

IMPACT OF A TARGETED SENSOR NETWORK AND ADVANCEMENTS IN PREDICTION MODELS ON WIND GENERATION FORECASTS IN THE TWRA

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Overview

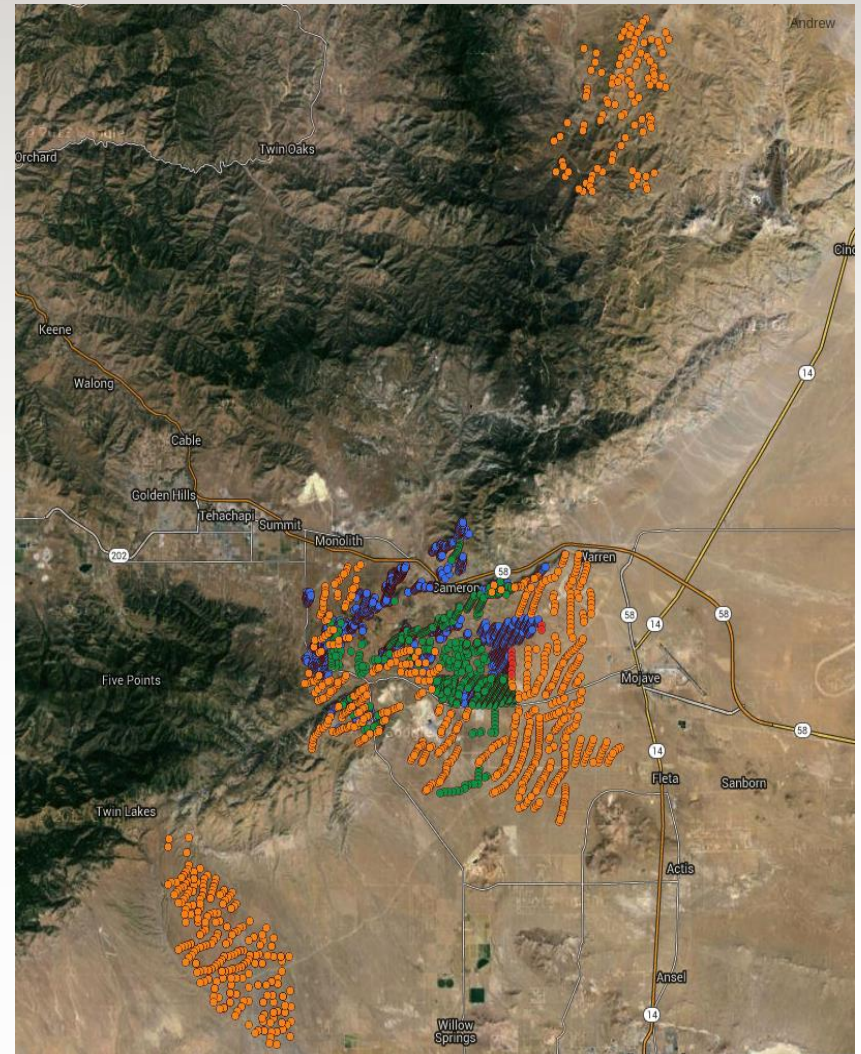
- **Background and Motivation**
- **Description of Forecast Improvement Focus Areas**
- **The Upcoming Final Steps:**
 - Putting together the pieces
 - Evaluating the integrated result

BACKGROUND AND MOTIVATION



Project Scope

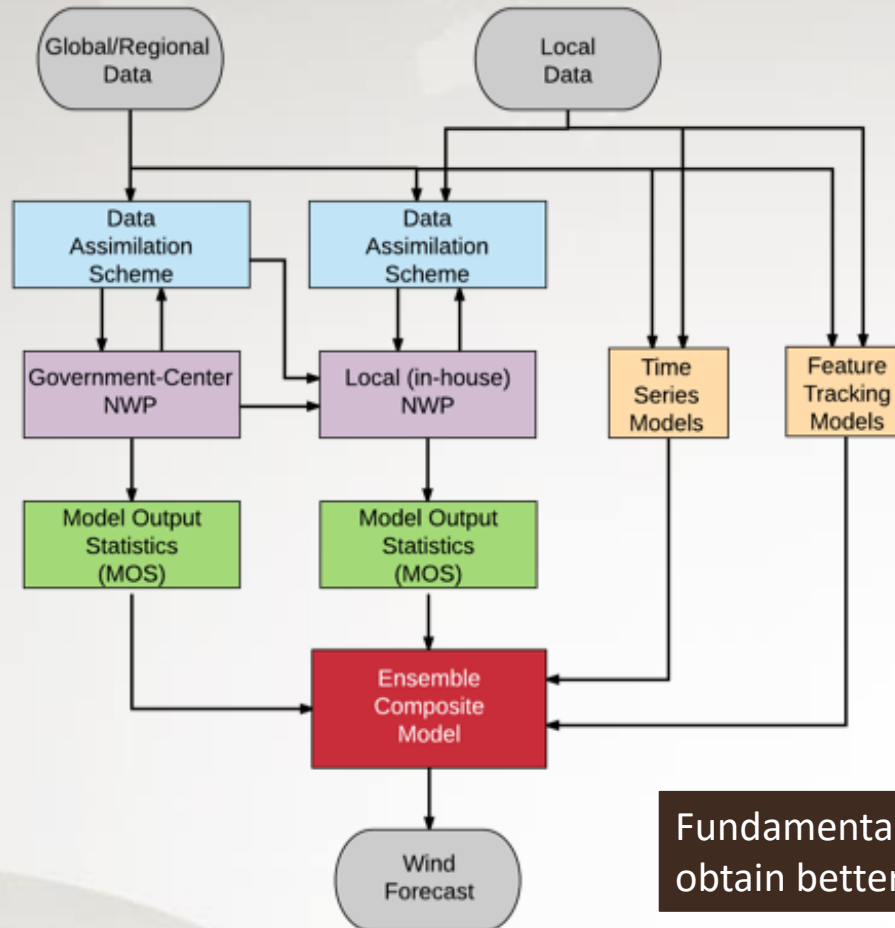
- 2.5-year project supported by the California Energy Commission (CEC) and Electric Power Research Institute (EPRI)
 - Original CEC funding for 2 years
 - Extended by EPRI
 - 2015-2017
- Tehachapi Wind Resource Area (TWRA)
 - > 3000 MW wind capacity (2319 MW in project)
 - Concentrated, highly correlated production
 - Complex terrain
 - Often driven by small-scale weather features
 - Data sparse area on the feature-scale
- **Multi-faceted approach to improve 0-12 hr power production forecast performance with focus on ramps**
- 1-yr evaluation period to assess integrated results of project (Oct 2015 – Sept 2016)



OVERVIEW OF FORECAST IMPROVEMENT EFFORTS



The Starting Point: A Typical State-of-the-Art Wind Forecast System

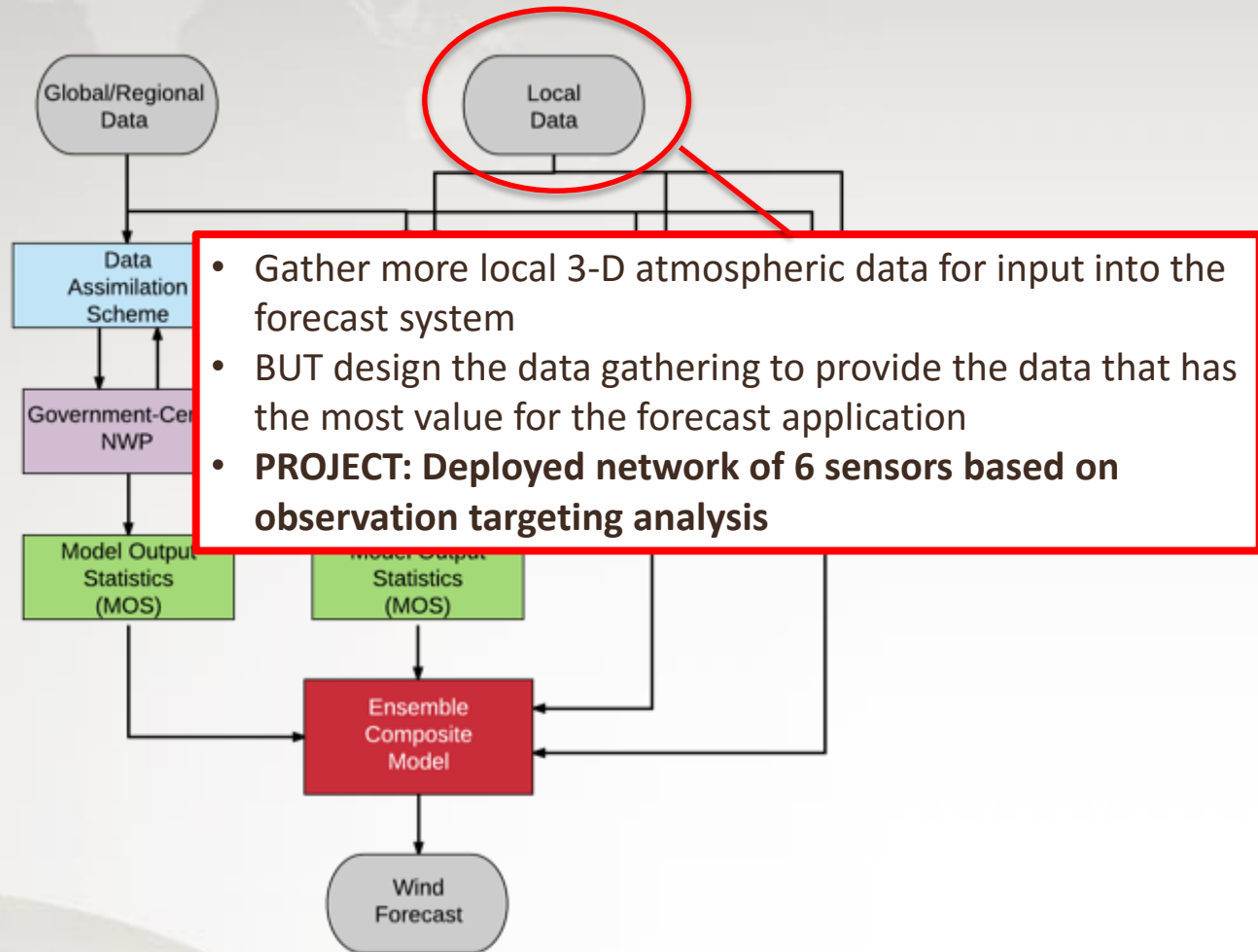


Fundamental Question: How can we obtain better forecasts from it?

Components of Forecasting Improvement Effort

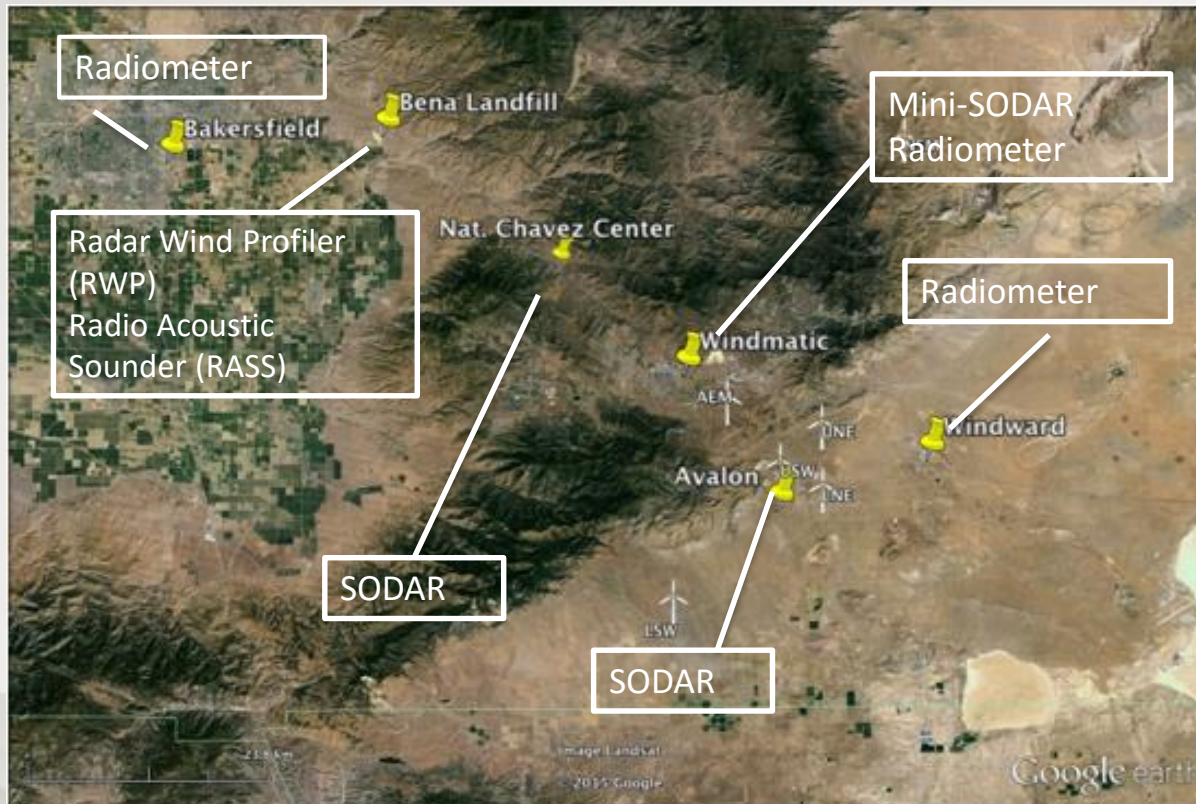
- 1. Gather More Data:** Deploy targeted network of 6 sensors based on observation targeting analysis
- 2. Optimize NWP Configuration:** Conduct WRF configuration sensitivity tests for a sample of 30 large ramp cases to determine best configuration for wind forecasting in the Tehachapi Pass area
- 3. Improve NWP Data Assimilation of Local Area Data:** Implement Hybrid EnKF/GSI data assimilation approach (flow dependent data blending to more accurately spread the influence of point measurements for model initialization)
- 4. Apply Latest Machine Learning (ML) Tools to NWP MOS:** Improve ability to correct regime-based systematic errors (biases) in NWP forecasts
- 5. Improve Time Series Prediction for 0-3 hr Forecasts:** Exploit information in off-site data (project sensor data and non-project off-site sensors) through application of latest ML methods

Improving a Wind Forecast System: Gathering Additional Data

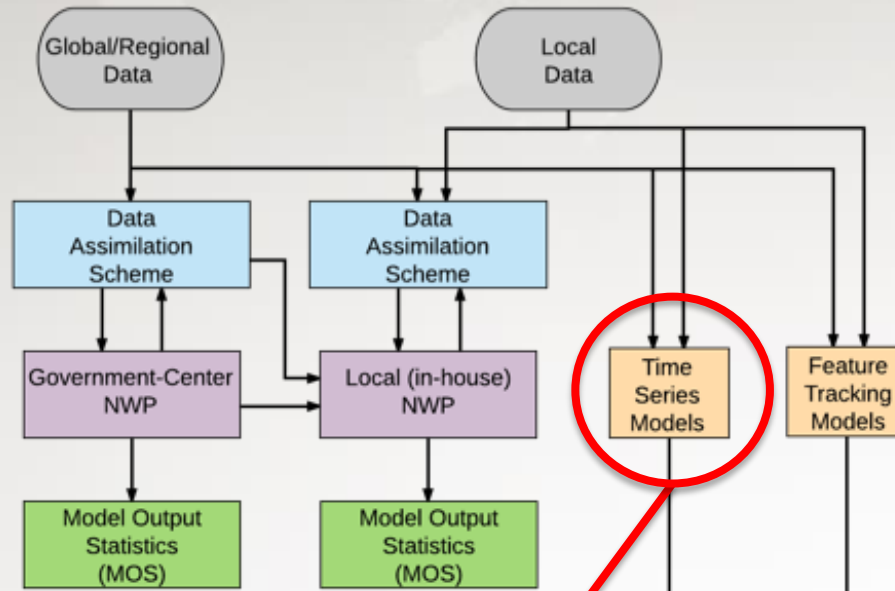


Targeted Sensor Network

- Sensors deployed at 6 targeted locations for a ~ 1-year period
- **Anticipated applications**
 - Provide additional real-time input data for the forecast models
 - Increase understanding of atmospheric processes that drive wind variability
 - Provide guidance for forecast model improvements and evaluation



Improving a Wind Forecast System: Time Series Modeling



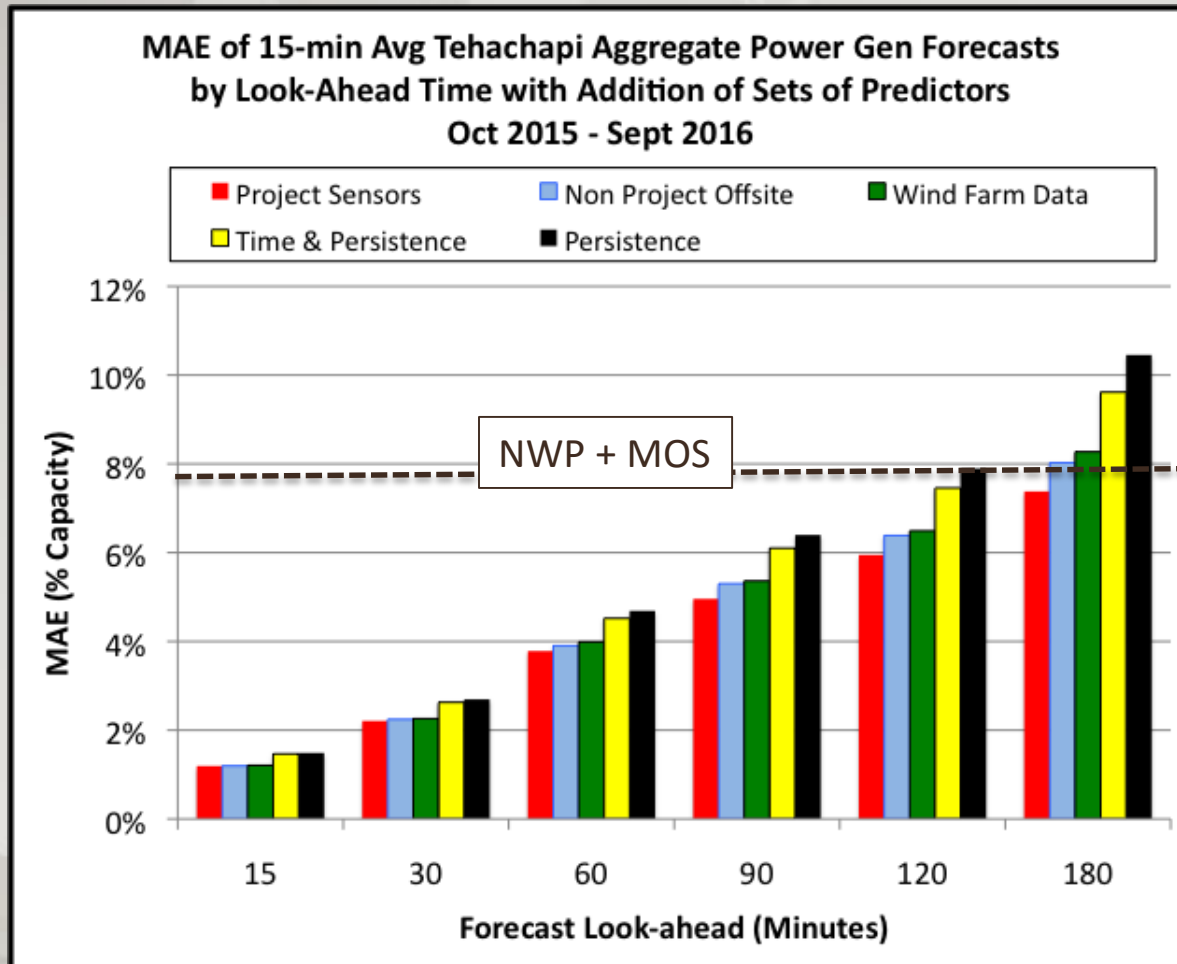
- Exploit information in off-site data (project sensor data and non-project off-site sensors)
- Use advanced Machine Learning (ML) methods for “big data”
- **PROJECT: Applied advanced several machine learning techniques for time series prediction with onsite and offsite data**

Forecast

Time Series Forecast Configuration

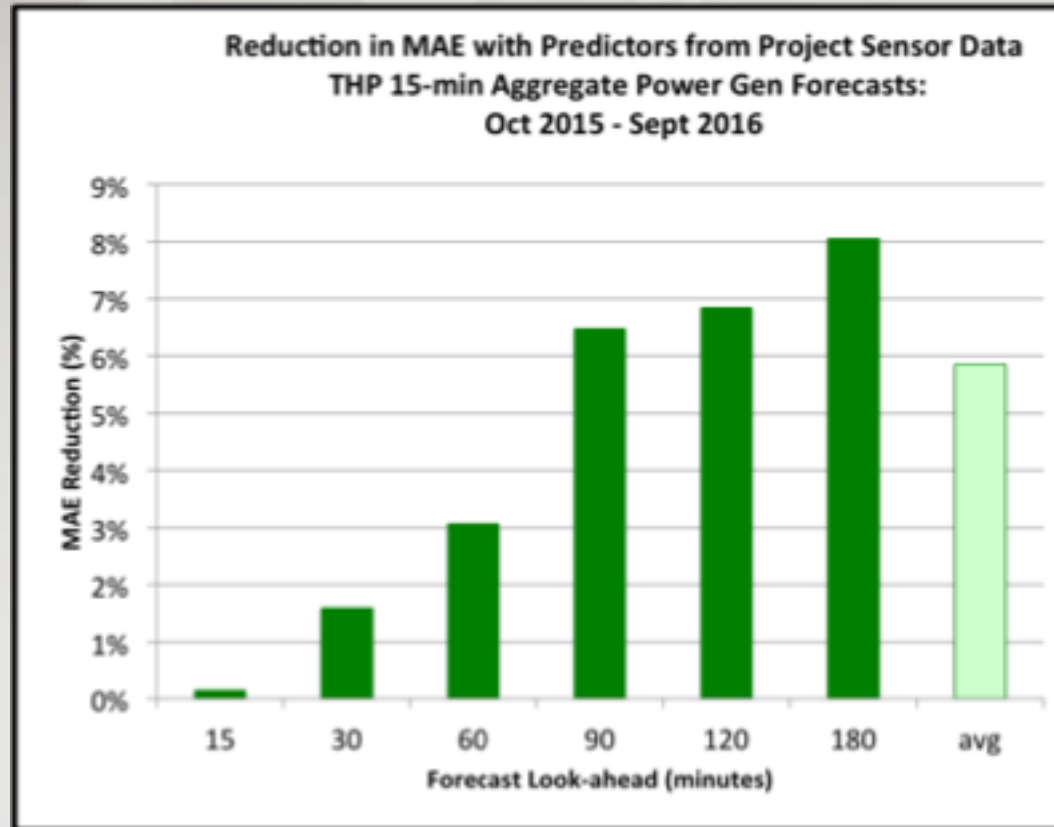
- 15-minute forecast cycles
 - More frequent updates than possible with current NWP
- Employed Gradient Boosted Machine (GBM)
 - Multi-step decision-tree technique
 - Each step attempts to forecast the residuals from the preceding step
- 1 year forecast evaluation period
 - Oct 2015 – Sept 2016
- 25 months of training data
 - Trained on 24 months, forecasted for 1 month
- Predictors: 61 subjectively selected variables
- Predictand: ramp rate from 0 to look-ahead time

Performance of Time Series Forecasts



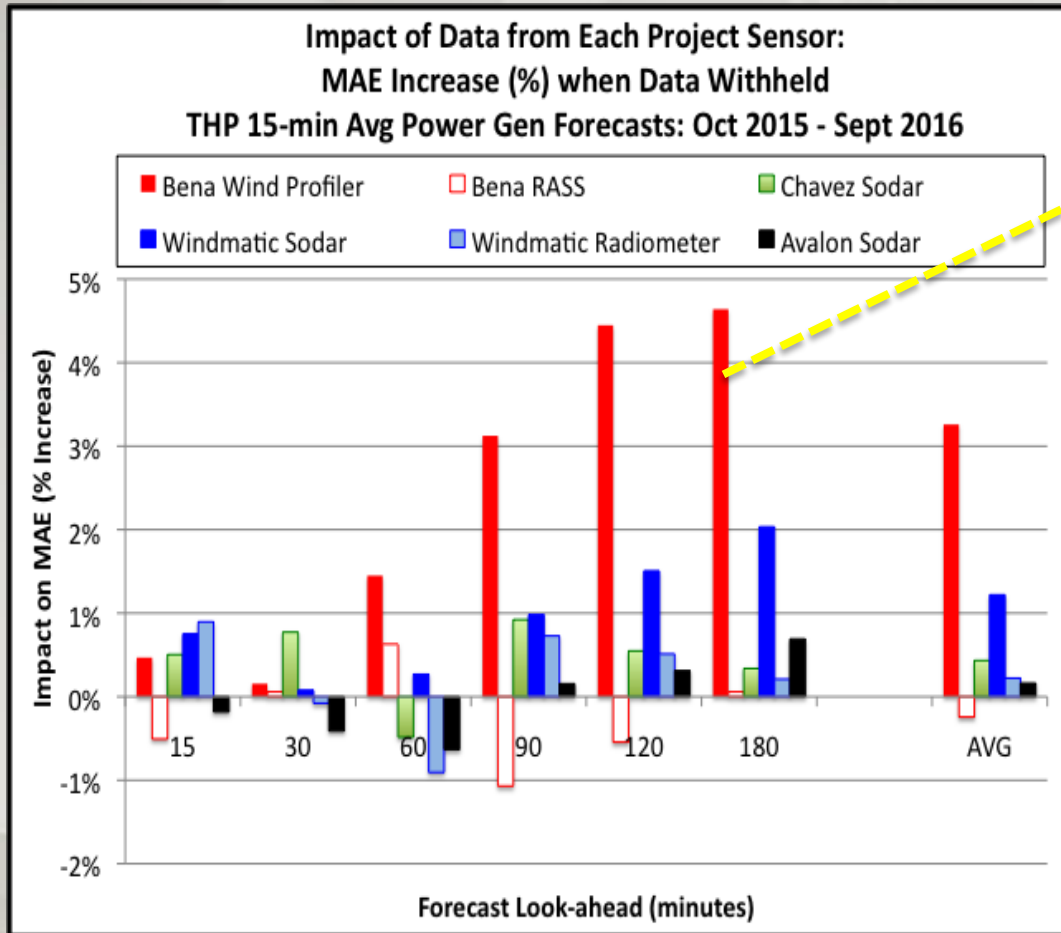
- Each successive group includes all of the predictors from the previous group plus the predictors from that group
- Same set of predictors for all look-ahead periods
- GBM model trained separately for each look-ahead period
- Results are for forecast intervals for which all data was available – 32.4% of the possible intervals in the 12-month period
- NWP + MOS method yields average MAE ~8% over 0-15 hour period

Overall Impact of Data from Project Sensors




- **MAE reduction relative to forecasts with all non-project predictors**
- Impact of project data increases with increasing look-ahead time out to 180 minutes
- Results are for all forecast intervals over the 1 yr period
- Next step: analyze ramp vs. no-ramp periods and optimize prediction method for ramp periods

Relative Impact of Data from Each Project Sensor



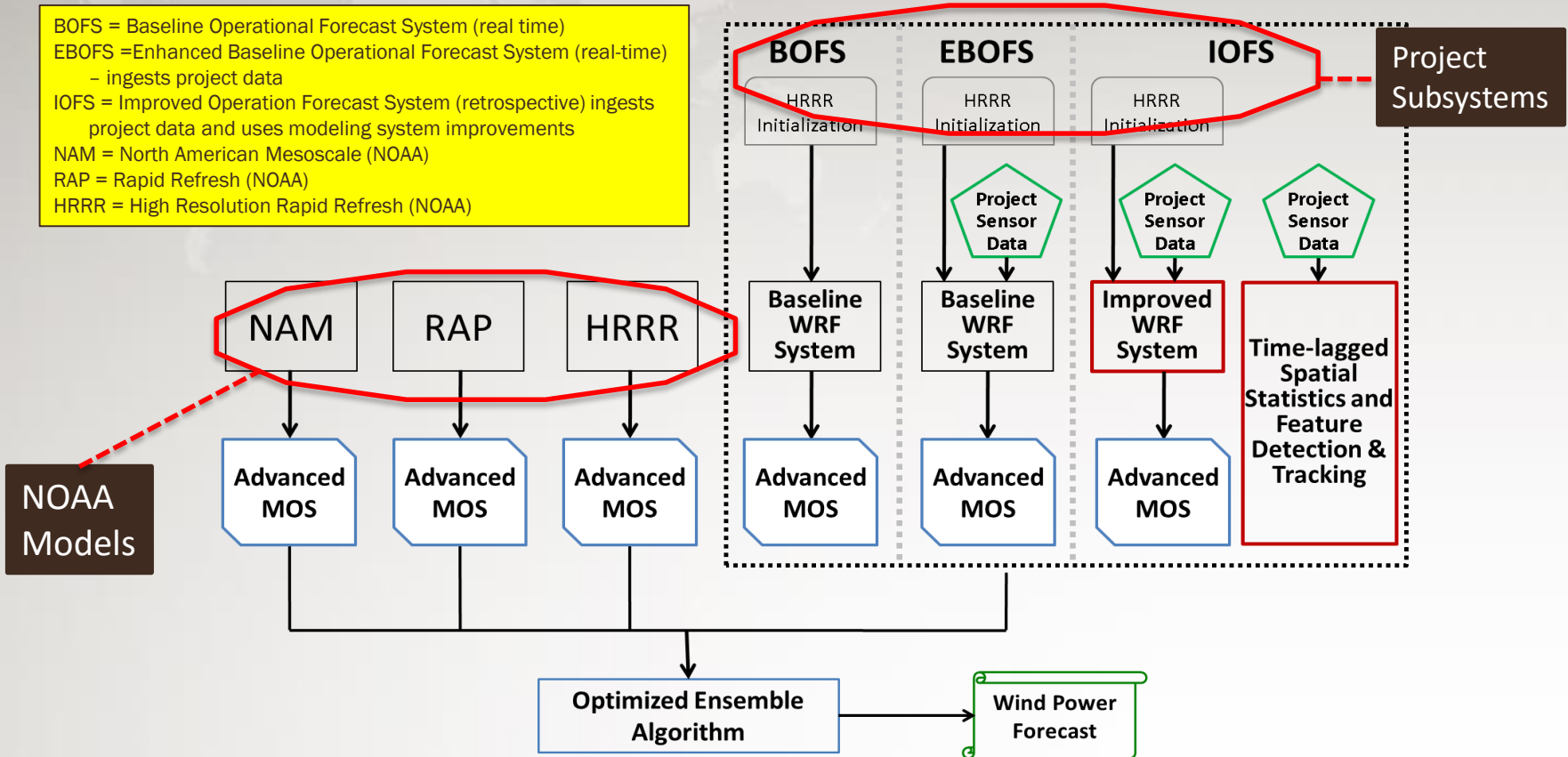
- Produced forecasts with data from each sensor sequentially withheld
- Metric: % change in MAE when data from each sensor is withheld
- Wind profiler at Bena provide the most forecast value – upstream winds above Pass level



**THE FINAL STEP:
PUTTING TOGETHER ALL THE PIECES AND
EVALUATING THE INTEGRATED RESULT**

Evaluation Experiment Design

BOFS = Baseline Operational Forecast System (real time)
 EBOFS = Enhanced Baseline Operational Forecast System (real-time)
 - ingests project data
 IOFS = Improved Operation Forecast System (retrospective) ingests
 project data and uses modeling system improvements
 NAM = North American Mesoscale (NOAA)
 RAP = Rapid Refresh (NOAA)
 HRRR = High Resolution Rapid Refresh (NOAA)



- Generate forecasts from three versions of the system over a one-year evaluation period
- Evaluate the differences in performance among the forecasts produced by each version

Next Steps

- Generate forecasts from improved system (IOFS) for 1-yr period
- Evaluate and analyze impact of system enhancements (data and methods)
- Deploy forecast system components into operational use where possible
- Stakeholder engagement to maximize value to applications

