Coordinated Ramping Product and Regulation Reserve Procurements in CAISO and MISO Using Multi-Scale Probabilistic Solar Power Forecasts

Johns Hopkins University (JHU), International Business Machine (IBM), National Renewable Energy Laboratory (NREL), University of Texas Dallas (UTD), California ISO, and Midcontinent ISO

FOA Topic Area 3: Power Forecasts and Operational Integration

Solar Forecasting FOA II

Kick-off Meeting

Washington DC

July 12, 2018

Outline

Introduction

Summary, Motivation, Outcomes & Team

Technical Approach

Thrusts (Methods, Tasks, Milestones, Impacts)

INTRODUCTION

Project Summary

Objective: Integrate probabilistic short- (0-6 hr ahead) and mid-term (day-ahead) solar power forecasts into operations of two ISOs:

- CAISO
- MISO

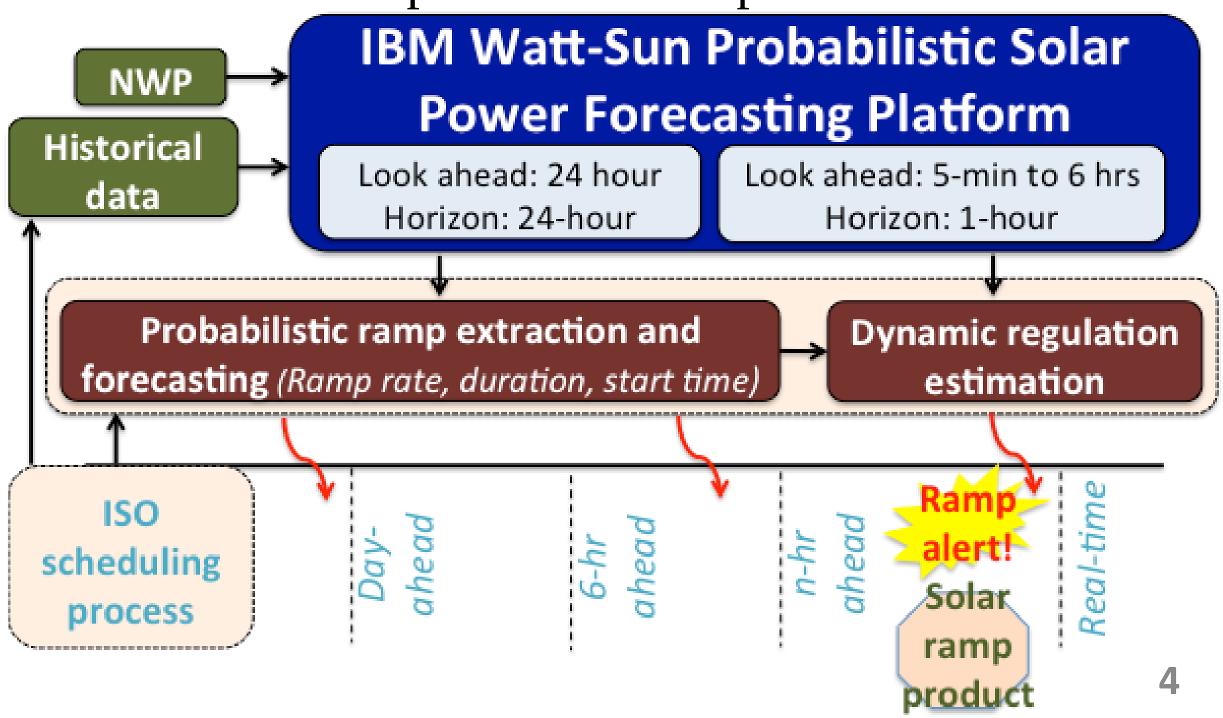
Approach:

1. Advanced big data-driven "probabilistic" solar power forecasting technology

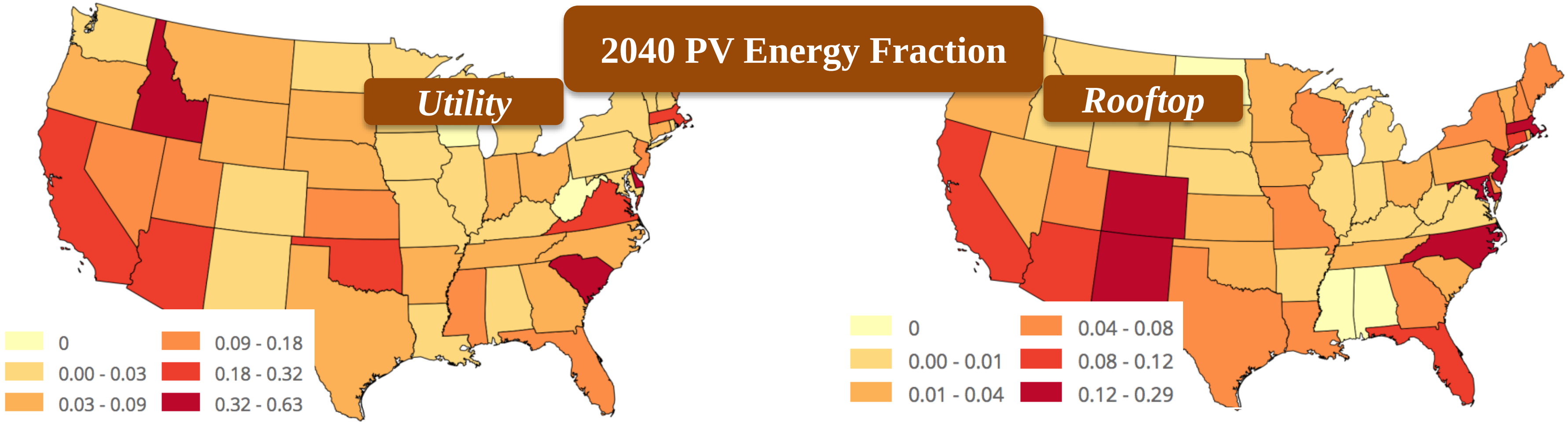
- IBM Watt-Sun & PAIRS: **Big data** information processing (Hadoop, HBase)
- **Machine learning approaches** to blend outputs from multiple models

2. Integrate probabilistic forecasts in ISO operations for *ramp product* & *regulation* requirements

3. Provide **situational awareness via control room visualizations** of probabilistic ramp forecasts & alerts

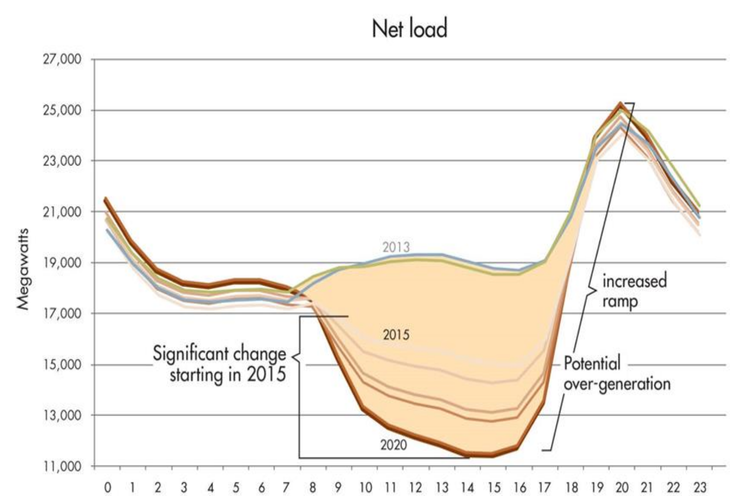


Project Motivation: (1) System Operations



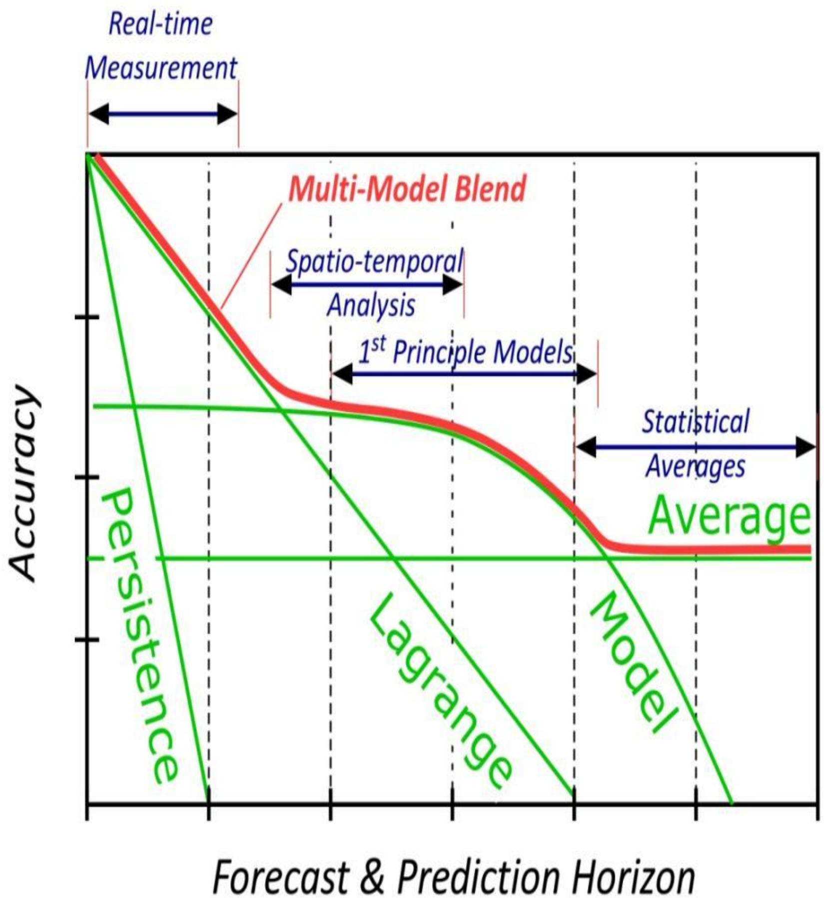
Source: NREL's Standard Scenarios 2016 from ReEDS model

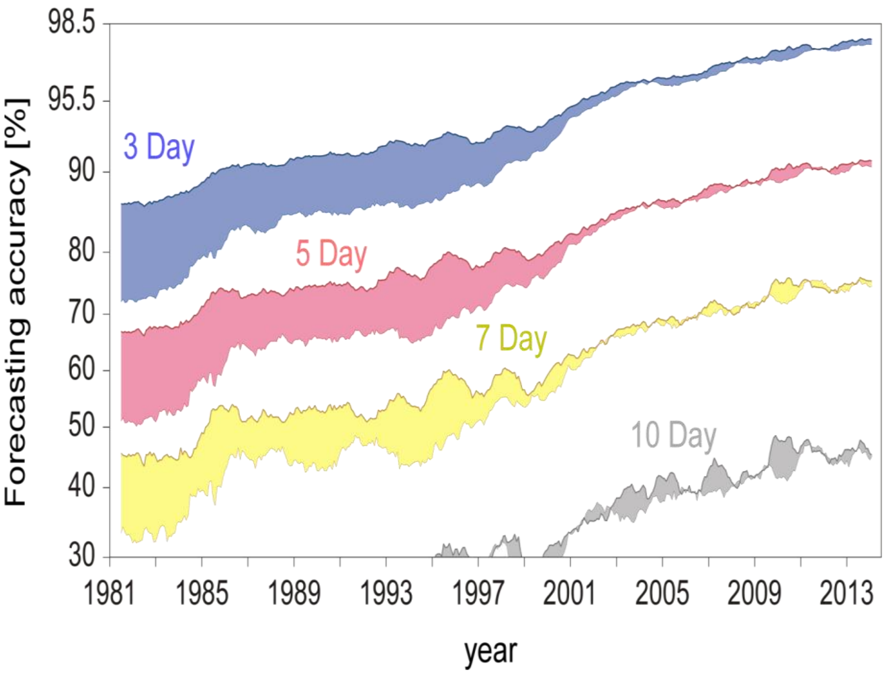
- Growing PV → Ramping & reserves issues
- **Current reserve procurement practice:** based on historical data and off-line analysis
  → Requirements that are ***too conservative*** for most conditions, but ***inadequate*** for other conditions



Procurement needs <u>up-to-date information on energy forecasts</u> and <u>their uncertainties</u> to reflect the actual risks of load imbalances

Project Motivation: (2) Solar Power Forecasts





Challenge: historic NWP model accuracy improvements (only) ~6% per decade

Source: P. Bauer et al., doi:10.1038/nature14956

Opportunity: Leverage *"big" data platform* & *advanced machine learning-based analytics* to complement NWP models
→ high-fidelity probabilistic forecasts, and adaptive & more accurate forecasts

Expected Outcomes

1. **Probabilistic solar power forecasting technology**, ensuring better:
    - *Accuracy* (>15-30% Brier Score compared to baseline (28 consecutive days))
    - *Reliability* (>80-90% coverage index of probabilistic forecasts)
2. **Forecast access** via IBM big data infrastructure & NREL visualizations:
    - *temporal* horizons of 5-mins to days-ahead
    - *spatial* resolution of 1-4 km across the continental US
3. **Improved ramping & regulation reserve procurement** across all time frames of market scheduling using probabilistic forecasts
4. **ISO testing that shows annual savings** of ≥10-25% ($O(\$10^7)$) **in regulation & flexible ramping product procurement** under high solar penetration conditions (→reduced customer costs)

Project Team

Collaboration of academia, a national laboratory, a private vendor, and ISOs

TEAM MEMBER	EXPERTISE
Benjamin F. Hobbs, Ph.D., **PI** Theodore M. and Kay W. Schad Chair of Environ. Mgmt., **Johns Hopkins U**	Chair of CAISO Market Surveillance Committee. Decision analysis & economics for power markets, planning, & operation
Hendrik F. Hamann, Ph.D. Senior Manager and Distinguished Research Staff, Physical Sciences Department, **IBM**	Sensor-based physical modeling, big data analytics, high performance microprocessor and storage designs. *Solar Forecasting FOA I awardee, NE-ISO BTM forecasts*
Jie Zhang, Ph.D Asst. Professor, Mech. Engineering, **U Texas-Dallas**	Optimization, complex systems, renewable energy forecasting, big data analytics & probabilistic design
Venkat K. Krishnan, Ph.D. Senior Engineer, Power System Design & Studies Group, **NREL**	Co-optimized electricity markets, capacity expansion planning, statistical simulations, and data analytics
Amber L. Motley, **California ISO**	Manager, Short Term Forecasting
Blagoy Borissov, **MISO**	Manager, Forecast Engineering

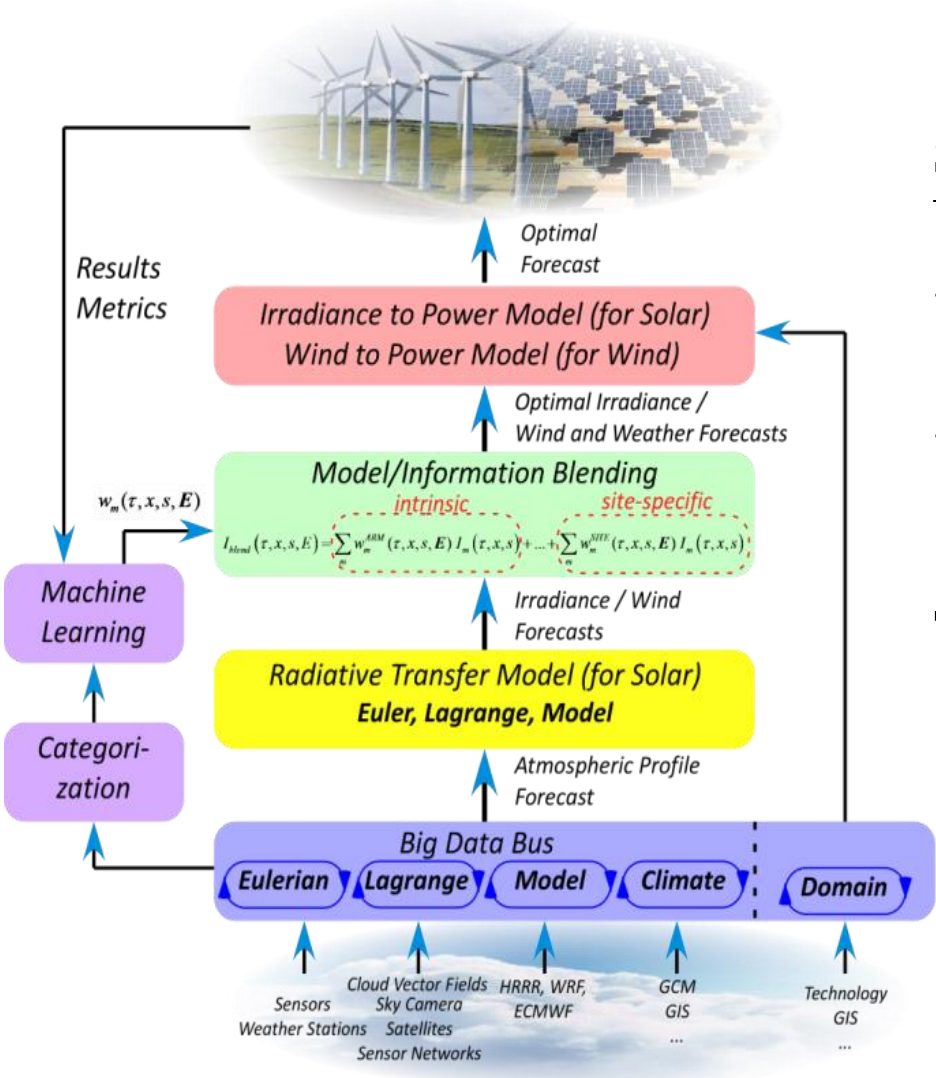
Co-ordination with Topic Area 1 team for validation: data formats and sharing, metrics for evaluating probabilistic solar power forecasts etc.

TECHNICAL APPROACH, TASKS & MILESTONES

Major Research Thrusts

Thrust 1	• Advanced big data-driven probabilistic forecasting
Thrust 2	• Flexible ramping & dynamic regulation procurement
Thrust 3	• Advanced visualization for situational awareness
Thrust 4	• Coordination with ISO and integration testing

Thrust 1: Advanced big data-driven probabilistic forecasting system



Situation-dependent model for blending-based forecasts:

- Apply deep machine learning with historical forecasts and weather data
- Learn which model is better, when & where

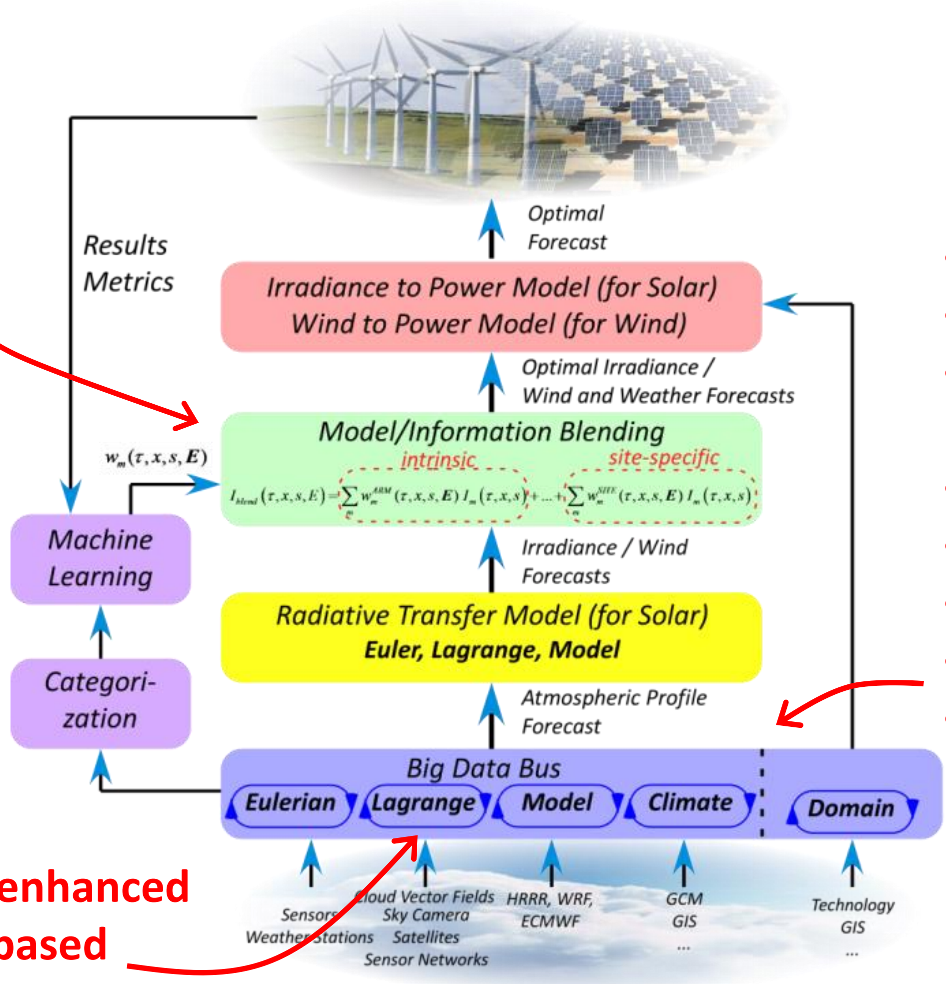
Technologies:

- Uses **big data** information processing (Hadoop, HBase) technologies
- Applies **machine learning approaches** to blend outputs from multiple models

Relationship of SF-I and SF-II
Four Enhancements to Watt-Sun

4. **Probabilistic forecasts**

3. **Deep learning** for categorization



1. **Replacement with PAIRS**
- Automatic data fusion
- Fully scalable
- Supports tens of Petabytes
- Improved curation speed
- Scalable API
- SDK
- Mapping service
- Enables "in-data" computation

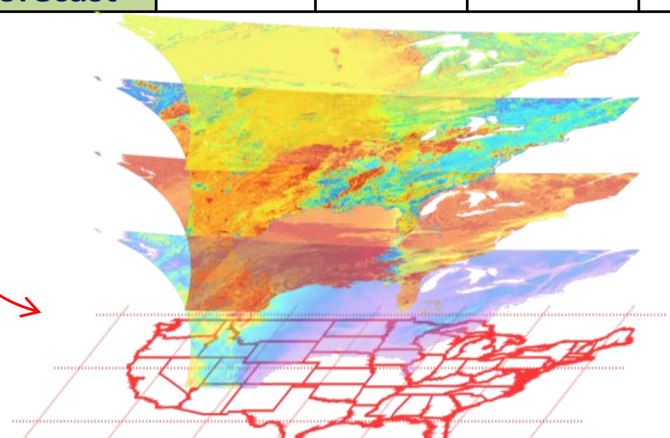
2. **Navier-Stokes enhanced optical flow based short-term forecasting**

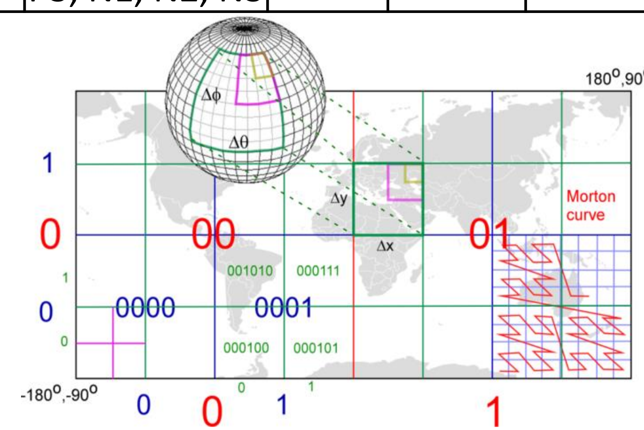
PAIRS Big Data Platform

Physical Analytics Integrated Data Repository and Services (PAIRS)

Harmonized data curation: Aligned to a global spatio-temporal reference & indexing system

	Lagrangian		*Weather Forecast Models*						*Climate*
Models	**Sky Cam**	**GOES**	**RAP**	**HRRR**	**SREF**	**NAM**	**GFS**	**ECMWF**	**CFS**
Spatial Res. & Coverage	Local 10 m	Global 4km	US 13km	US 3km	US 16km/ 40km	US 5km	Global 0.5 deg	Global 0.1 deg	Global 0.5 deg
Temporal Resolution	1 min	15 min	15 min 2D, 1 h 3D	15 min 2D, 1h 3D	1 h (40 km); 3 hr (16 km)	1 hr	3 h	1 h	6 h
Forecasting Horizon	10 min	4 h	18 h	15 h	0-87 h	0-60 h	6-192 h	0 -60 h	6 mo
Ensemble Forecast	No	No	No	No	CTL, P1, P2, P3, N1, N2, N3	No	No	N.A.	4 members





Innovation

- **Multi-expert machine-learning systems** for probabilistic forecasting: characterize errors & uncertainties

- **Improve PAIRS to achieve higher data ingestion** and curation rates of >50TB/day through parallel computation. Challenges due to sheer data volume:
    - Global forecast system data @1.5 TB/day
    - Global ensemble forecast system data @3 TB/day
    - GOES-R/16 satellite can generate up to 16 TB/day

- **Behind the meter (BTM) solar forecasting** using ISO load data plus selective irradiance measurements across a region

Goal: Improve accuracy of short-term forecasts by ≥10-20% compared to the state of the art, including rare ramp events

Thrust # 1 Milestones

List of key milestones related to forecast products.
(Publications, release of products via web links, etc. not shown in tables)

Due	Description	Success Value
BP 1		
Q1	Demo #1- **Watt-Sun V0.0 probabilistic** solar power forecasts. Purpose: demonstrate probabilistic scores capability	**Mean Brier Score** < 0.5 for 28 consecutive days (1 site using 4-hr forecasts)
Q4	Demo #2- Improved **Watt-Sun** (**V1.0**) **probabilistic** solar power forecasts (4-hr ahead, every 15-min.)	• Average > 10% for 28 consecutive days for 3 point sites • Brier accuracy > 10% better than best persistence-based baseline models
BP 2		
Q7	**V2.0-** Advanced **Watt-Sun probabilistic** forecasts (4-hr & 24-hr ahead), **shared with Topic Area 1 validation team**.	Average > 15% improvement for 28 consecutive days for >6 point sites in CAISO & MISO
Q5	PAIRS platform advancement complete for continental US regions, (scalable data curation rate and multiple data sources integrated)	At least 10 TB/day for > 5 consecutive days.
BP 3		
Q11	**V3.0-** Advanced **Watt-Sun probabilistic** forecasts (4-hr, 24-hr ahead) for 6 points, **shared with Topic Area 1 validation team.**	Average > 30% improvement for 28 consecutive days in 3 separate months for >6 points sites in CAISO & MISO

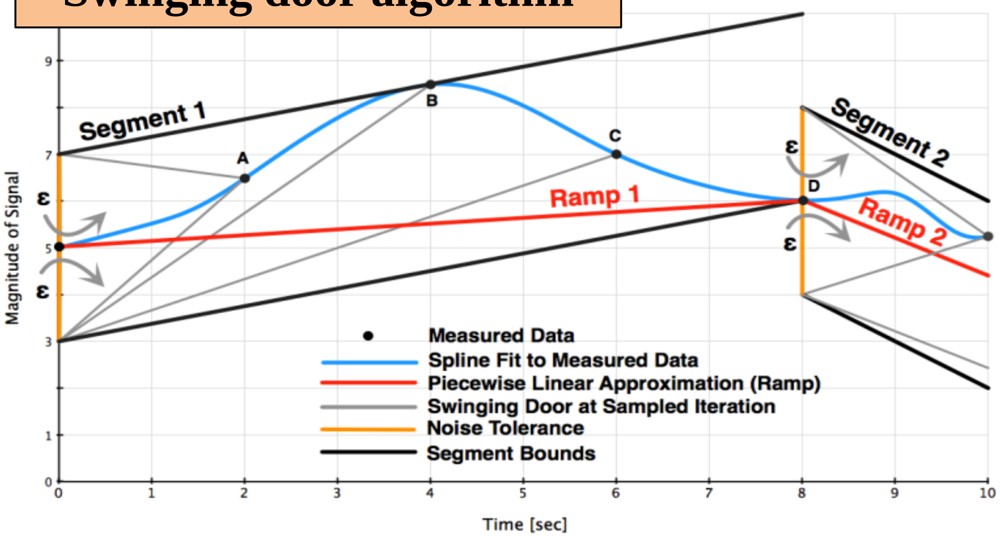
Thrust 2: Modeling coordinated reserve requirements using probabilistic forecasts

CAISO & MISO: Base reserve requirements on off-line analysis of historical data

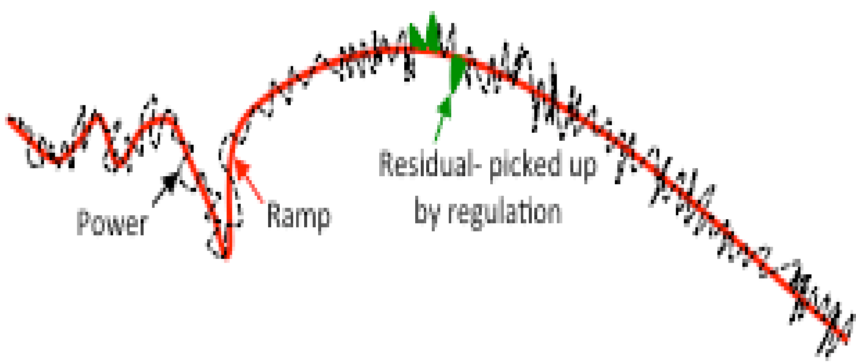
→ Costly over-procurement, & risky under-procurement

→ Need a robust, dynamic update of requirements based on latest *probabilistic* forecasts and realistic error probability distributions

Swinging door algorithm



Ramp and regulation services: intrinsic relationship



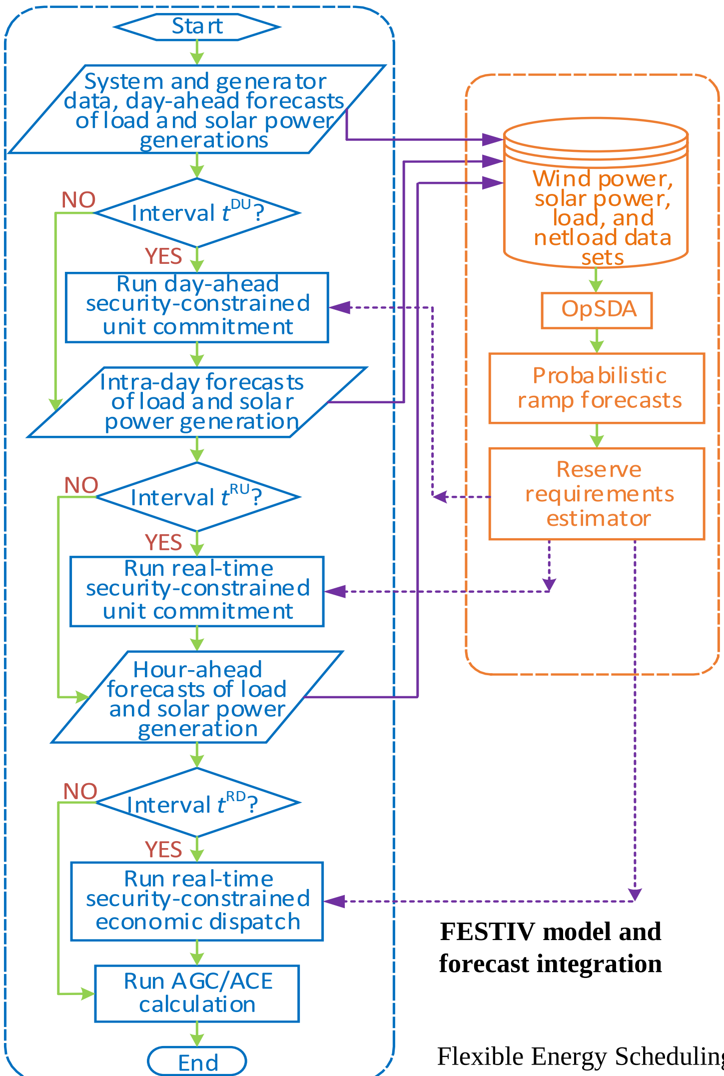
$$Ramp\ Up\ Req_t = \max\{0, \widehat{Netload\ forecast}_{t+5min} - Netload_t + \alpha\sigma_{t,5min}\}$$

$$Ramp\ Down\ Req_t = \max\{0, Netload_t - \widehat{Netload\ forecast}_{t+5min} + \beta\sigma_{t,5min}\}$$

Probabilistic forecasts

Cui, M., Zhang, J., et al. (2016), An Optimized Swinging Door Algorithm for Identifying Wind Ramping Events, *IEEE Trans. Sust. Energy*, 7(1), 150-162

Market Impact Assessment



FESTIV model and forecast integration

Flexible Energy Scheduling Tool for Integration of Variable Generation (FESTIV)

- Ramp & regulation procurement passed on to ISO scheduling procedures
  - Align process with well-documented ISO procedures
- Test on Modified IEEE 118-bus test system with high solar penetration
  - Resource mix, load, and solar profiles that mimic ISOs
- Metrics:
  - *Economic:* Production costs, prices (average & spikes), make-whole payments
  - *Reliability:* Quick starts, area control error, and Control Performance Standard 2

Thrust # 2 Milestones

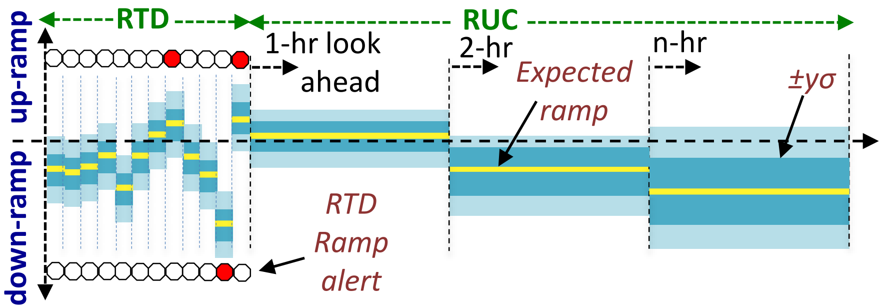
Most important ones related to testing with IEEE 118 bus system listed.

Due	Description	Success Value
BP 1		
Q3	Solar production & net load ramp predictions from OpSDA using **V0.0** of Watt-Sun forecasts. *Predictive intervals coverage probability* (PICP) to measure reliability of ramp predictions.	Targets for key ramp features (magnitude, duration, rate) in solar power and netload: • PICP>90% (1-hr or intra-hr forecasts) • PICP>80% (day-ahead forecasts) For 3 points in high solar system for day-ahead and hours-ahead forecasts.
Q4	Ramp product and regulation requirements estimates using **V0.0 & 1.0** probabilistic forecasts	Requirements with probabilistic solar forecasts 10% less than those with deterministic forecasts.
Q4	Integrate flexible ramp product procurement estimates from probabilistic net-load forecasts. IEEE 118 bus system simulations under high solar conditions	10-25% yearly cost savings, based on incremental costs of ramp product procurement from solar forecasting errors
BP 2		
Q8	Ramp product & regulation requirements estimate using **V2.0** probabilistic forecasts	Requirements with probabilistic solar forecasts 15% less than those with deterministic forecasts

Go/No-Go # 1

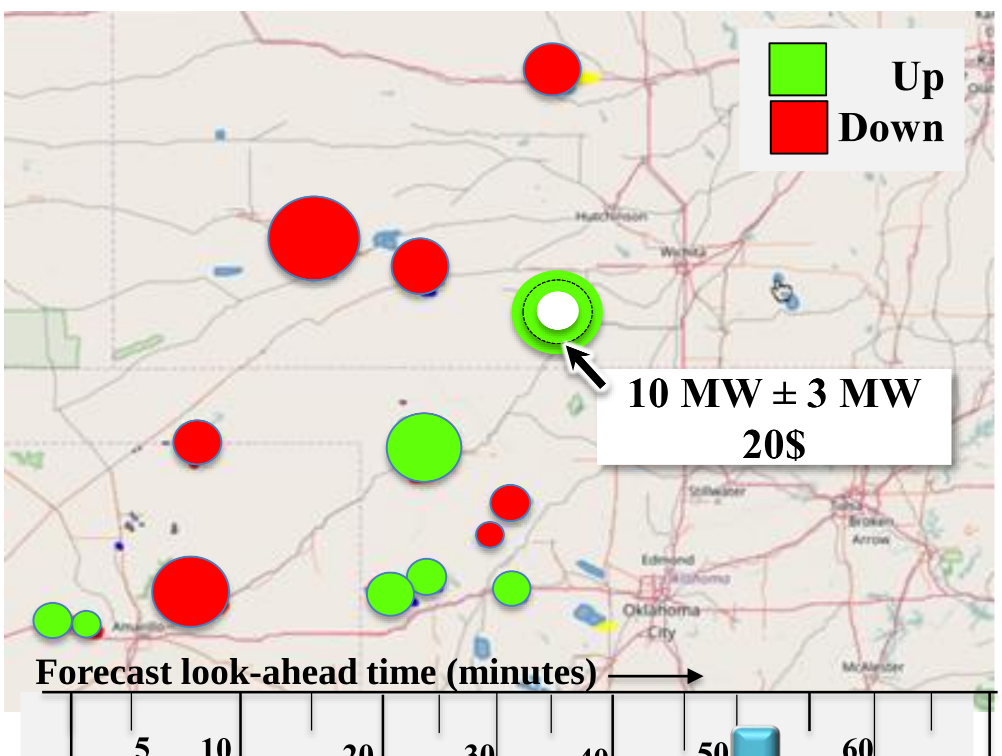
For Thrust #4 testing on ISO scale systems

Thrust 3: Visualization of probabilistic ramp forecasts for situational awareness



Will provide:

1) **Forecasted net-load ramps and their uncertainties**
2) **"Ramp alerts"** at shorter time scales, *when ramp forecast > available capability*



Site-specific solar ramp visualization

Regional solar power ramp forecasts: Can identify economic curtailment options in event of ramping alerts

Thrust # 3 Milestones

Due	Description	Success Value
BP 1		
Q2	**Prototype #1- tool** demonstration & functional specification with **V0.0 Watt-Sun** outputs.	Demo of visualization to ISO and DOE, with Watt-Sun data at backend.
BP 2		
Q6	**Prototype #2- tool** demonstration & functional specification with **V1.0 Watt-Sun** outputs.	Same
BP 3		
Q12	**Final Version** - tool demonstration and functional specification with **V3.0 Watt-Sun** outputs. Demo of ramp alerts, regional ramps, and identification of possible economic solar curtailment under ramp deficit conditions	Same

Milestones also target definitions of visualization tool's functional requirements, software layers, input-output requirements, forecast update rates, scripting language, & qualitative comparisons to existing EMS visualizations

Thrust 4: Co-ordination with ISOs to test forecast integration

<u>Testing 1</u>- Market simulations of ISO systems under different scenarios (e.g., baseline, %solar energy, gen retirements, gas prices, %reserves)

- Using large-scale, extensively reviewed power system models & data

<u>Testing 2</u>- Testing & demonstration in coordination with ISO in-house simulation capabilities and/or market dispatch data

- Forecasting methods & performance to be validated with ISO data (internal validation)
- Operator consultations

Integration Benefit Assessment

Using the most up-to-date information will allow requirements to better reflect the actual risks of load imbalances, and avoid over-conservativism

- CAISO real-time ramp product costs ~$25M/yr
  - *Likely increase with day-ahead procurement*
- CAISO regulation services ~$80M/yr (2016-2017)
  - *~Doubled recently due to more variable renewables*

Preliminary ISO reports on deployment uncertainties → ~10-25% reduction in ramp forecast error appears achievable if forecast information can be better reflected

→ ~$10M-$25M/yr savings

CAISO Department of Market Monitoring, "Report on Market Issues and Performance", various years & quarters

Thrust # 4 Milestones

Most important ones related to integration success listed.

Due	Description	Success Value
BP 2		
Q6	**Technical feasibility** of probabilistic forecasts: • integration forecast formats • frequency of updates for DA & RT integration • reserve requirements formats. **Logistical feasibility**: Integration with ISO energy management systems (dispatch, unit commitment).	Report developed with ISO collaboration
Q8	**ISO system simulations** and cost-benefits of forecast integration under different scenarios	Identify conditions achieving >10-25% yearly cost savings in flexible ramping product procurement (compared to baseline)
BP 3		
Q10	**Testing:** Forecast & ramping product/regulation estimation integration for several days; observe: • generation dispatches • clearing prices • system costs.	Report to ISO and DOE, with ISO feedback
Q12	**Final report** on feasibility & economic impacts from testing integration of probabilistic solar power forecasts for coordinated ISO ramp product & regulation procurement (ISO and/or NREL in-house simulations).	• >12% cost savings compared to baseline. • Report to ISO and DOE, with ISO comments and pathways for market adoption

Go/No-Go # 2

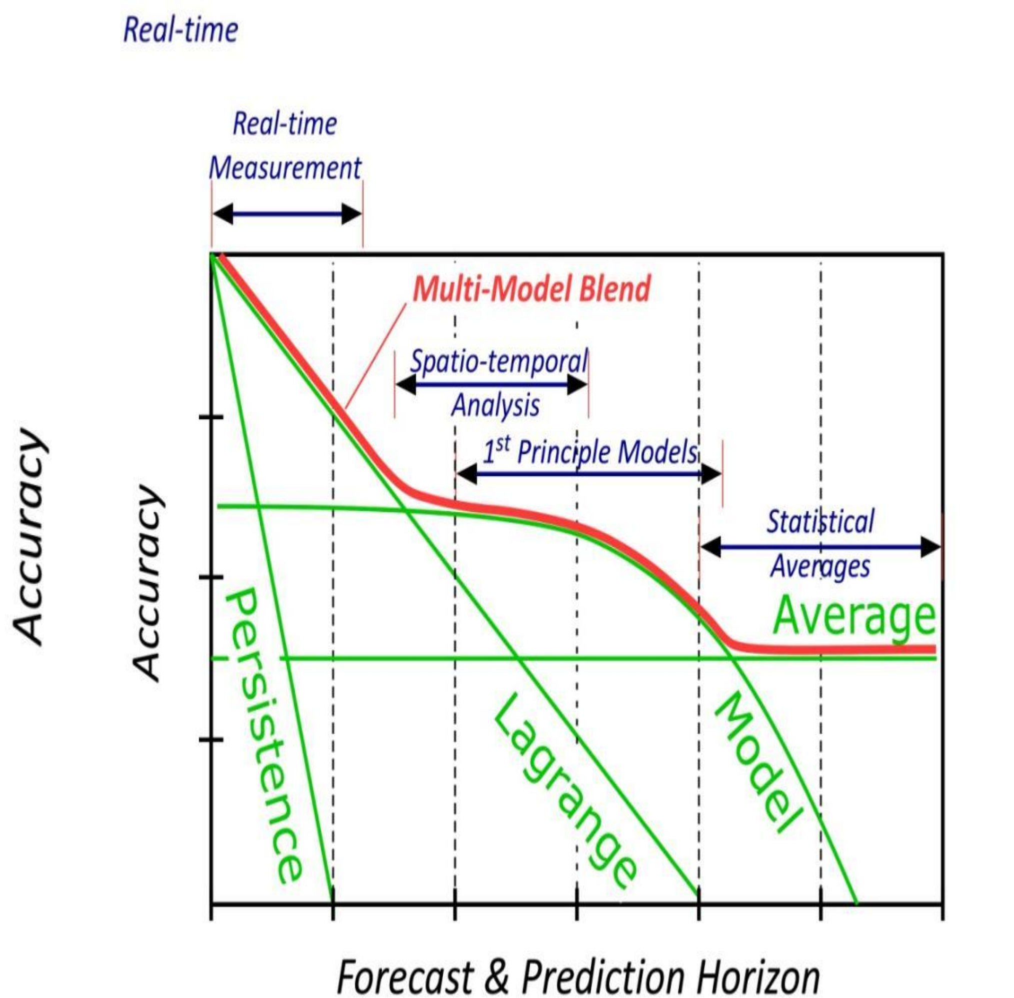
Summary: Impact & Significance

- Probabilistic forecasting approach will **significantly transform the forecasting software market** (for solar power, load and wind)
- **First-of-a-kind integration testing of probabilistic forecast integration in a ISO environment**:
  - → Pave way for grid transformation
  - → Facilitate meeting SunShot goals (100s GW of solar; lower customer costs)
- Enhance, but not reformulate, existing ISO optimizations by supplying probabilistic forecasts in the form of reserve procurement targets & visualization aids.
  - → **Creates a low risk, fast-track, & high impact pathway for integrating probabilistic forecasts**

Extra Slides

Multiple information and data sources are being fused to create a super forecast

- **Persistence:**
  - Real-time power data
  - Weather station data
- **Lagrangrian Forecast Models:**
  - Sky camera model
  - Satellite-based (GOES), advectio models
  - Time-series models
- **Weather Forecast Models:**
  - Rapid Refresh (RAP)
  - Hi-Resolution Rapid Refresh (HR
  - Short-Range Ensemble Forecast (S
  - North American Mesoscale Foreca (NAM)
  - Global Forecast System (GFS)
  - European Center for Medium rang Weather Forecasting (ECMWF)
- **Climate Models:**
  - Climate Forecasting System (CFS)



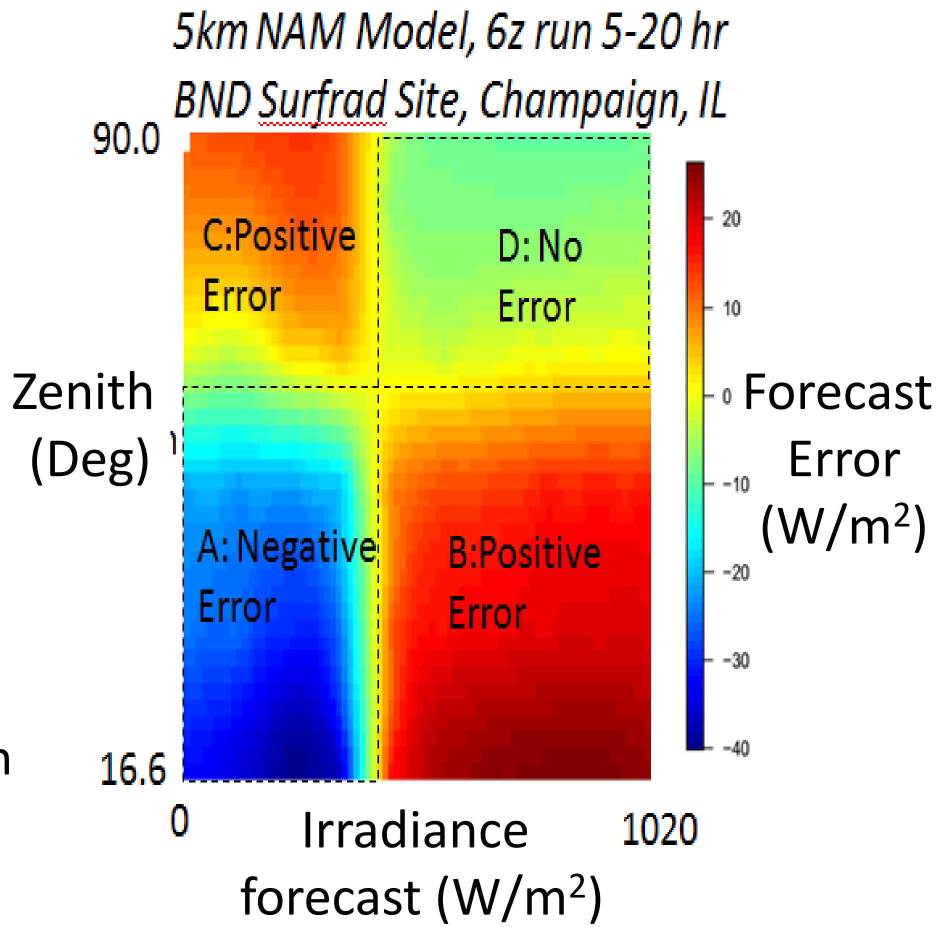
Improving accuracy using situation dependent, machine-learnt, multi-model blending

Question: Which model is more accurate, when, where, under what weather situation?

- Apply functional analysis of variance to understand 1st,2nd,3rd, ….order errors
- Model accuracy can depend strongly on **“weather situation”** category**.**
- “Weather situation” is determined using a set of parameters including forecasted ones on which model error depends on strongly.

Example, NAM solar irradiance forecast

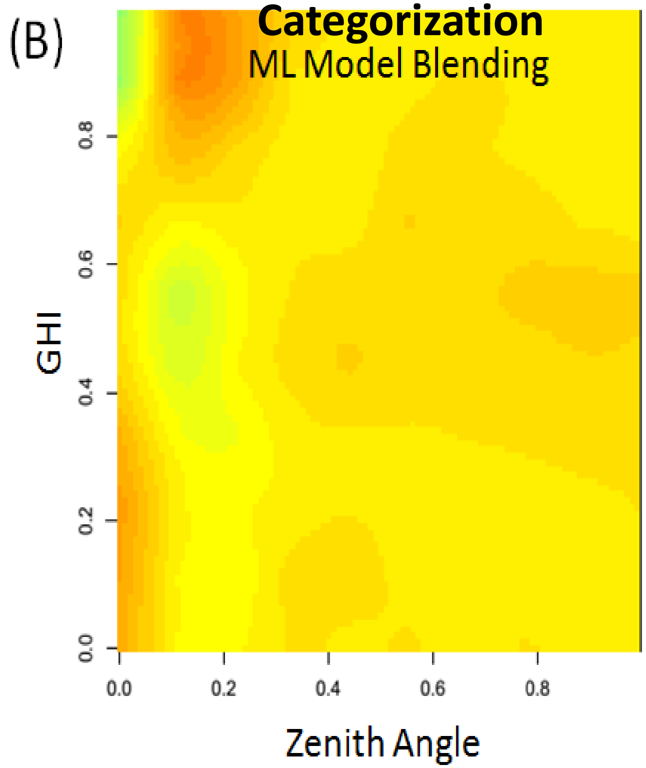
- Depends strongly GHI and solar zenith angle.
- The two parameters create four categories of situations below.



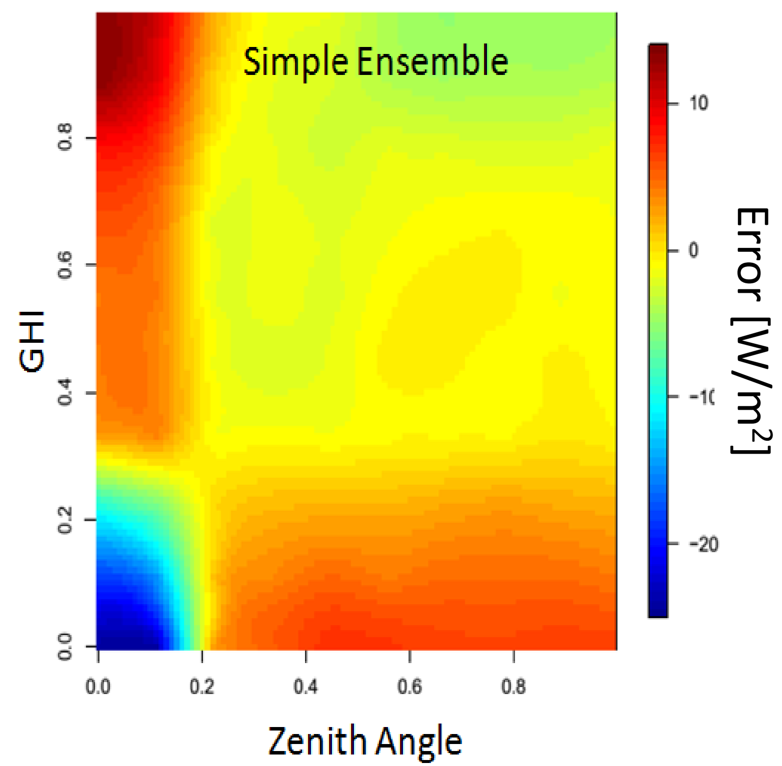
Reduction of forecast error using situation dependent machine learning based multi-model blending

Three models: RAP 11z (0-15hr), HRRR 11z (0-15hr), NAM 6z (5 to 20 hr ahead)
Average d for Seven Surfrad Stations.

Blending with Situation Categorization



Regression without Categorization

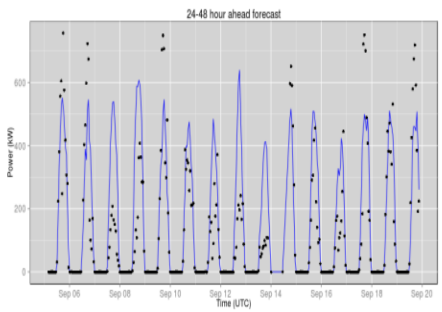


After model blending, "situation dependent " bias error is essentially eliminated.

Local, regional, and probabilistic forecasts

Single Plant – Fixed Systems

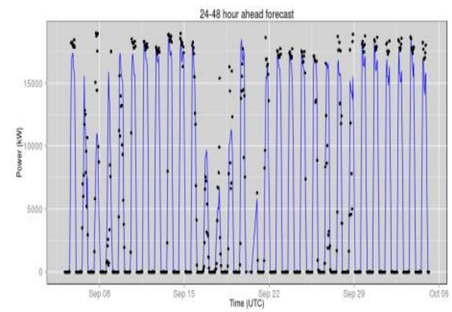
- Smyrna, TN
- 1MW Nameplate Capacity
- 24 to 48 hr ahead forecasts
- **MAPE 11% (2014-5-1 to 2014-10-31)**



Metrics	24-47 hr 2nd Yr
Correlation coef.	0.766
RMSE (MW)	0.15
NRMSE by capacity	0.155
MaxAE (MW)	0.48
MAE (MW)	0.111
MAPE by capacity	0.115
MBE (MW)	0.0211
KSIPer (%)	12.601
Stdev. (MW)	0.148
Skewness	0.296
Kurtosis	0.238
4RMQE (MW)	0.203
N4RMQE	0.21
95th percent (MW)	0.301

Single Plant – 1D Tracking System

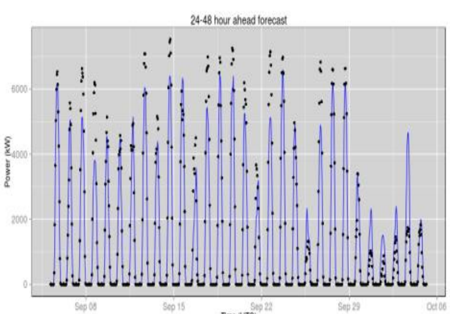
- TEP FRV Site, Marana, AZ
- 20MW AC Capacity
- 24 to 48 hr ahead forecasts
- **MAPE 11% (2014-5-1 to 2014-10-31)**



Metrics	24-47 hr ,2nd Yr
Correlation coef.	0.854
RMSE (MW)	3.4
NRMSE by capacity	0.17
MaxAE (MW)	18.5
MAE (MW)	2.23
MAPE by capacity	0.111
MBE (MW)	-0.194
KSIPer (%)	20.076
Stdev. (MW)	3.43
Skewness	1.41
Kurtosis	4.9
4RMQE (MW)	5.69
N4RMQE	0.282
95th percent(MW)	6.36

Regional Forecast for ISO-NE

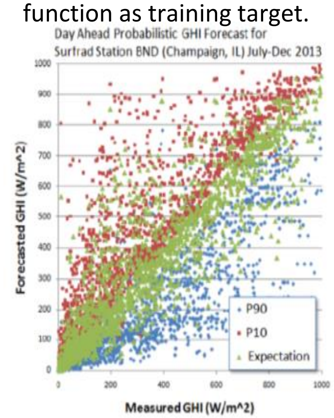
- South East Massachusetts Region
- 158 PV Plants, Total 10.4 MW
- 24-48 hr ahead forecasts at 3:30am EST daily
- **MAPE 5.0% (2014-5-1 to 2014-10-31)**



Metrics	24-48 hr, 2nd Yr
Correlation coef.	0.936
RMSE (MW)	79
NRMSE by capacity	0.0757
MaxAE (MW)	466
MAE (MW)	52.6
MAPE by capacity	0.0504
MBE (MW)	-7.2
KSIPer (%)	6.648
Std dev. (MW)	78.8
Skewness	0.539
Kurtosis	3.35
4RMQE (MW)	124
N4RMQE	0.119

Probabilistic Forecasting

Built into the machine learning approach using "Weighted absolute deviations" type loss function as training target.

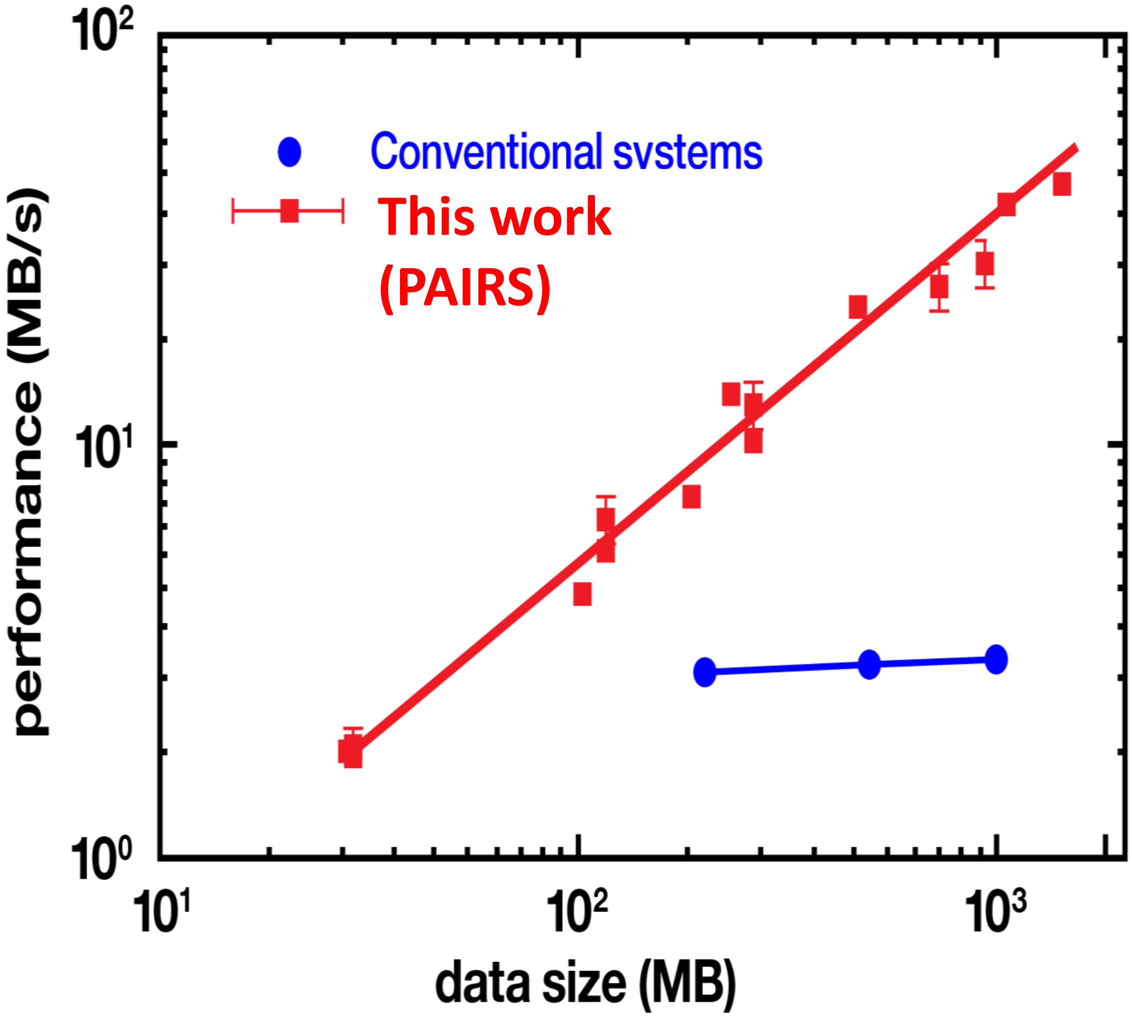


Quantile Reliability

Targeted Quantile	Actual Quantile
99%	99.4%
90%	92.2%
10%	9.9%
1%	0.8%

NOAA BND Surfrad Station 05/2013 to 01/2014

Improvements and Uniqueness



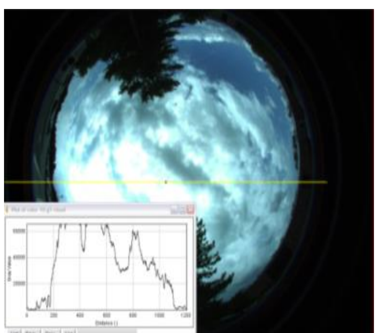
- Machine learning performance of this technology is (almost) independent of data size
- Time to result is independent of how much data is processed
- Conventional systems require more time for

Lagrangrian forecasts using sky cameras

IBM Cloud Imaging System without mechanical shutter

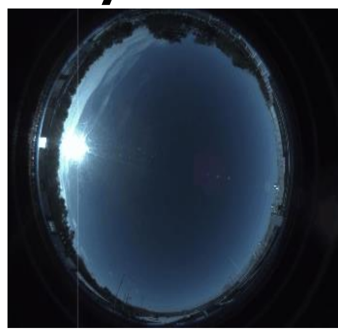
"Fish eye" lens

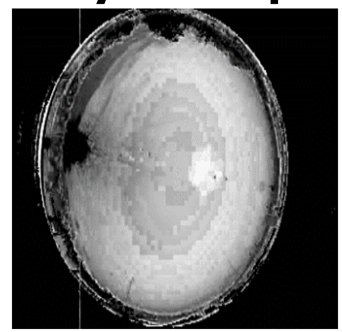
24 bit camera with several gain stages



- Sky camera with fish eye lenses detects arrival incoming clouds
  - Field of view ~ 2 miles, no mechanical parts
- Multiple sky cameras increases prediction horizons and allow cloud height detection

SkyCam Image **Sky Transparency**



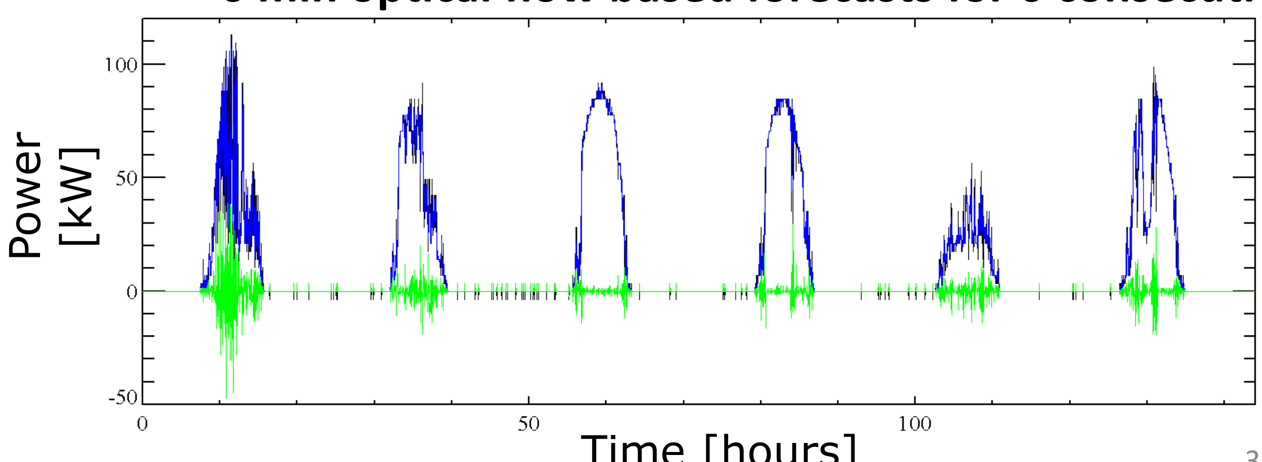


Measured

Forecast

Error

6 min optical flow based forecasts for 6 consecutive day



Short-term optical flow based forecasting with Navier-Stokes Modeling using GOES Satellites

Conventional Cloud Propagation:

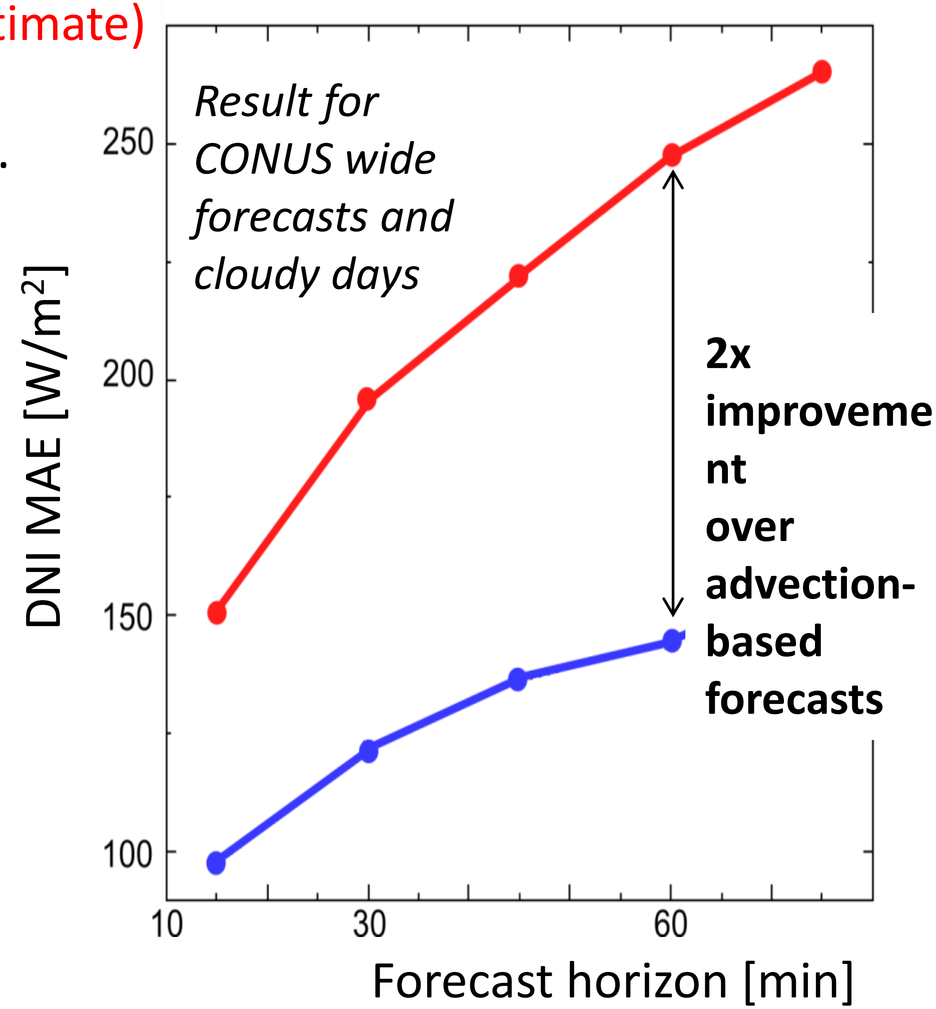
- Using (filtered) NWP wind field
  Inaccurate wind (error in cloud height estimate)
- Using wind field from optical flow
  Neglecting wind dynamics in hour-ahead.

***New method** keeps accurate wind field determined by optical flow, but captures basic wind dynamics.*

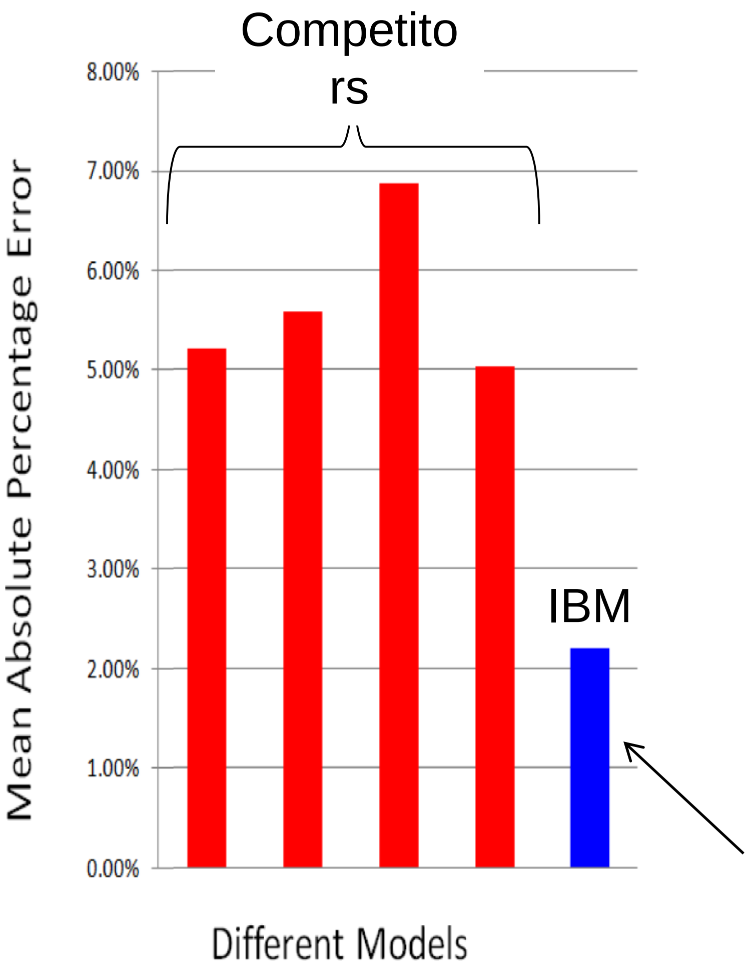
1. Optical flow estimates wind field using two consecutive cloud images (optical depth)

2.Fit an initial condition of 2D Navier-Stokes Equation to two consecutive optical flows

3.Forecast optical flow and use it to predict cloud images

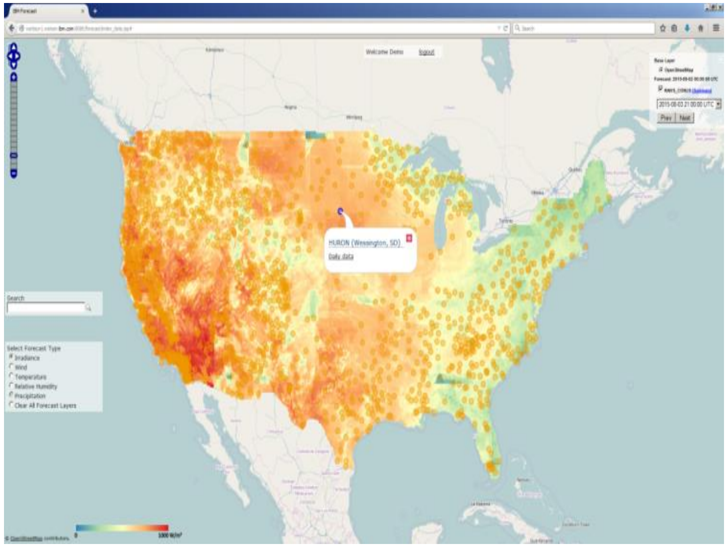


In Vendor trials we reduced forecast error by more than 30% over the next best forecasts



1.935 MW Fixed Array in Italy

We scaled the technology to continental wide forecasting and beyond.



- **> 35 % improved accuracy with respect to next best model at 1600 sites across the United States**
- **SMT provides gridded forecasts**
- **Continuously learns and improves**

Publically available web access to forecasts of 1600 sites across the US
http://server01.mmthub.com:9080/forecast/
User id: demo; Password: demo

Performance Metrics

2015-05-10 to 2015-05-24

IBM Blended GHI 0-48hr Ahead

SiteSet	# of Sites	MAE* (W/m^2)	MAPE(%)	RMSE (W/m^2)	NRMSE (%)	MBE (W/m^2)	MaxAE (W/m^2)	KSIPer (%)	pcoe
RAWS_CONUS	1641	135.54	13.55	192.99	19.29	19.84	668.06	16.62	0.78

NOAA NAM GHI 0-48hr Ahead

SiteSet	# of Sites	MAE* (W/m^2)	MAPE(%)	RMSE (W/m^2)	NRMSE (%)	MBE (W/m^2)	MaxAE (W/m^2)	KSIPer (%)	pcoe
RAWS_CONUS	1641	179.06	17.91	253.60	25.37	118.94	814.81	22.27	0.75

NOAA SREF GHI 0-48hr Ahead

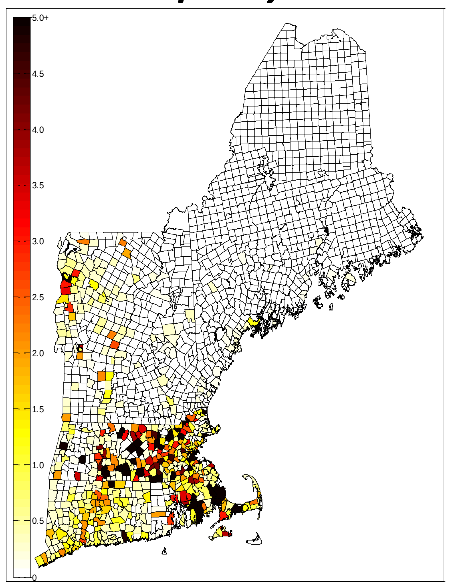
SiteSet	# of Sites	MAE* (W/m^2)	MAPE(%)	RMSE (W/m^2)	NRMSE (%)	MBE (W/m^2)	MaxAE (W/m^2)	KSIPer (%)	pcoe
RAWS_CONUS	1641	188.44	18.84	262.97	26.30	129.56	837.83	23.64	0.74

*Metrics Suites: Excluding night time values for solar. Hover mouse over the acronyms to see full definition.

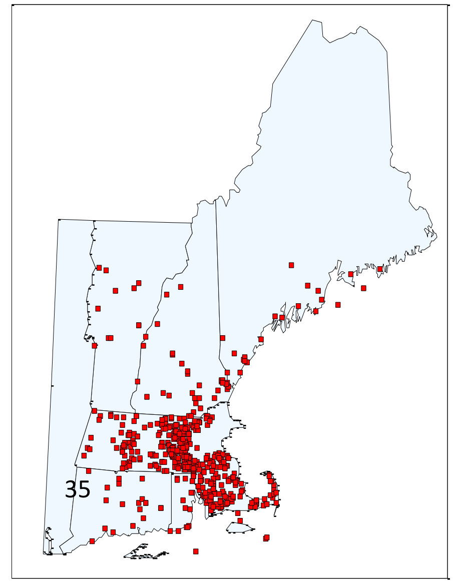
IBM Blended GHI 0-48hr Ahead

Load forecasting for ISO-New England

Estimated PV capacity in ISO-NE

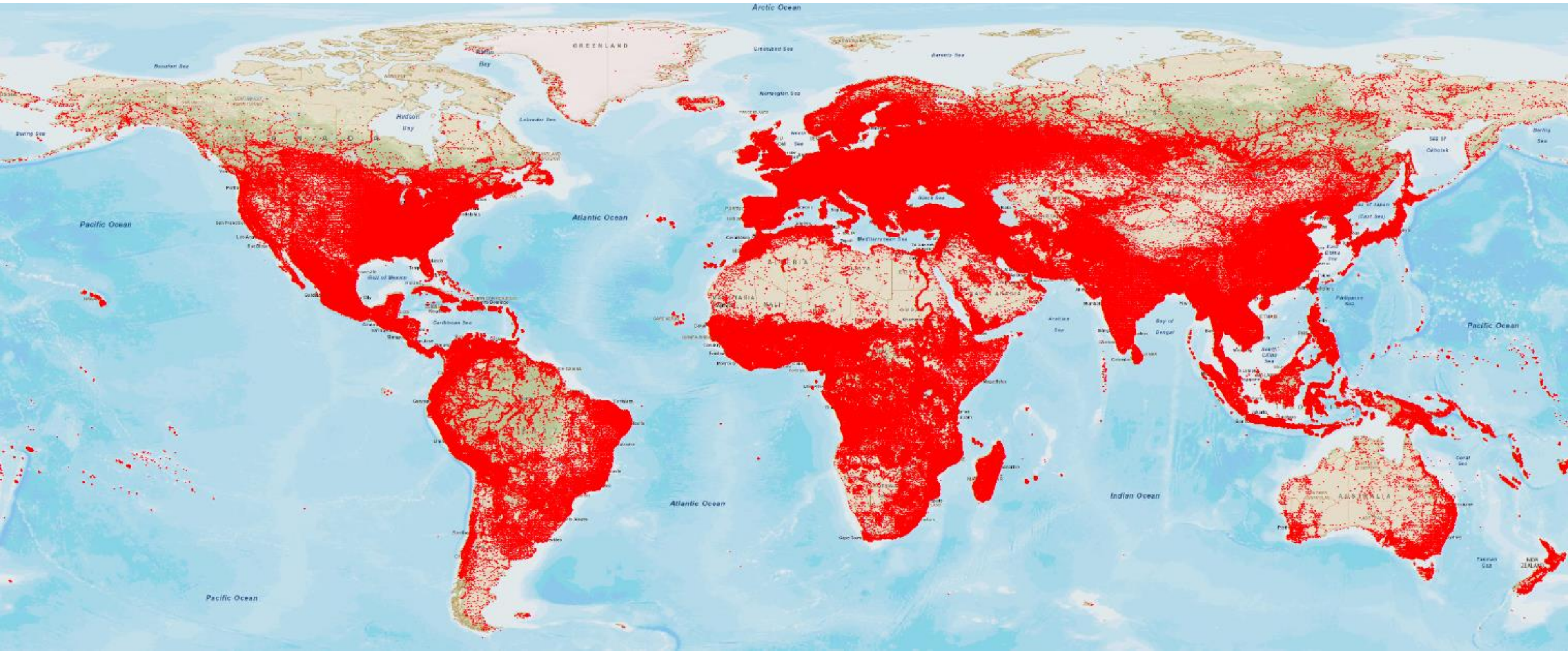


Measurement station in ISO-NE

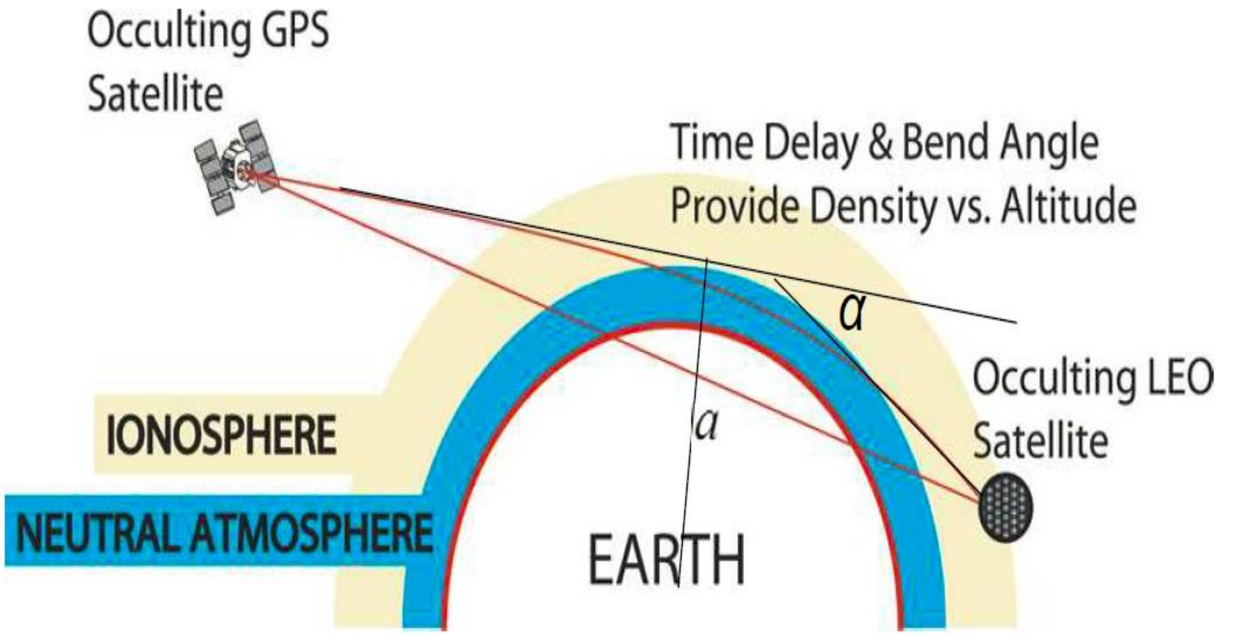


- IBM provides point forecasts for 665 sites in 9 dispatch zones
- Trains the model on 665 sites
- IBM scales forecast using estimated PV capacity for each dispatch zone
- ISO-NE feeds the forecasted data as an input into a neural network for load predictions

IBM's World Wide Weather Monitoring Network using Weather Underground



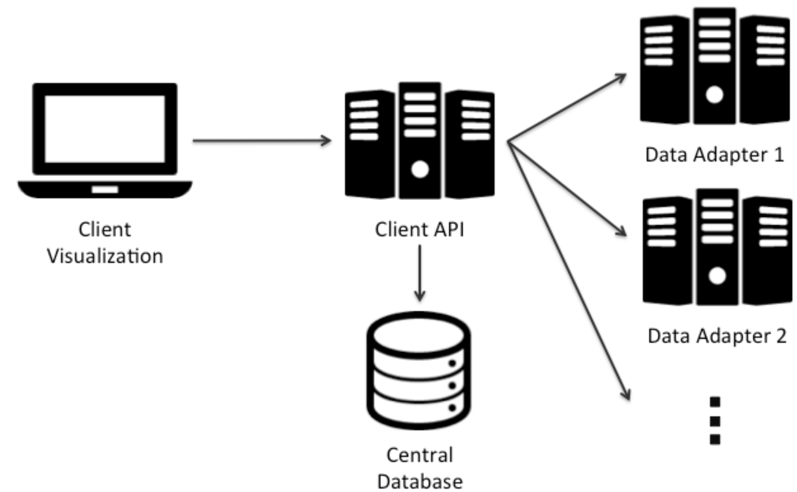
What is next? GPS-RO



- GPS Radio Occultation (GPS-RO) is an technique for measuring 3D weather variables (temperature, humidity etc) of the Earth’s atmosphere from space
- Explore opportunities to leverage GPS-RO for enhanced machine-learning
- Early results show drastic improvements

Visualization Design

Integration of visualizations with forecasts & other data streams → separating framework into multiple interacting logical layers, each with a clearly defined API



The front-end visualization: typical stack of web technologies (HTML; JavaScript; Cascading Style Sheet)

Web stack technologies we used previously: Node.js, Ruby on Rails, and PostgreSQL to create the logical layers of the back end

Simulation Tools

Tool	Capability	Role
<u>F</u>lexible <u>E</u>nergy <u>S</u>cheduling <u>T</u>ool for <u>I</u>ntegration of <u>V</u>ariable generation	Simulate decisions for: • DA SCUC • RT SCUC • RT SCED • AGC	• Thrust #2: UC/ED impacts & cost-benefit analysis using IEEE system • Ramp & regulation procurement extracted from probabilistic net-load forecast, using OpSDA algorithm
PLEXOS & PSST production costing simulation	Access to large-scale, extensively reviewed power system models & data • Western Wind & Solar Integration Study (Phase 2) • Calif Low Carbon Grid Study • Eastern Renewable Generation Integration Study)	• Thrust #4: UC-ED impacts & cost-benefit analysis using ISO scale systems under different scenarios
In-house ISO simulations and/or dispatch data	Testing of probabilistic solar & net-load forecasts integration in ISO in-house simulation settings	• Thrust #4: Work with CAISO & MISO to integrate and/or evaluate estimates of ramping & regulation products procurements using probabilistic forecasts, & visualizations