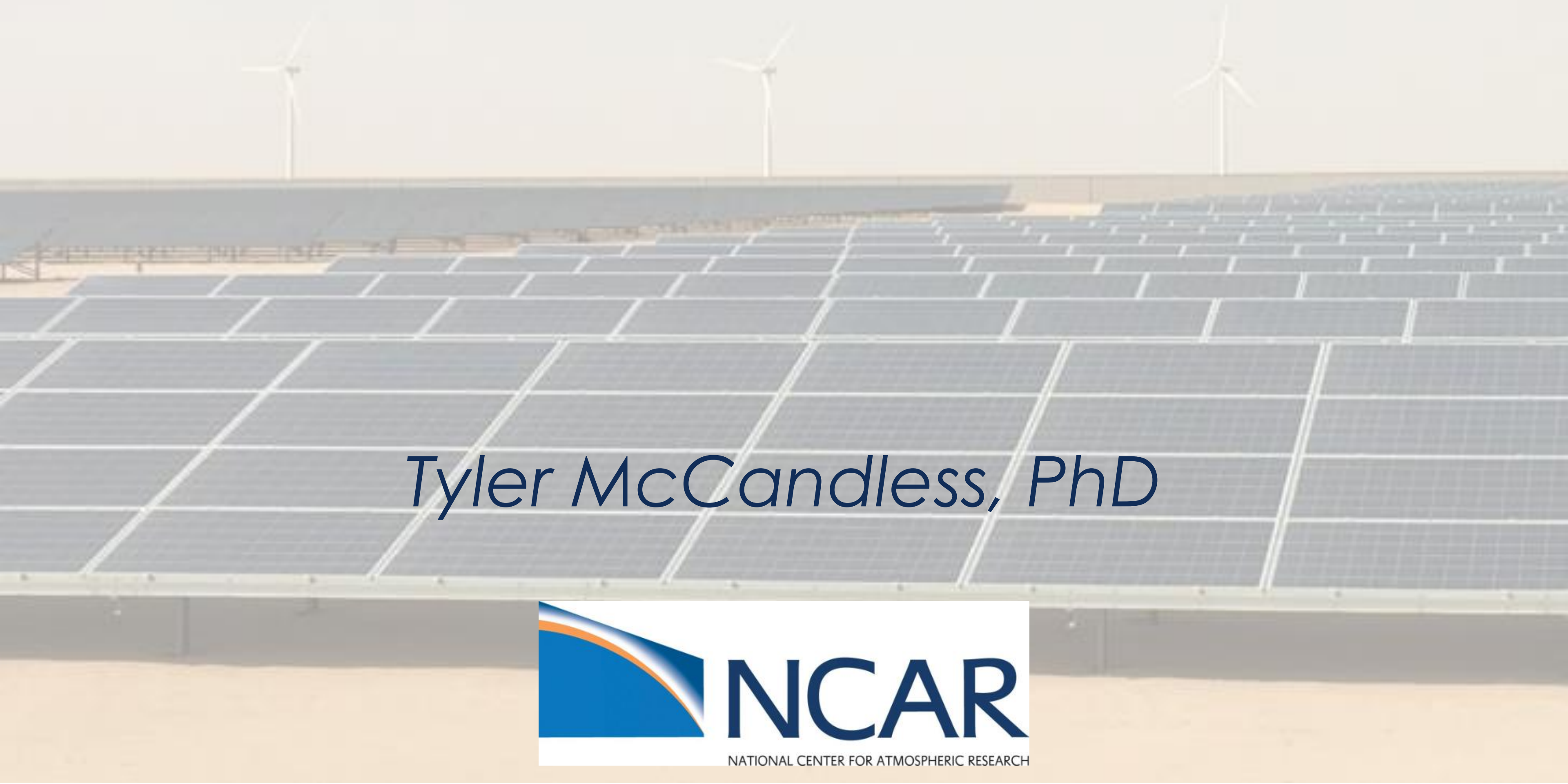
Wind and Solar Forecasting Advances and The Potential Utilization for Improved Battery Storage Integration



Tyler McCandless, PhD

NCAR
NATIONAL CENTER FOR ATMOSPHERIC RESEARCH

Wind, Solar and Battery Storage Optimization

Outline

NCAR Wind and Solar Power Forecasting

Xcel Energy System, DOE Solar Project

Recent Advancements

Machine Learning Innovations to
Solar and Wind Power Forecasting

Motivation for Battery Optimization

Many Opportunities Require Accurate
Forecasts for Hybrid Storage Systems

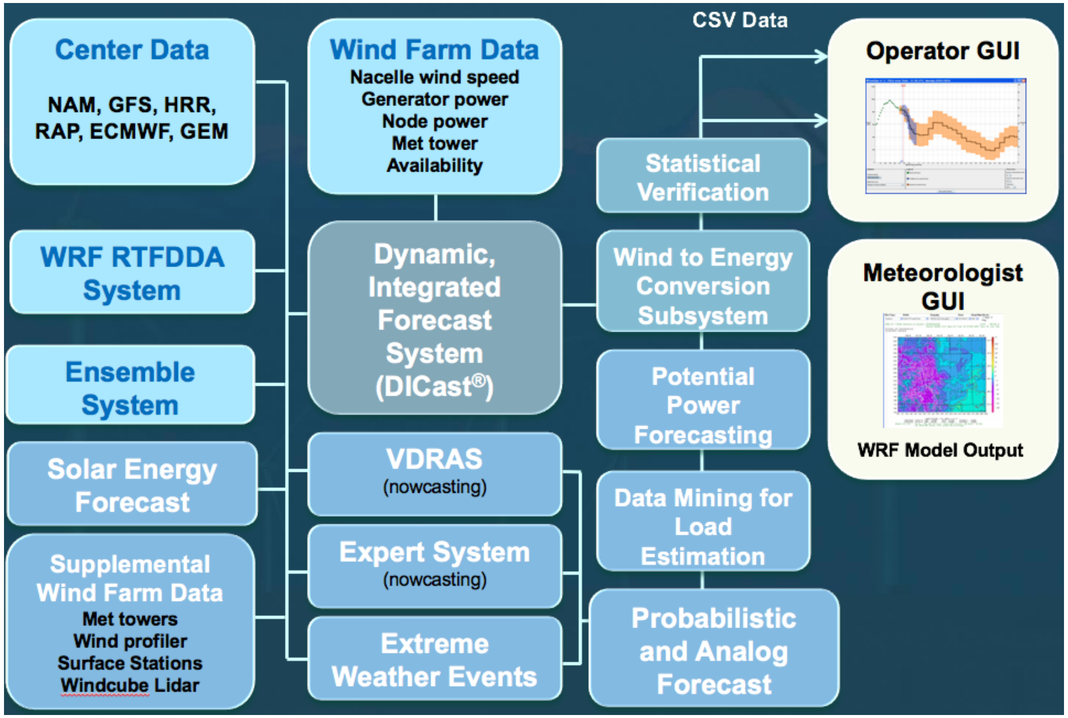
Summary and Next Steps

Lessons Learned and Future Work

Wind Power Forecasting at NCAR

Xcel Energy System (2008-2011)

+ Xcel Energy has used WindWx since 2009, which was developed through a multi-year R&D project
+ Provides forecasts every 15-min over Xcel Energy's entire service territory
+ Xcel estimated **$60.6M** in fuel cost saving through end of 2015 through WindWx*

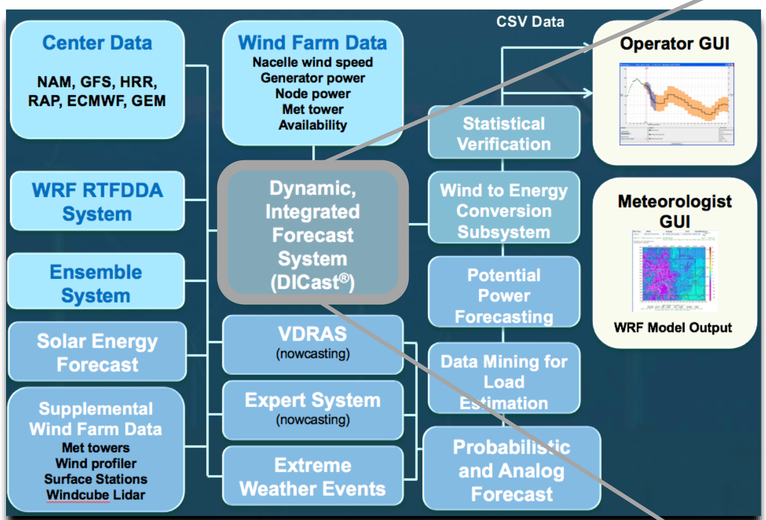


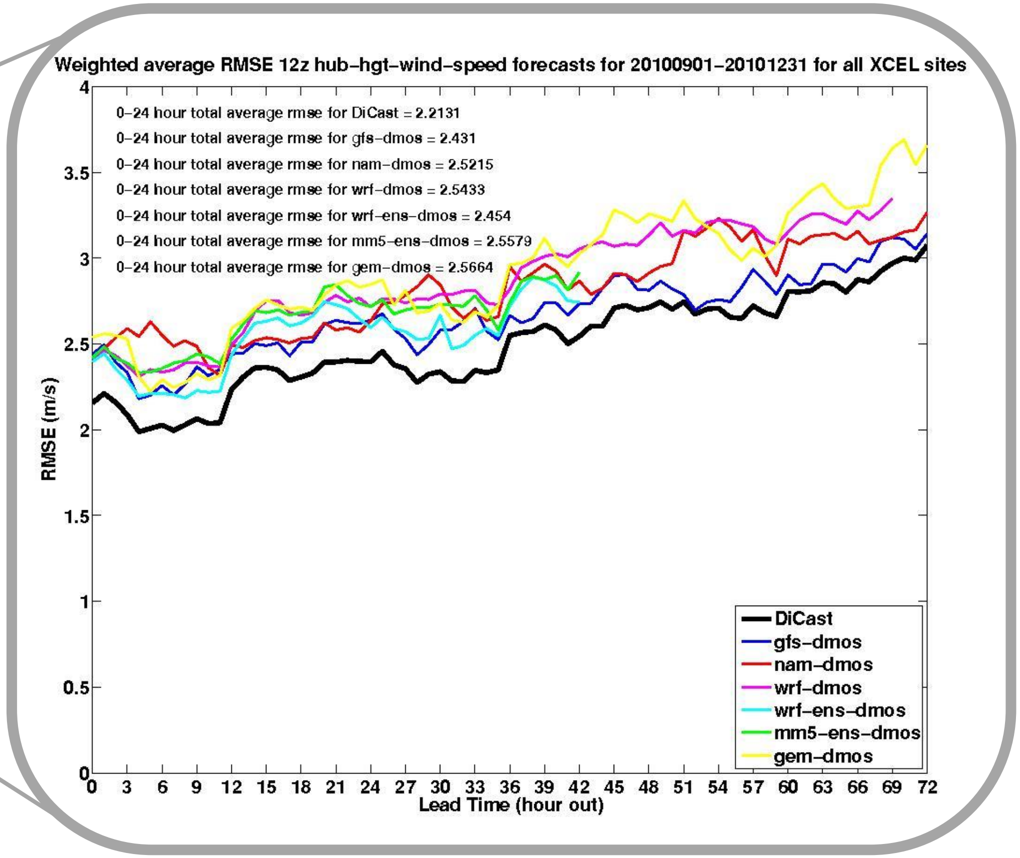
* https://www.xcelenergy.com/staticfiles/xe-responsive/Company/Corporate%20Responsibility%20Report/16-03-341-Wind-Energy.pdf

Wind Power Forecasting at NCAR

Xcel Energy System (2008-2011)

+ DICast uses machine learning to post-process NWP model output and has generally shown to improve error by 10-15% from 1-hr to 72-hrs

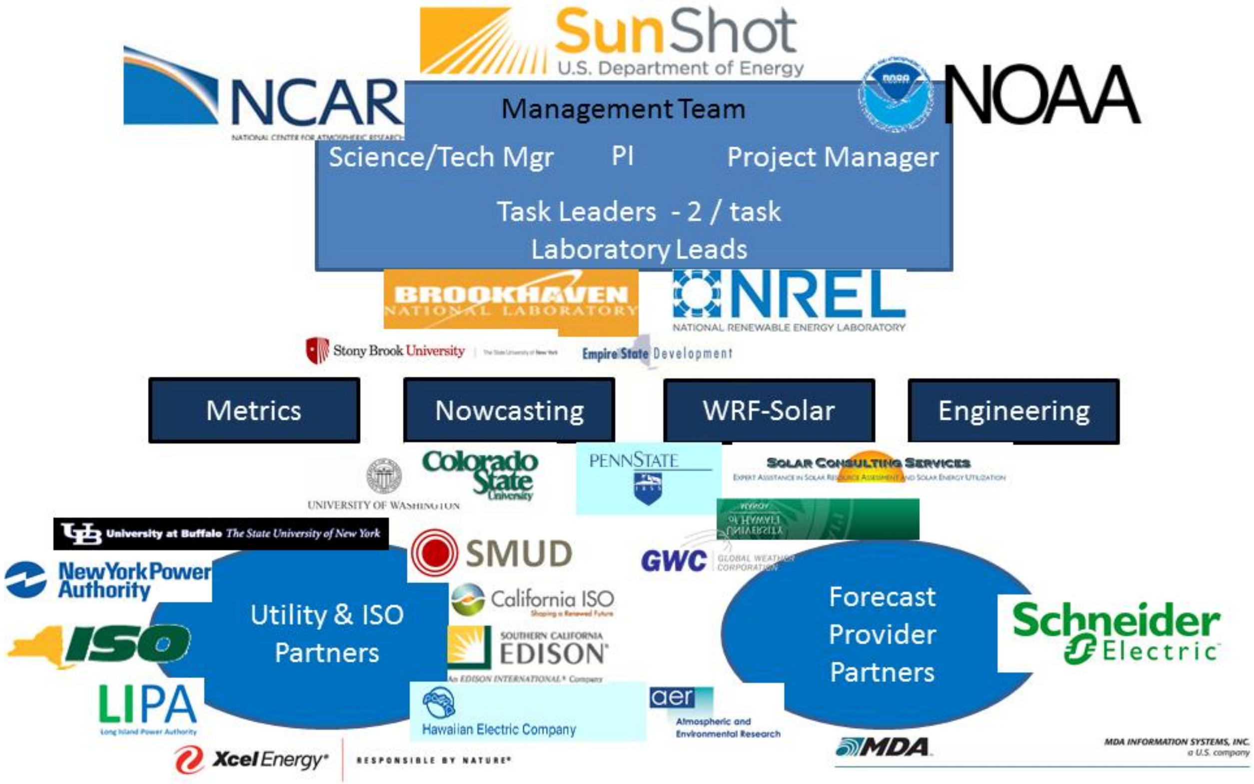




Solar Power Forecasting at NCAR

DOE SunShot Solar Project

+ DOE SunShot sponsored solar power forecasting project led by NCAR in 2012-2015 advanced the state of the science for solar power forecasting



Haupt et al, 2018: [Building the Sun4Cast System: Improvements in Solar Power Forecasting.](https://doi.org/10.1175/BAMS-D-16-0221.1) *Bull. Amer. Meteor. Soc.*, **99**, 121–136, https://doi.org/10.1175/BAMS-D-16-0221.1

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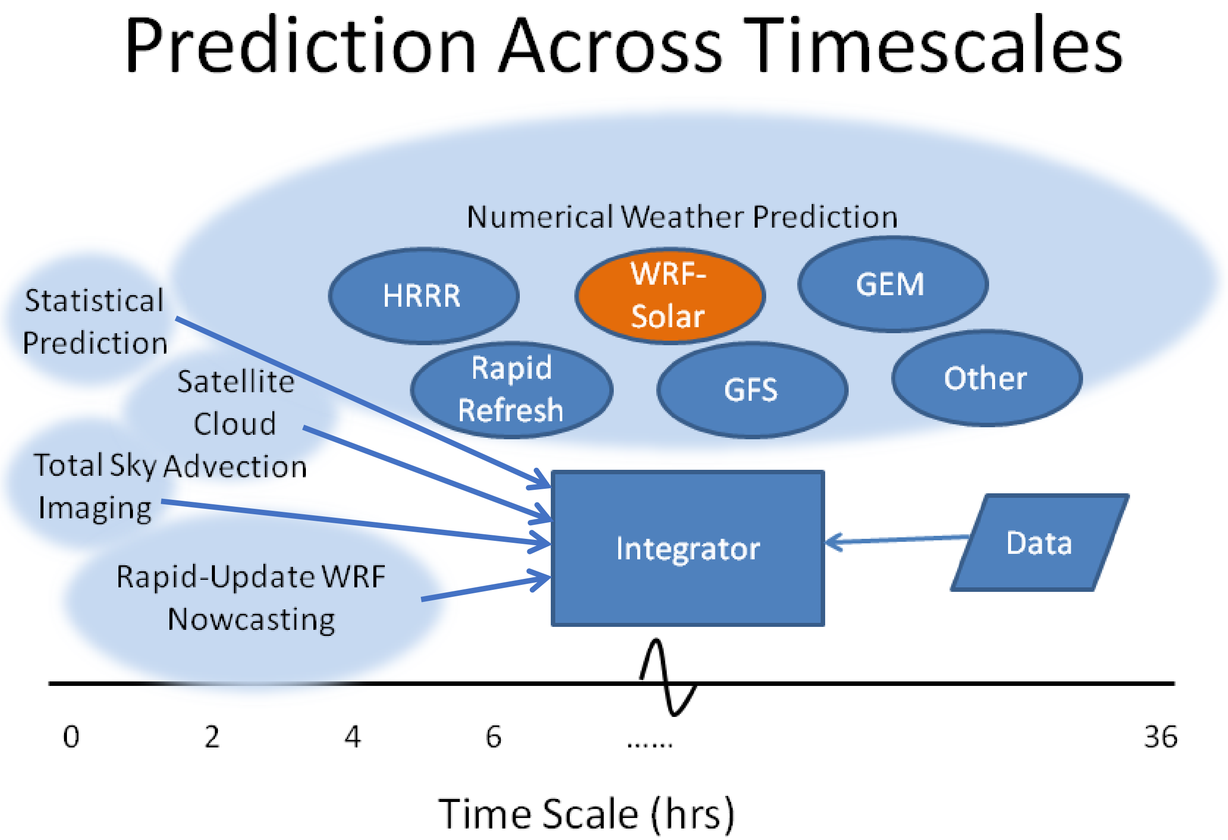

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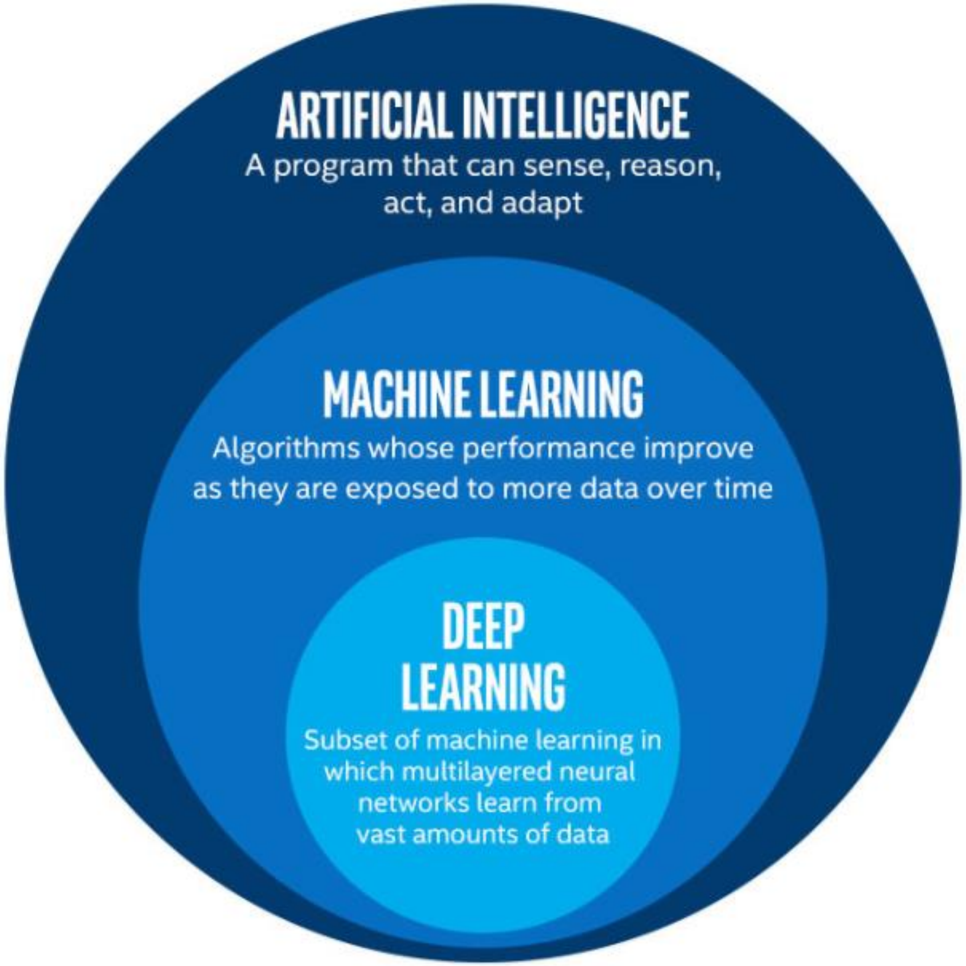
Recent Advancements

Machine Learning for Renewable Energy Prediction

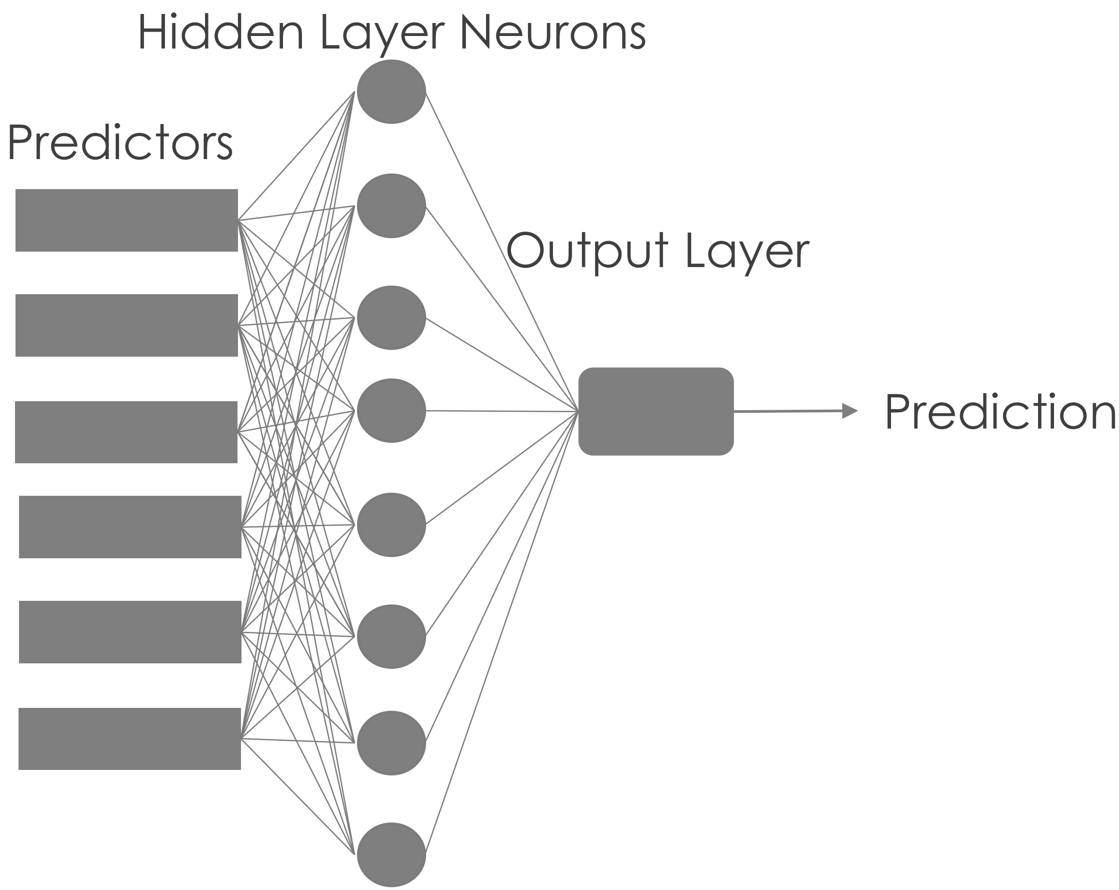


https://towardsdatascience.com/cousins-of-artificial-intelligence-dda4edc27b55

Recent Advancements

Artificial Neural Networks

Machine learning method modeled after neurons in the human brain. Each predictor is mapped to every neuron in a hidden layer, which is mapped to the output layer that makes the final prediction.



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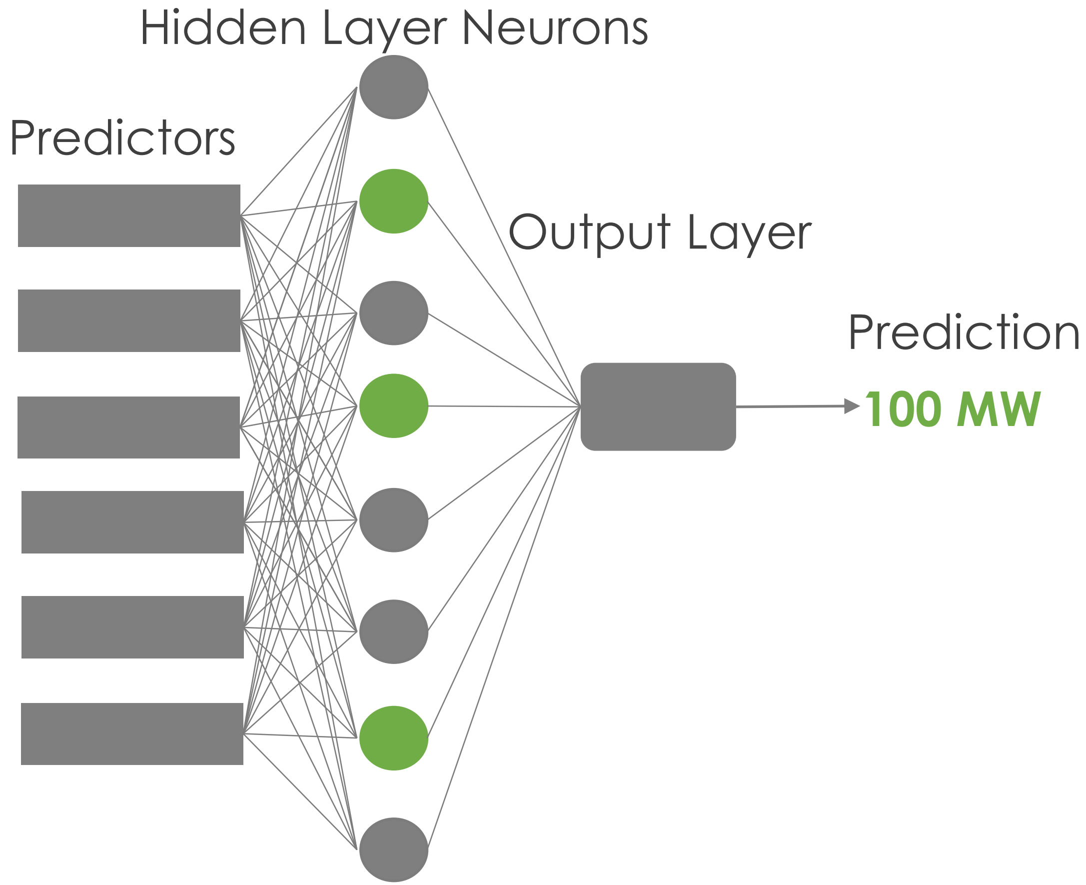

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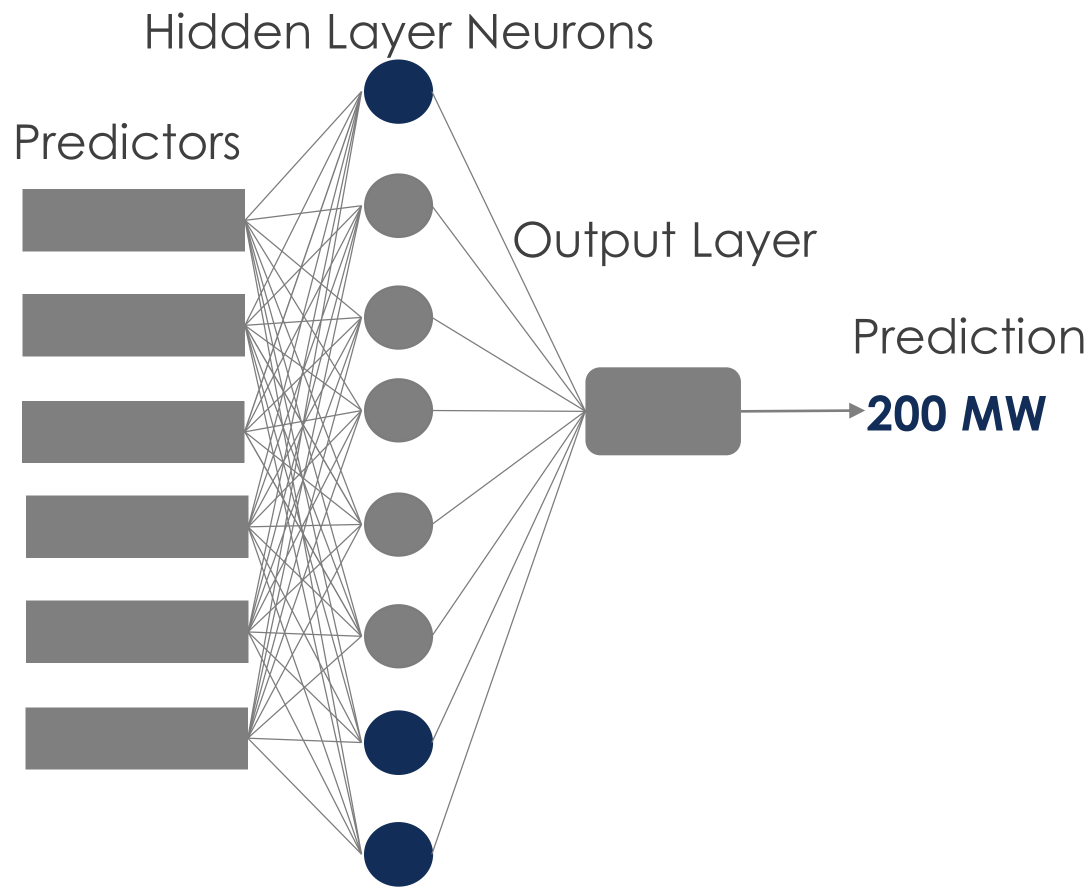

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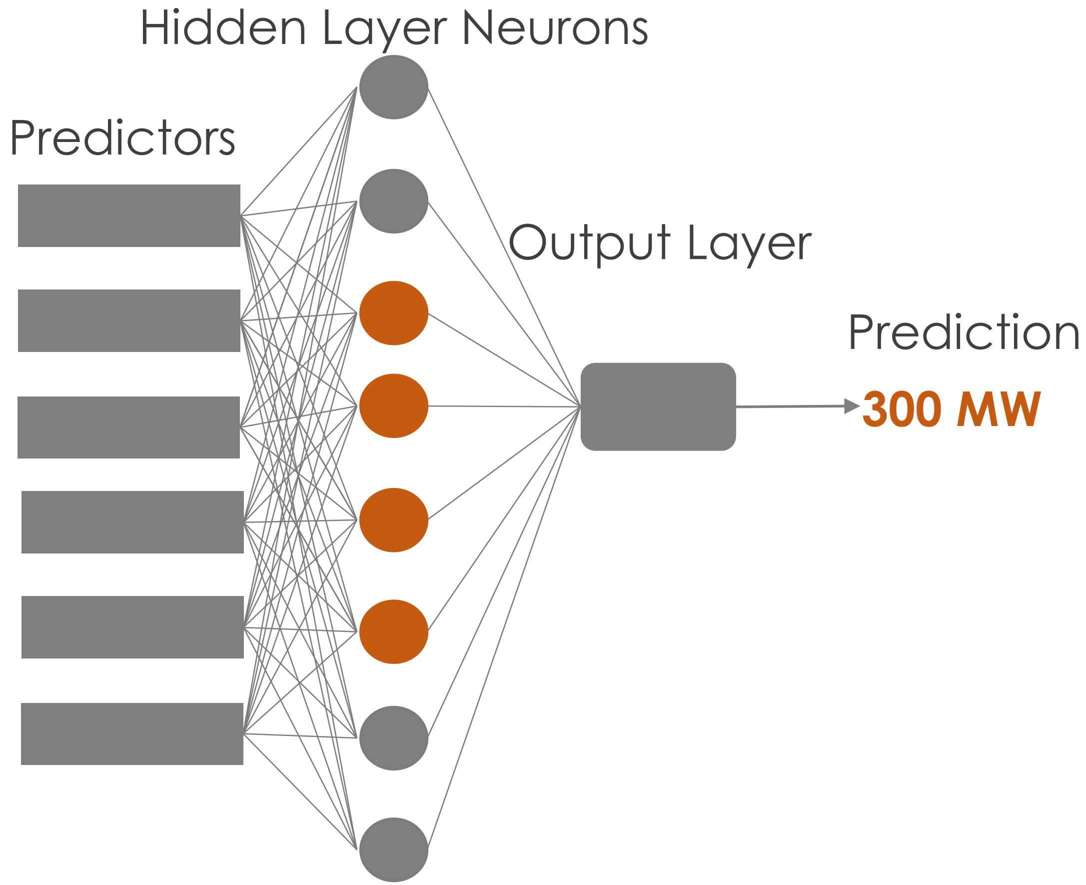


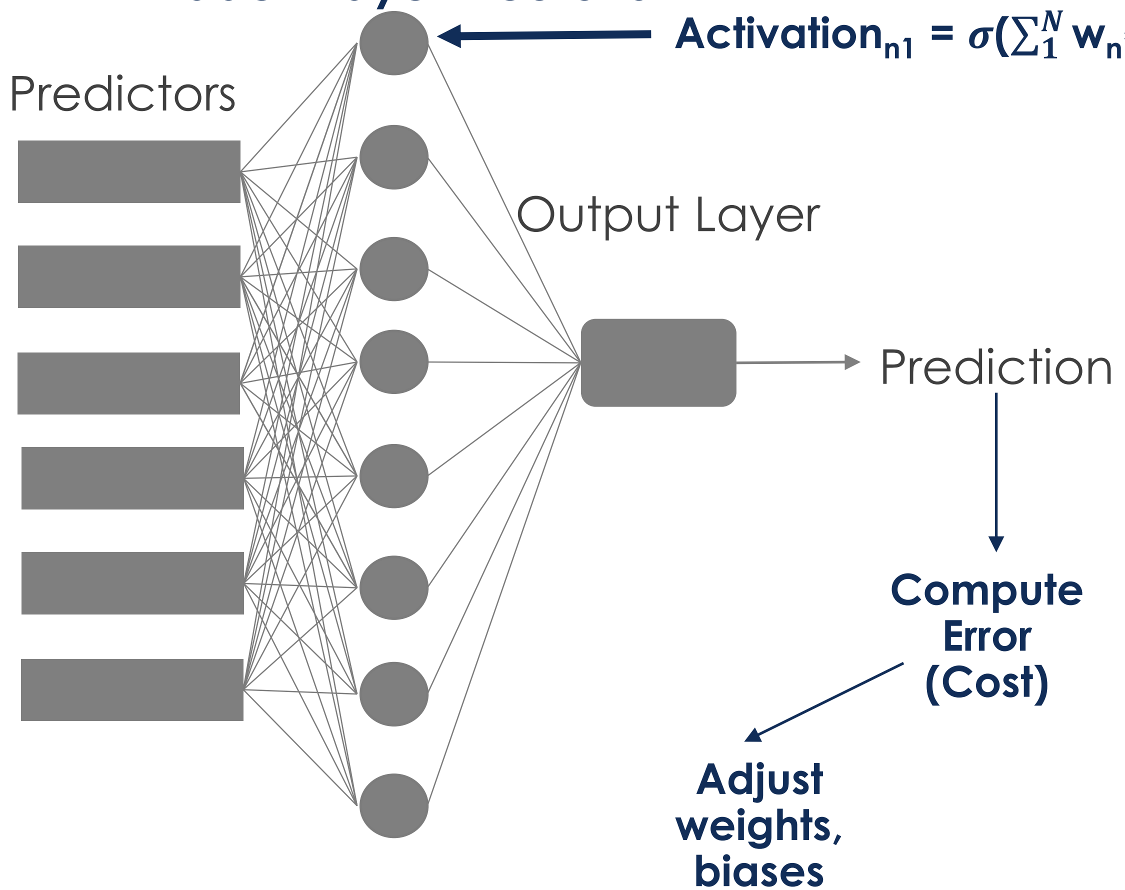
Recent Advancements

Artificial Neural Networks

Back-propagation training iterates over the samples and computes the error, or cost, of the prediction. Each weight and bias is tuned by gradient descent to lower the error. *Goal is to find the global minima in cost function*

Hidden Layer Neurons

$\text{Activation}_{n1} = \sigma(\sum_{1}^{N} w_n * P_n + b_{n1})$

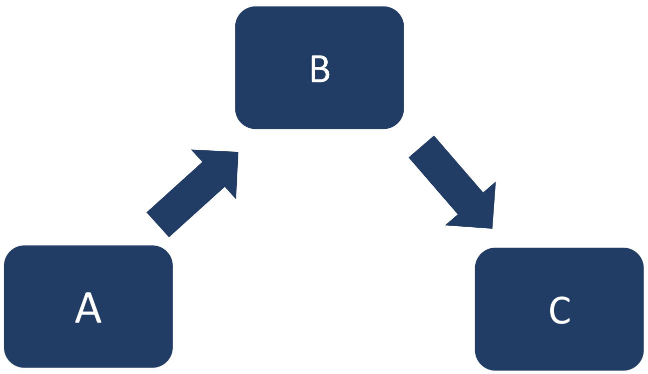


ANN with 784 predictors and 2 hidden layers of 16 neurons would have a total of 13,002 tunable parameters!

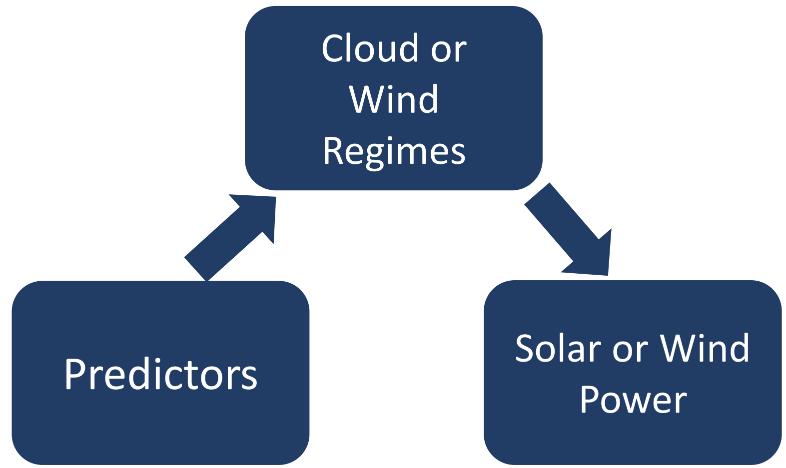
Recent Advancements

Causal Discovery and Regime-Dependent Methods

Causal Discovery



RD-ANN Methods



"…causal discovery is always a process that involves both domain experts and AI experts, working together"*

*Imme Ebert-Uphoff, Colorado State University, https://www.engr.colostate.edu/~iebert/

Recent Advancements

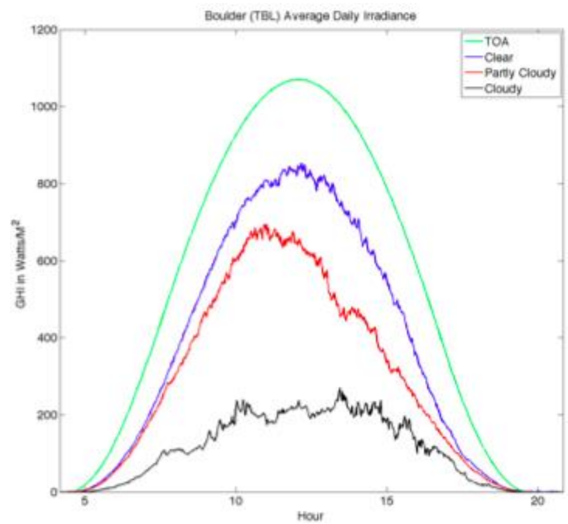
Regime-Dependent Methodology

Mission Statement:

*Combine knowledge of **key fundamental drivers of the underlying meteorological phenomena** with artificial intelligence techniques* to improve renewable energy prediction

Cloud Types

Solar Irradiance Regimes



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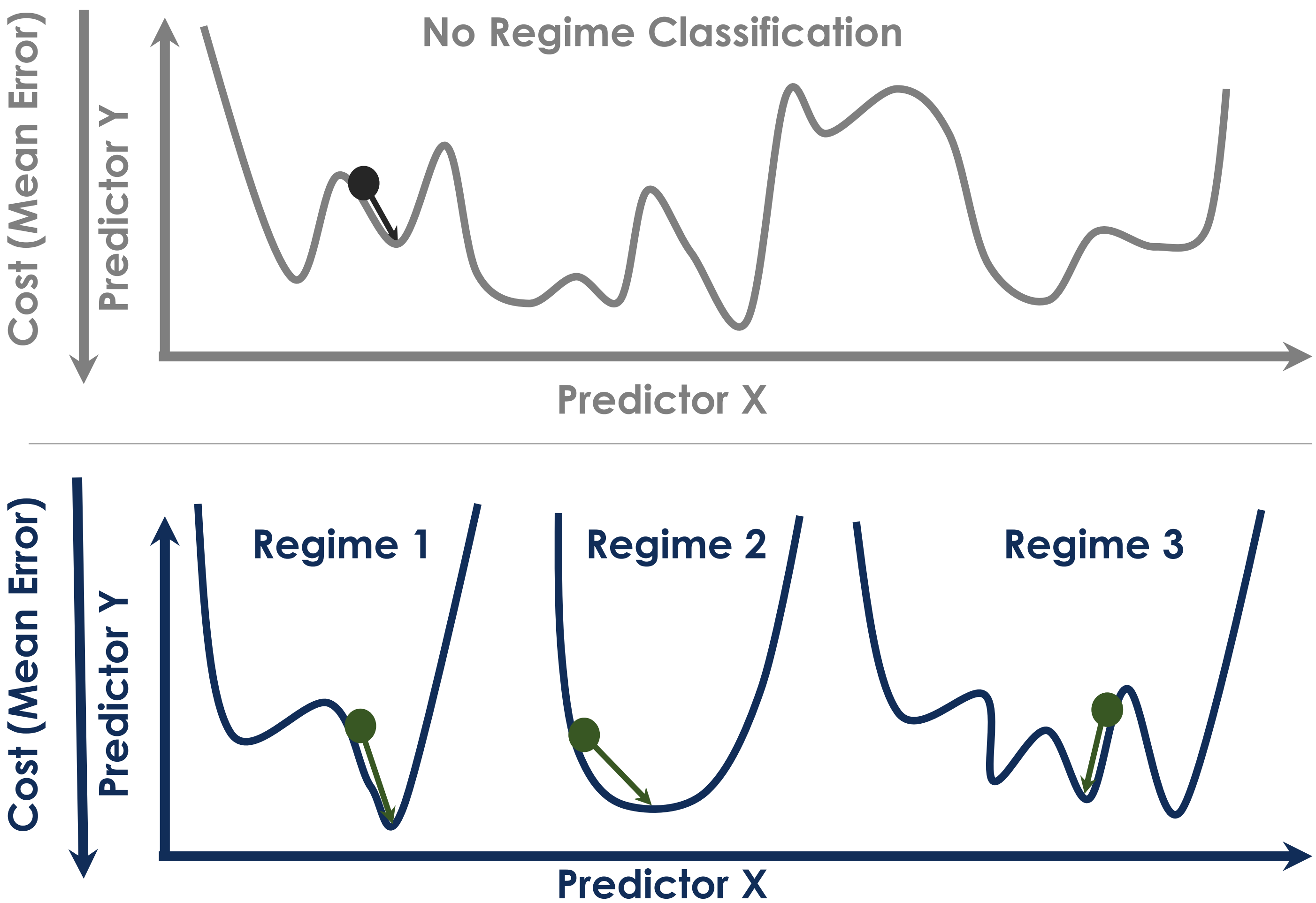
Recent Advancements

Regime-Dependent Model Theory



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Recent Advancements

Regime Classification with K-Means Clustering

Goal: statistically classify regimes **specific** to forecasting solar irradiance

K-Means clustering minimizes the variance within clusters and maximizes the variance between clusters

Satellite Predictors

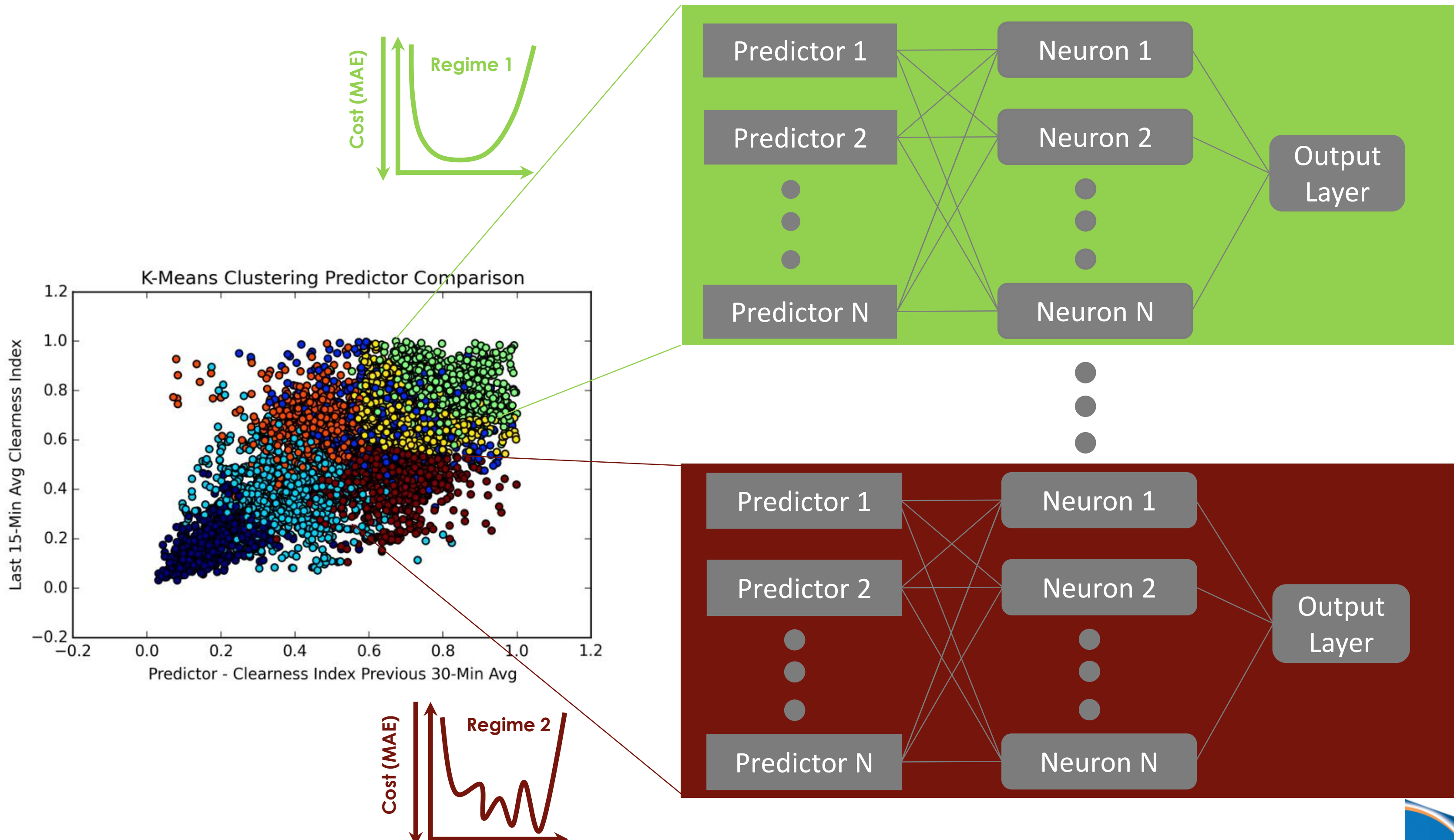
Regime Classification Variables (SMUD)	
Satellite Derived Cloud Fraction	Kt Previous 15 min
Satellite Derived Cloud Top Temperature	Kt Temporal Variability
Satellite Derived Cloud Optical Depth	Kt Most Recent Change (Kt 15 min – Kt 30 min)
Satellite Derived Hydrometeor Radius	Kt Spatial Mean
Satellite Measured Reflectance at 6.5um	Kt Spatial Variability
Satellite Measure Temperature at 6.5um	Kt Slope
Satellite Measure Reflectance at 3.75um	Cloud Cover Variability
Satellite Measured Temperature at 3.75um	Cloud Cover Squared

Derived Predictors

Recent Advancements

RD-ANN for Solar Power Forecasting

K-Means Clustering | *Artificial Neural Networks*



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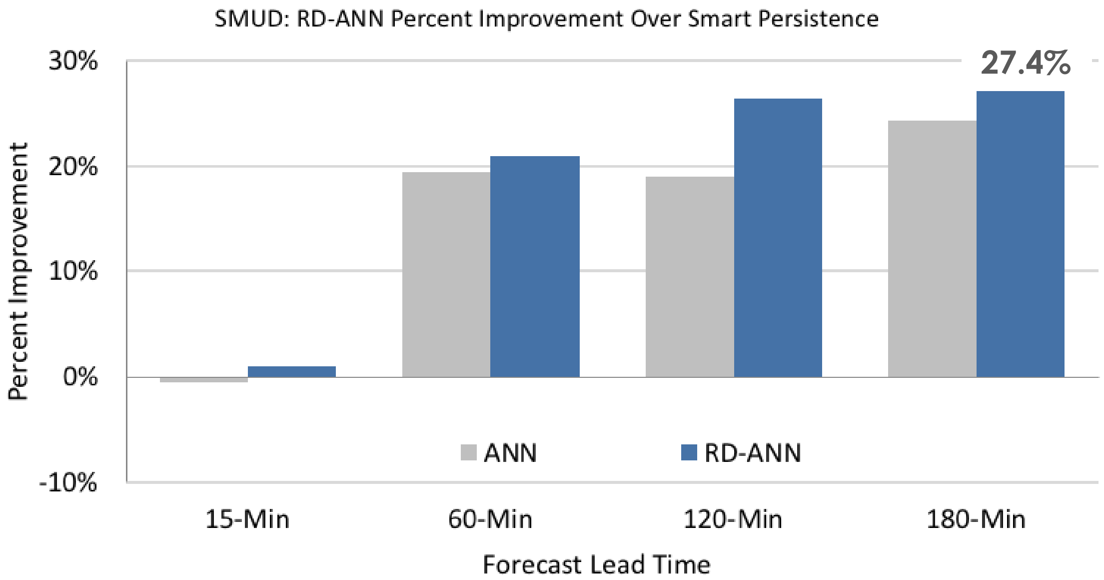
Recent Advancements

Results for Most Challenging Weather Regimes in Sacramento, CA

- RD-ANN improves over ANN for all lead times
- RD-ANN skill increases as forecast lead time increases



18.6% improvement the RD-ANN trained to predict the variability (standard deviation) had over smart persistence by compared to an ANN at 13.7%

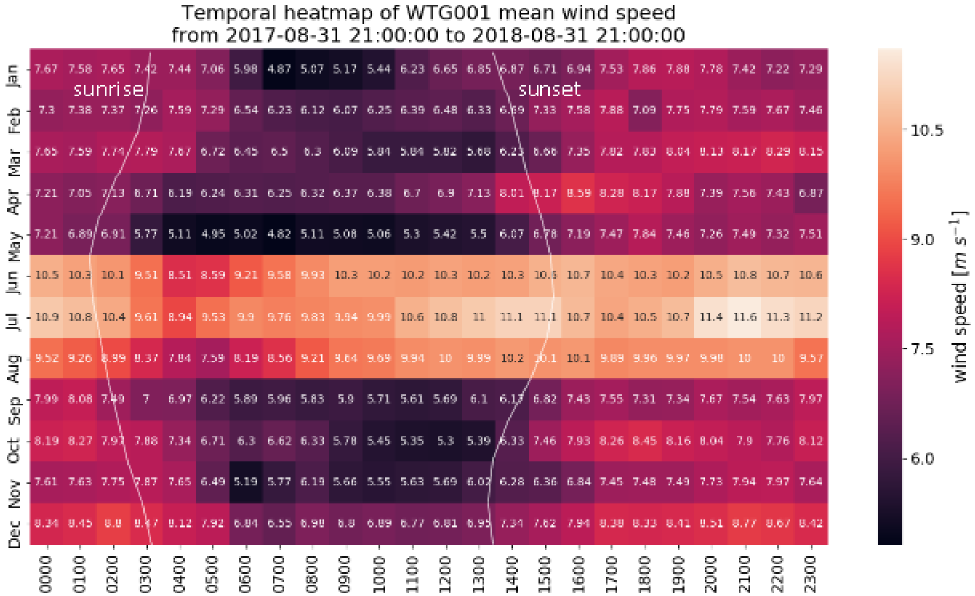
McCandless, T.C., G.S. Young, S.E. Haupt, and L.M Hinkelman, 2016: Regime-Dependent Short-Range Solar Irradiance Forecasting, Journal of Applied Meteorology and Climatology, 55, 1599-1613.

Recent Advancements

Regime-Dependent Methodology for Wind Power Forecasting

- Machine learning based nowcasting method under development for Shagaya, Kuwait Power Plant

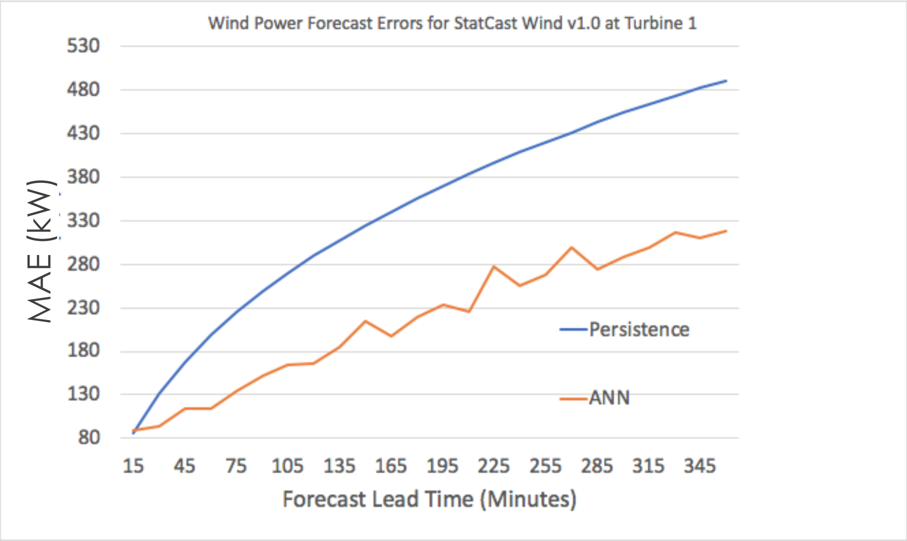
- Weather regimes identification under development
  - Shamal wind events
  - Diurnal induced low-level jet

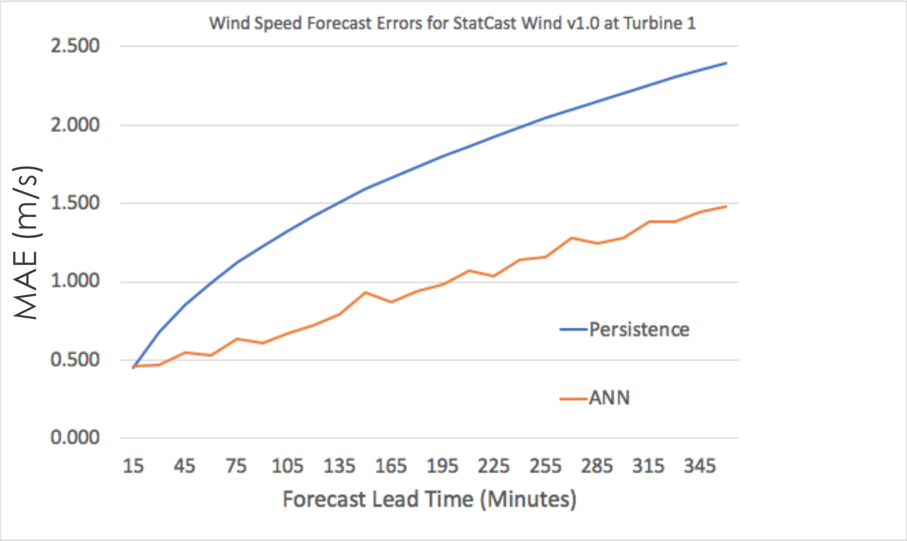


Recent Advancements

Regime-Dependent Methodology for Wind Power Forecasting

- Current ANN implementation
- 1 hidden layer with 10 neurons
- Predictors include
  - 3-hr time series of wind speed or power observations
  - Hour of day
  - Month of year





Recent Advancements

Machine Learning for Renewable Energy Prediction

Standard Methodology

Data → *Models* → *Predictions* → *Evaluate Errors*

NCAR Methodology

Define relevant metrics: MAE, RMSE separated by cloud regime

NCAR Scientists, Statisticians and Metrics Team

Multi-Stage: first predict cloud regime, then predict the irradiance (or solar power)

NCAR Subject Matter Experts and Domain Expertise

Artificial Neural Networks of various complexity and optimal predictor selection

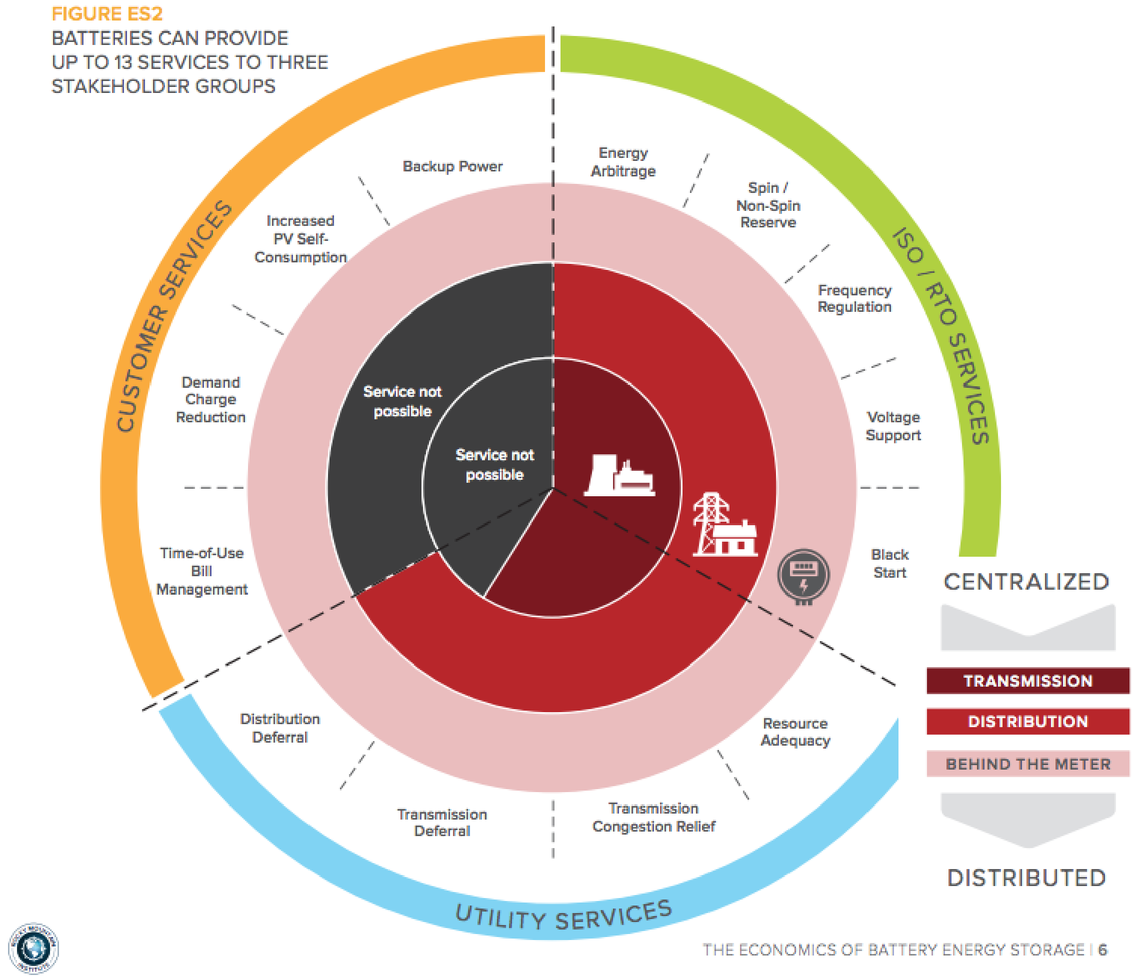
NCAR Machine Learning Scientists

Data quality control, define additional predictors relevant for predictand

NCAR Scientists, Software Engineers

Motivation for Battery Optimization

Potential Customization of Solar and Wind for Optimizing Battery Usage

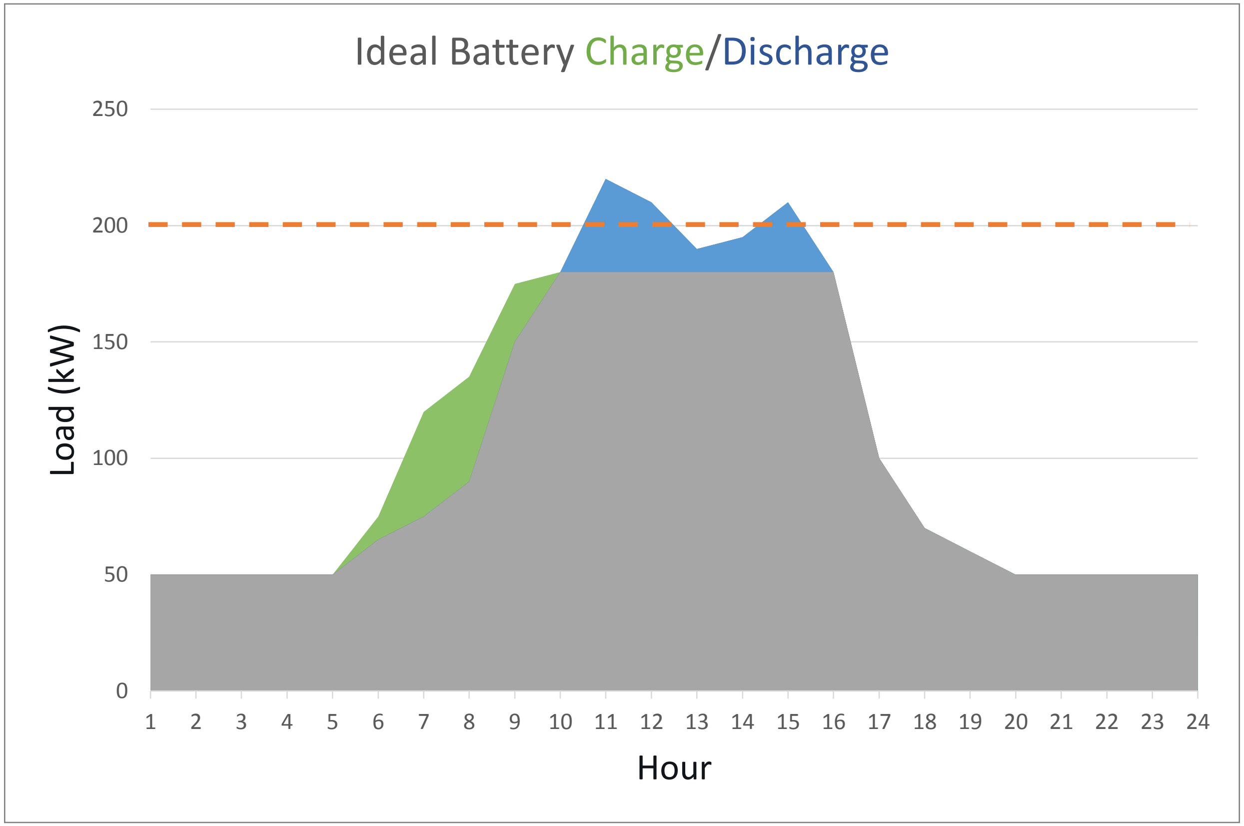


https://rmi.org/wp-content/uploads/2017/03/RMI-TheEconomicsOfBatteryEnergyStorage-FullReport-FINAL.pdf

Motivation for Battery Optimization

Potential Customization of Solar and Wind for Optimizing Battery Usage

- Optimally charge and discharge for both:
  - Demand charge reduction
  - Reducing net load (esp for TOU rates)



Motivation for Battery Optimization

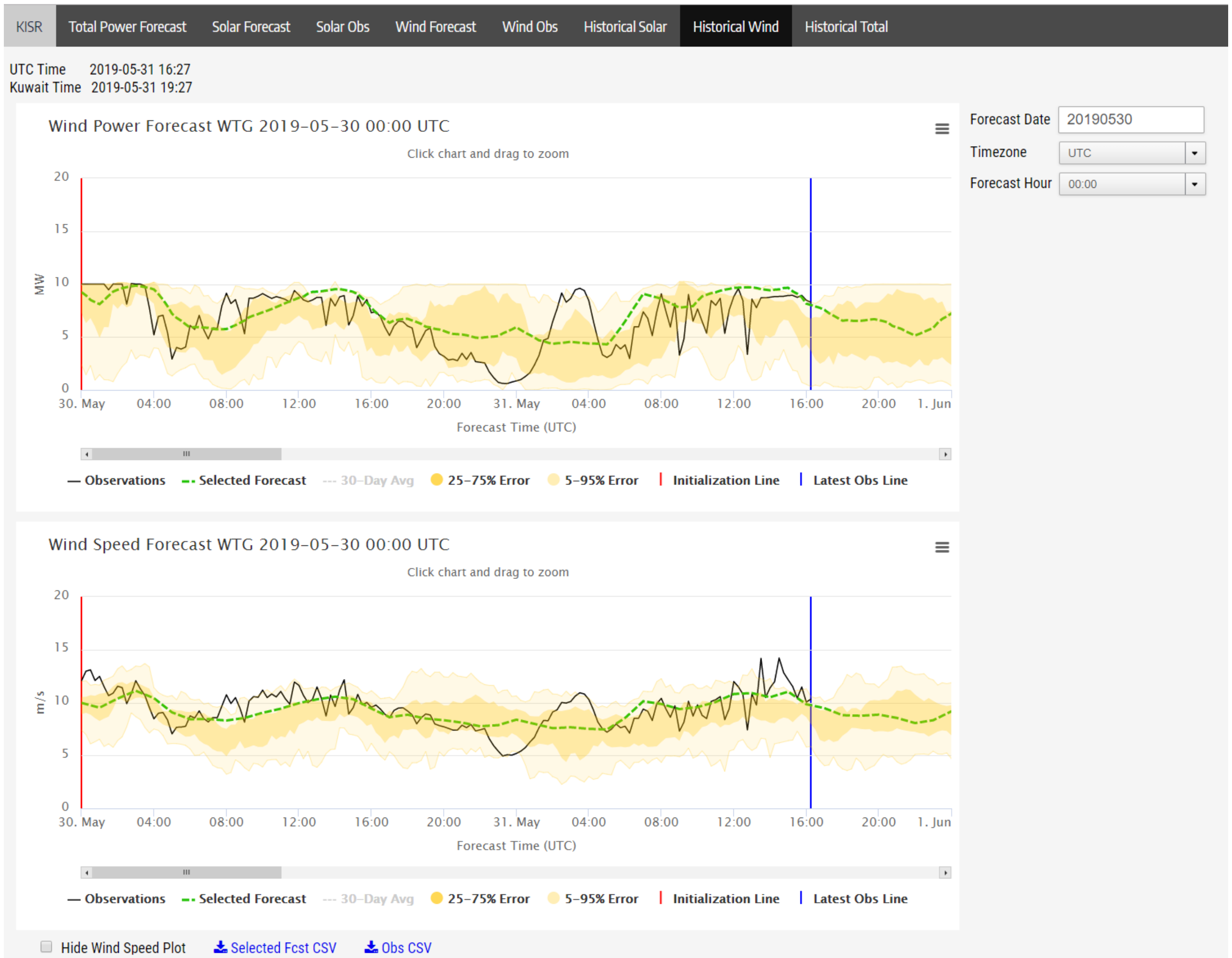
Solar Power Forecast Display

+ Combing machine learning based DICast prediction with machine learning analog ensemble for uncertainty quantification

Motivation for Battery Optimization

Wind Power Forecast Display

+ Combing machine learning based DICast prediction with machine learning analog ensemble for uncertainty quantification



Lessons Learned and Next Steps

Summary and Potential Future Work

- *Improvement in solar power forecasting accuracy via machine learning for short timescales of minutes to hours*
  - *Potential for gaining more customer services from batteries by integrating solar forecasts with battery storage optimization*
    - *Customized solar power prediction to be specific to charging and discharging a co-located battery*
    - *Site-specific solar forecasts may be more important for solar + storage*
  - *At the utility scale, there are multiple ancillary services where short-term power fluctuations significantly matter (reliability, regulation, voltage control) and predicting solar variability directly may add value for utility scale solar*
    - *Moving from 15-min to 5-min resolution*
    - *Adding probabilistic information*
    - *Could allow utility scale battery to provide more ISO/RTO services by understanding expected short-term variability*

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Questions?