assembled from the individual constituent components



Dynamic based on grid conditions…

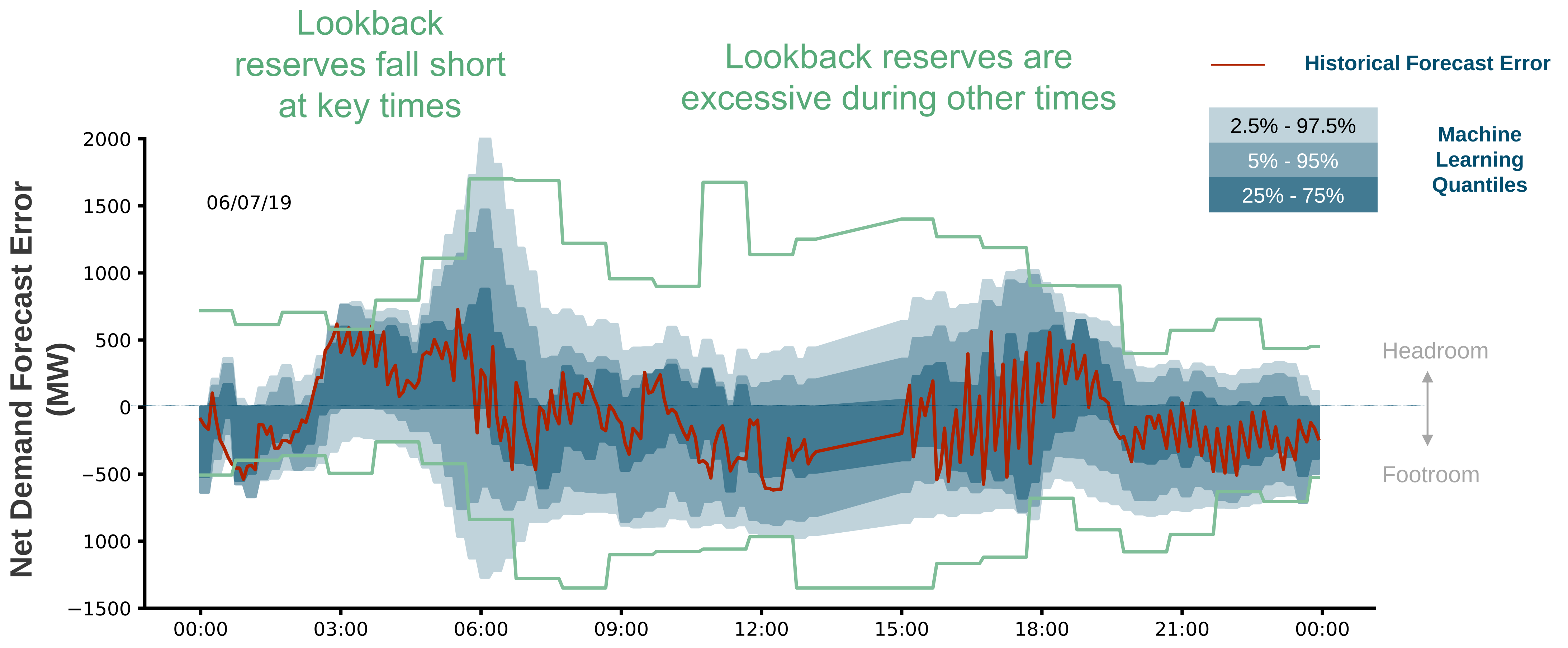


More dynamic when grid conditions are more dynamic…



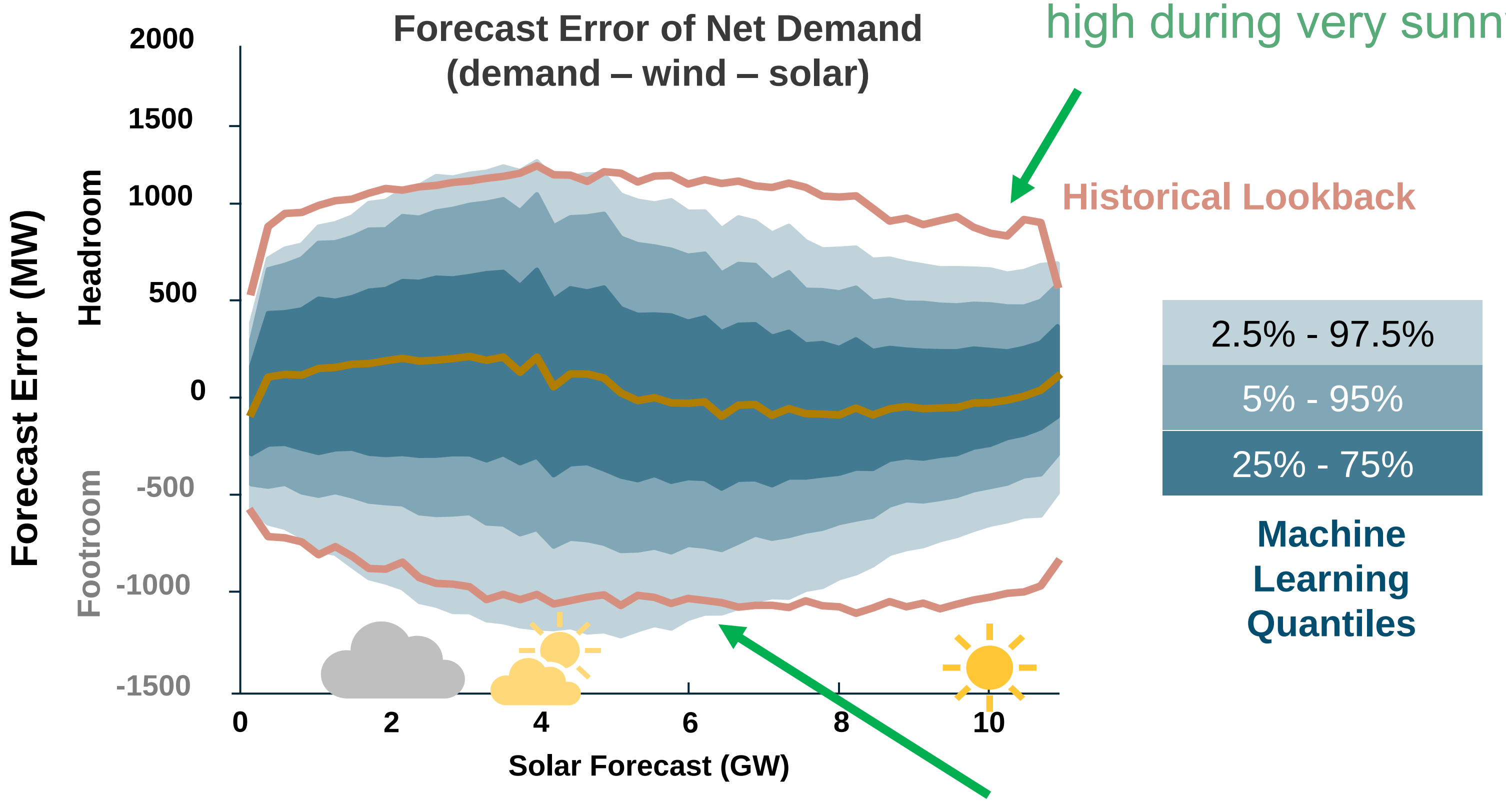
CAISO's historical lookback reserves are not as dynamic as E3's machine learning reserves

CAISO's current "histogram" method uses a rolling 20-40 day window before the current day to calculate reserves needs



Machine learning predictions capture error trends as a function of renewable generation

Lookback reserves are too high during very sunny hours



Lookback reserves are too low during partly-cloudy periods

Reserve needs are asymmetrical and are a function of VRE generation

RESERVE performance is a significant improvement compared to CAISO histogram method

- RESERVE gets close to 97.5% coverage target
- RESERVE reduces FRP need by 20% on average
- RESERVE's "misses" are 30% smaller
- RESERVE max misses are *much* smaller

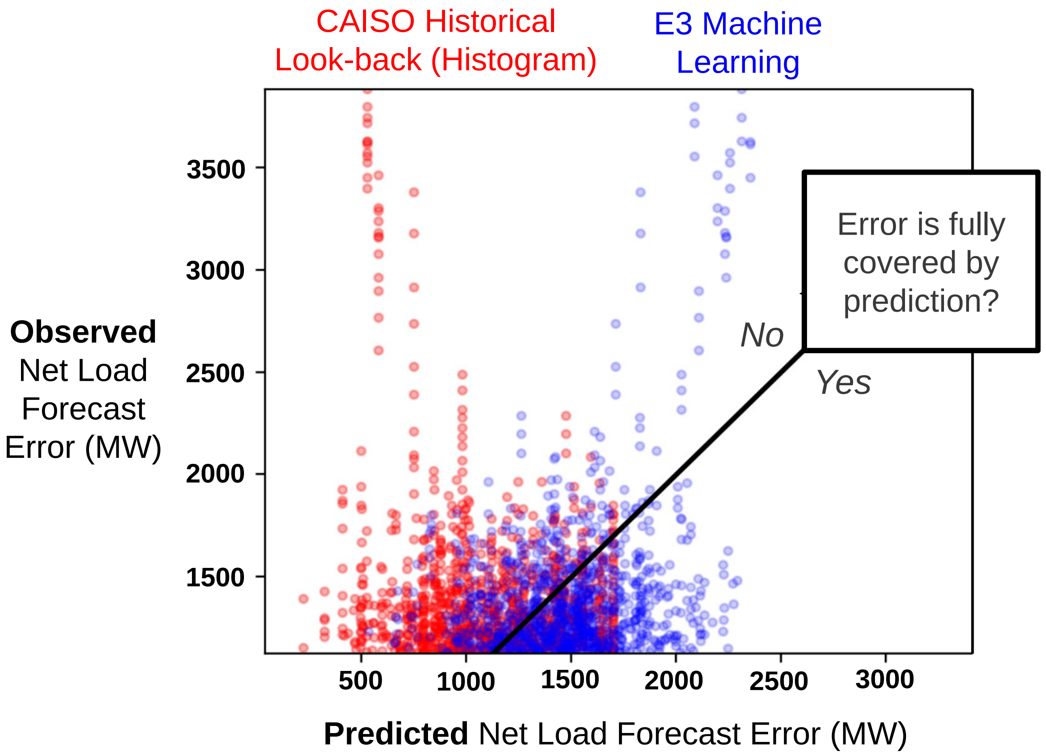
Performance Metric	Definition	Units	Headroom (Upward Ramping)		Footroom (Downward Ramping)	
			CAISO Incumbent	RESERVE	CAISO Incumbent	RESERVE
Coverage	Percent of forecast errors covered by reserve requirement (target is 97.5% coverage)	%	94.4	97.3	92.8	96.6
Average Requirement	Average of predicted forecast error at targeted quantile	MW	776	614	786	726
Average Exceeding	Average size of excesses when observed forecast error exceeds model prediction	MW	234	152	220	175
Maximum Exceeding	Maximum size of excess when observed forecast error exceeds model prediction	MW	3,353	1,705	2,652	1,983

Note: CAISO is updating to a quantile regression methodology which is expected to improve performance metrics relative to the incumbent histogram method

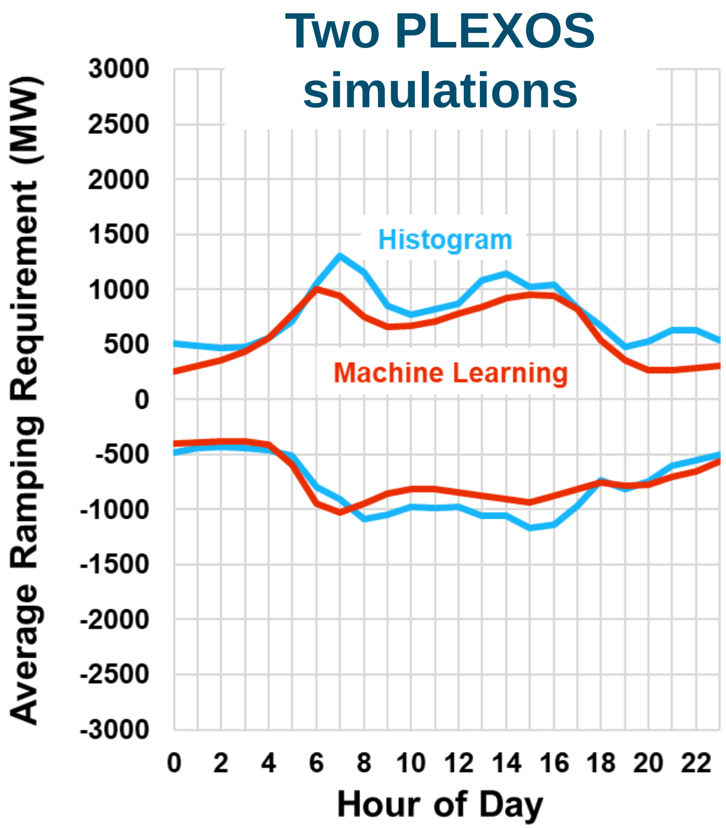
RESERVE performance advantage is magnified under extreme forecast error events

- Under extreme net load underforecast, RESERVE significantly reduces exceedance versus the CAISO histogram method
- RESERVE increases FRP by as much as 2000 MW over the histogram method during the most extreme events
- Reducing exceedance under extreme forecast error can be beneficial for system reliability

Predicted vs. observed forecast error during **extreme net load under-forecasts**



Retrospective modeling of 2019 using PLEXOS demonstrates potential cost and GHG savings



What are the savings from machine learning reserves?

Production cost savings	$19 M/year = 0.4% of production costs
GHG Savings	0.13 $MMTCO_2$/year = 0.2% of CAISO GHG emissions
Solar curtailment reduction	225 GWh = 19% reduction in curtailment

Savings are approximately doubled if flexible solar ramping is included

Savings are reduced significantly under very high battery penetrations

+ **Actual savings may be lower due to ability to procure ramping capacity from outside of CAISO**
+ **CAISO is updating their FRP requirement calculation methodology, likely capturing some of the benefits shown here**

Next Steps for RESERVE

- **E3 is utilizing RESERVE for planning projects with multiple utility clients**
  - Training utility staff to operate RESERVE to easily generate vectors of operating reserves under alternative renewable penetrations to inform resource planning and procurement
- **E3 is discussing additional applications of RESERVE in day-ahead scheduling and operations**
  - Calculate operating day headroom and footroom needs to inform day-ahead unit commitments and wholesale power trading activities
- **E3 is working on additional applications of machine learning techniques to related problems**
  - Inform battery state of charge requirements to ensure sufficient reliability services
  - Incorporate thermal power plant outage risks

Upcoming publication: Sun, Nelson, Stevens, Au, Venugopal, Gulian, Kasina, O'Neill, Yuan and Olson, "Machine Learning Derived Dynamic Operating Reserve Requirements in High-Renewable Power Systems", Journal of Renewable and Sustainable Energy (in press) (2022); https://doi.org/10.1063/5.0087144

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Thank You!

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