Final Technical Report (FTR)

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Executive Summary:

The National Center for Atmospheric Research (NCAR) is pleased to have led a partnership to advance the state-of-the-science of solar power forecasting by designing, developing, building, deploying, testing, and assessing the SunCast™ Solar Power Forecasting System. The project has included cutting edge research, testing in several geographically- and climatologically-diverse high penetration solar utilities and Independent System Operators (ISOs), and wide dissemination of the research results to raise the bar on solar power forecasting technology. The partners include three other national laboratories, six universities, and industry partners. This public-private-academic team has worked in concert to perform use-inspired research to advance solar power forecasting through cutting-edge research to advance both the necessary forecasting technologies and the metrics for evaluating them. The project has culminated in a year-long, full-scale demonstration of provide irradiance and power forecasts to utilities and ISOs to use in their operations.

The project focused on providing elements of a value chain, beginning with the weather that causes a deviation from clear sky irradiance and progresses through monitoring and observations, modeling, forecasting, dissemination and communication of the forecasts, interpretation of the forecast, and through decision-making, which produces outcomes that have an economic value. The system has been evaluated using metrics developed specifically for this project, which has provided rich information on model and system performance.

Research was accomplished on the very short range (0-6 hours) Nowcasting system as well as on the longer term (6-72 hour) forecasting system. The shortest range forecasts are based on observations in the field. The shortest range system, built by Brookhaven National Laboratory (BNL) and based on Total Sky Imagers (TSIs) is TSICast, which operates on the shortest time scale with a latency of only a few minutes and forecasts that currently go out to about 15 min. This project has facilitated research in improving the hardware and software so that the new high definition cameras deployed at multiple nearby locations allow discernment of the clouds at varying levels and advection according to the winds observed at those levels. Improvements over "smart persistence" are about 29% for even these very short forecasts. StatCast is based on pyranometer data measured at the site as well as concurrent meteorological observations and forecasts. StatCast is based on regime-dependent artificial intelligence forecasting techniques and has been shown to improve on "smart persistence" forecasts by 15-50%. A second category of short-range forecasting systems employ satellite imagery and use that information to discern clouds and their motion, allowing them to project the clouds, and the resulting blockage of irradiance, in time. CIRACast (the system produced by the Cooperative Institute for Atmospheric Research [CIRA] at Colorado State University) was already one of the more advanced cloud motion systems, which is the reason that team was brought to this project. During the project timeframe, the CIRA team was able to advance cloud shadowing, parallax removal, and implementation of better advecting winds at different altitudes. CIRACast shows generally a 25-40% improvement over Smart Persistence between sunrise and approximately 1600 UTC (Coordinated Universal Time)[1]. A second satellite-based system, MADCast (Multi-sensor Advective Diffusive foreCast system), assimilates data from multiple satellite imagers and profilers to assimilate a fully three-dimensional picture of the cloud into the dynamic core of WRF.

[1] UTC is 5-8 hours ahead of US time zones during standard time. Thus, 1600 UTC represents 1100 EST-0800 PST.

During 2015, MADCast (provided at least 70% improvement over Smart Persistence, with most of that skill being derived during partly cloudy conditions. That allows advection of the clouds via the Weather Research and Forecasting (WRF) model dynamics directly. After WRF-Solar™ showed initial success, it was also deployed in nowcasting mode with coarser runs out to 6 hours made hourly. It provided improvements on the order of 50-60% over Smart Persistence for forecasts up to 1600 UTC. The advantages of WRF-Solar-Nowcasting and MADCast were then blended to develop the new MAD-WRF model that incorporates the most important features of each of those models, both assimilating satellite cloud fields and using WRF-So far physics to develop and dissipate clouds. MAE improvements for MAD-WRF for forecasts from 3-6 hours are improved over WRF-Solar-Now by 20%. While all the Nowcasting system components by themselves provide improvement over Smart Persistence, the largest benefit is derived when they are smartly blended together by the Nowcasting Integrator to produce an integrated forecast.

The development of WRF-Solar™ under this project has provided the first numerical weather prediction (NWP) model specifically designed to meet the needs of irradiance forecasting. The first augmentation improved the solar tracking algorithm to account for deviations associated with the eccentricity of the Earth's orbit and the obliquity of the Earth. Second, WRF-Solar™ added the direct normal irradiance (DNI) and diffuse (DIF) components from the radiation parameterization to the model output. Third, efficient parameterizations were implemented to either interpolate the irradiance in between calls to the expensive radiative transfer parameterization, or to use a fast radiative transfer code that avoids computing three-dimensional heating rates but provides the surface irradiance. Fourth, a new parameterization was developed to improve the representation of absorption and scattering of radiation by aerosols (aerosol direct effect). A fifth advance is that the aerosols now interact with the cloud microphysics, altering the cloud evolution and radiative properties, an effect that has been traditionally only implemented in atmospheric computationally costly chemistry models. A sixth development accounts for the feedbacks that sub-grid scale clouds produce in shortwave irradiance as implemented in a shallow cumulus parameterization Finally, WRF-Solar™ also allows assimilation of infrared irradiances from satellites to determine the three dimensional cloud field, allowing for an improved initialization of the cloud field that increases the performance of short-range forecasts. We find that WRF-Solar™ can improve clear sky irradiance prediction by 15-80% over a standard version of WRF, depending on location and cloud conditions. In a formal comparison to the NAM baseline, WRF-Solar™ showed improvements in the Day-Ahead forecast of 22-42%.

The SunCast™ system requires substantial software engineering to blend all of the new model components as well as existing publically available NWP model runs. To do this we use an expert system for the Nowcasting blender and the Dynamic Integrated foreCast (DICast®) system for the NWP models. These two systems are then blended, we use an empirical power conversion method to convert the irradiance predictions to power, then apply an analog ensemble (AnEn) approach to further tune the forecast as well as to estimate its uncertainty. The AnEn module decreased RMSE (root mean squared error) by 17% over the blended SunCast™ power forecasts and provided skill in the probabilistic forecast with a Brier Skill Score of 0.55. In addition, we have also developed a Gridded Atmospheric Forecast System (GRAFS) in parallel, leveraging cost share funds.

An economic evaluation based on Production Cost Modeling in the Public Service Company of Colorado showed that the observed 50% improvement in forecast accuracy will save their customers $819,200 with the projected MW deployment for 2024. Using econometrics, NCAR has scaled this savings to a national level and shown that an annual expected savings for this 50% forecast error reduction ranges from $11M in 2015 to $43M expected in 2040 with increased solar deployment. This amounts to a $455M discounted savings over the 26 year period of analysis.

Table of Contents:

List of Acronyms:

AnEn: Analog Ensemble method
ANN: Artificial neural network
BM: block-matching model
BND: Bondville, IL SURFRAD site
BNL: Brookhaven National Laboratory
BP: Budget Period
CIRA: Cooperative Institute for Atmospheric Research at Colorado State University
CMV: cloud-motion vector
CRTM: Community Radiative Transfer Model
DICast: Dynamic Integrated forecast system
DIFF: Diffuse irradiance

DNI: Direct normal irradiance
DRA: Desert Rock, NV SURFRAD site
ECMWF: European Centre for Medium-Range Weather Forecasts
EIA: Energy Information Administration
EPRI: Electric Power Research Institute
FPK: Fort Peck, MT SURFRAD site
GCM: Goodwind Creek, MS SURFRAD site
GEM: Canadian Global Environment Multiscale Model
GHI: Global horizontal irradiance
GFS: NOAA's Global Forecast System model
GRAFS: Gridded Atmospheric Forecast System
GSD: NOAA's Earth System Research Laboratory's Global Systems Division
GSI: Gridpoint Statistical Interpolation system
HRRR: NOAA's High Resolution Rapid Refresh model
ISIS: Integrated Surface Irradiance Study
ISO: Independent System Operator
LISF: Long Island Solar Farm
MADCast: Multi-sensor Advective Diffusive foreCast system
MAD-WRF: blend of MadCast and WRF-Solar for nowcasting
MAE: Mean Absolute Error
MAPE: Mean Absolute Percent Error
MMR: multivariate minimum residual method
NCAR: National Center for Atmospheric Research
NCEP: National Centers for Environmental Prediction
NOAA: National Oceanic and Atmospheric Administration
RMSE: root mean squared error
NAM: NOAA's North American Mesoscale model
NWP: numerical weather prediction
OF: optical flow model
PSCo: Public Service Company of Colorado
PSU: Penn State University, PA SURFRAD site
RAP: Rapid Refresh model
RD: regime dependent
SMUD: Sacramento Municipal Utility District
SURFRAD: SURface RADiation network
SXF: Sioux Falls, SD SURFRAD site
TBL: Table Mountain, CO SURFRAD Site
TSI: Total Sky Imager
WRF: Weather Research and Forecasting
WRF-Solar: WRF tuned for solar irradiance prediction
WRF-Solar-Now: WRF-Solar applied to nowcasting

Background:

The NCAR-led team was already immersed in solar forecasting research at the time of the award, along with other research teams throughout the world. Real-time solar power forecasting is reviewed in chapters in a few recent books, including Kleissl (2013) and Troccoli, Dubus, and Haupt (2014). The issue is well motivated in works like Dubus (2014) among others. Lorenz et al. (2014) reviews the extensive work of the team at the University of Oldenburg in Germany. The Australian initiative is ongoing as motivated in Davy and Troccoli (2012). Schroedter-Homscheidt et al. (2013) point out the need for excellent aerosol prediction for solar power prediction and discuss techniques leveraging European Centre for Medium-Range Weather Forecasts (ECMWF) chemistry forecasts. The difficulties in predicting cloud cover at specific locations are well known. Solar power prediction is accomplished by different techniques for differing time scales.

Solar energy is particularly variable over space and time because of its myriad complexities caused by the dynamic evolution of clouds. Lew et al. (2012) provides evidence of the challenge of solar power integration with the results showing the variability of power output was higher with high penetrations of solar than with high penetrations of wind. The response speed (ramp rate and start time), response duration, frequency of use (continuously or only during rare events), direction of use (up or down), and type of control characterize a utility company's operating reserves (Ela et al. 2013). These operating reserves are appropriately managed with accurate solar forecasts, as Curtright and Apt (2008) have shown that the cost of energy can be strategically minimized with knowledge of the short- and long-term PV variations. The quantification of temporal solar irradiance variability caused by the dynamic evolution of clouds has been extensively studied. Hinkelman (2013) found that not only are the irradiances themselves larger in the middle of the day but also the fractional change in irradiance from one time to another is larger. She also determined that cloud optical depth and cloud height are the best predictors of irradiance variability at one-minute time resolution. Gueymard and Wilcox (2011) analyzed the regional dependence of solar power and showed greater variability tends to occur in coastal areas, particularly along the California coast and in mountainous areas because of the micro-climate effects of topography. Kuszmaul et al. (2010) analyzed 1-sec PV output data and showed it is linearly proportional to the spatial average of irradiance. Rayl et al. (2013) performed an irradiance co-spectrum analysis and concluded that solar power site aggregation could greatly reduce power variability on short time scales depending on the distance between sites.

The non-linear variations of solar irradiance result from the complex evolution of clouds in the atmosphere; thus, many studies have tested non-linear solar irradiance prediction methods (Mellit 2008; Martin et al. 2010; Bouzerdoum et al. 2013; Fu and Cheng 2013; Marquez et al. 2013a; Inman et al. 2013; Fernandez et al. 2014; Chu et al. 2014). These studies, however, have not focused on the explicit prediction of both the temporal variability and the spatial variability of solar irradiance.

There have been multiple recent studies focused on the prediction of solar radiation or solar power with statistical learning (also known as artificial intelligence or data mining). Mellit (2008) provides a summary of techniques for forecasting solar radiation and states that 37 studies have used neural networks in the modeling and prediction of solar radiation with the second most frequent method, fuzzy logic, used five times. More recently, Martin et al. (2010) showed a final model based on Artificial Neural Networks (ANN) improves accuracy 4.84% to 25.58% over persistence for half-daily radiation forecasts. Fernandez et al. (2014) concluded that the ANN model has accurate performance for days characterized by direct irradiance (clear days) and for days characterized by diffuse irradiance (cloudy days). Chu et al. (2013) used an ANN with sky image processing to predict 1-minute average direct normal irradiance (DNI) for time horizons of 5 and 10 minutes. Another short-term prediction study used a regression technique on all-sky images to predict solar radiation five minutes in advance with a mean absolute error of around 22% (Fu and Cheng 2013). Autoregressive techniques have also shown solar power prediction capability, with Bouzerdoum et al. (2013) using a hybrid seasonal autoregressive moving average and support vector model to predict hourly power output. All of these studies advanced prediction of solar irradiance, but none claim to be optimal.

Sky imaging is another approach to very-short-range solar forecasting. The team has been aware of high-quality work being done at the University of San Diego and elsewhere, and has interacted with Jan Kleissl of USCD and his collaborators on several occasions. His team's work with total sky imagers (TSIs) is reported in Urquhart et al. (2015) and Bosch and Kleissl (2013). The BNL approach is unique and different from what Kleissl and his team are doing. Huang et al. (2013) describe the initial methodology for nowcasting solar irradiance with a single TSI. There are three main steps to their algorithm: 1) TSI image preprocessing, 2) cloud motion estimation, and 3) solar radiation estimation. They showed positive results for their 1-minute and 2-minute irradiance forecasts. Peng et al. (2015) extended the BNL algorithm of Huang et al. (2013) to use three TSIs to better estimate the 3D cloud field. By comparing overlapping cloud regions in multiple TSIs (located several hundred meters to about 1-2 kilometers apart), estimates of the height of each cloud feature are derived using geometry. Knowing the height of each cloud feature greatly aids in estimating cloud motion vectors, and allows for improved tracking of clouds at different levels (i.e., cumulus vs. cirrus clouds) over the single-TSI algorithm. Peng et al. (2015) also developed a support vector regression model with a radial basis function to forecast solar irradiance based on recent TSI frames and pyranometer data. This new irradiance prediction model was shown to have improved error metrics compared to other radiation prediction models tested out to 3-minute forecasts. Even with multiple TSIs, however, the irradiance prediction horizon is limited to approximately 10-15 minutes when low cumulus clouds are present, as they will typically transit across the image scene in that amount of time. In situations where high cirrus clouds are present, however, irradiance forecasts could potentially be extended to 30-60 minutes, as they take longer to transit across the image scene. BNL continues these advances as shown below.

Satellite based cloud prediction is another important method that lies between the very-short-range and the medium-range time scales. An overview of the current state-of-the-art in solar forecasting is provided in the book edited by Kleissl (2013), including details of physically based satellite methods for short-term forecasting, provided in Chapter 3 by Miller et al. The problem is rooted in our ability to utilize multi-spectral satellite imagery (preferentially from the geostationary constellation) to characterize the geometric and microphysical properties of meteorological clouds. Knowledge of cloud locations, heights, and properties can be used to estimate the down-welling solar irradiance (direct and diffuse components) at the cloud shadow locations. Provided information on cloud motion, the shadows can be propagated forward in space/time to provide a time-series of solar irradiance at a given location.

For longer time scales beyond about 6 hours, it is necessary to employ numerical weather prediction (NWP). The initialization of clouds in NWP models is a difficult problem that has recently received increased scrutiny. Current data assimilation methods are challenged by the high spatio-temporal variability of clouds, strong non-linearities in the radiative transfer calculation and simulated microphysical properties, and non-Gaussian error distributions. Model balance via ensembles of forecasts is affected by sampling error and systematic model errors. For these reasons, NWP forecasts are usually inferior to simpler advection methods in the first few hours of the forecast (i.e. nowcasting).

Under cloudless or partly cloudy conditions, aerosols have a strong impact on surface irradiance, particularly its direct and diffuse components. Under such circumstances, the solar forecasting performance of NWP models, such as the Weather Research and Forecasting (WRF) model or the one built by the European Centre for Medium Range Forecasting (ECMWF), has been found to be highly biased (Gerstmaier et al. 2012; Ruiz-Arias et al. 2012; Troccoli and Morcrette 2012). An appropriate way to handle aerosols is to apply aerosol transport models, such as put forth in the Monitoring Atmospheric Carbon and Climate (MACC) project (Schroedter-Homscheidt et al. (2013). The aerosol model developed at ECMWF (Morcrette et al. 2008) has a remarkable 3-hourly resolution, a relatively good spatial resolution (~120-km grid spacing), and benefits from the assimilation of Moderate Resolution Imaging Spectroradiometer (MODIS) observations. Outputs of this model are now commercially used in the prediction of solar irradiance on a global scale, with noticeable improvements in the resulting global horizontal irradiance (GHI) and DNI accuracy (Cebecauer et al. 2011a,b). Data from the MACC project must be validated over the U.S. Day-ahead high-quality aerosol forecasts and could be used to predict GHI and DNI with WRF. The NASA (National Aeronautics and Space Administration) Goddard Earth Observing System, version 5 (GEOS-5), offers another real-time analysis and prediction of aerosols (Randles et al. 2013). Substantial improvements in day-ahead solar forecasts under cloudless or partly cloudy days, particularly over areas of large aerosol variability, can be expected from these developments.

In a recent comparison of various solar forecasting models for the U.S., Perez et al. (2011) showed that NOAA's operational models (that use WRF as the underlying numerical model) lagged other international forecasting models in terms of accuracy of their solar irradiance predictions. So far, this has been interpreted partly due to shortcomings in cloud modeling and data assimilation. It is possible that the radiative transfer algorithms in the U.S. forecast models are not optimal for this application. This hypothesis was confirmed by Ruiz-Arias et al. (2012) in the case of the WRF model. That study highlighted biases in one frequently used radiative algorithm in WRF, and a need for adding aerosol data for its improvement.

The conversion of irradiance to power depends on the particular type of hardware installed at the solar farm as well as local conditions. There are models, such as PVWatts (http://pvwatts.nrel.gov/) that can do this power conversion. In prior work with wind energy, we have found however, that site-specific empirical power conversion methods using machine learning methods can outperform models (typically power curves for wind energy) because they take into account local effects such as terrain blocking, impact of upstream turbines, density, etc. (Parks et al. 2011). For solar energy, such effects could include dust, shadowing, etc., that cannot be captured in any general model. Thus, as part of this project, we have developed such empirical methods to use across a broad range of solar technologies and geographic locations.

Any forecast requires state-of-the-science evaluation. Traditional metrics are commonly used for evaluation, such as in Marquez and Coimbra (2011). Diagnostic methods provide information that is user-relevant, such as metrics related to ramp variability. Such metrics may include application of spatial methods such as "object-based" approaches that identify and compare characteristics of spatial objects (Davis et al. 2009). In addition, they may identify specific events in time, such as changes in magnitude of insolation at a point location. They also may identify rates of change, such as ramp rates (e.g., Mathiesen et al. 2012), and they may consider temporal and spatial attributes of the forecasts (e.g., Brown et al. 2012) that are often very relevant for decision-making based on the forecasts. Metrics related to economic and other benefits are the most complex to derive, but may be the most meaningful for end users.

In summary, although there have been some important recent accomplishments in predicting solar power, there is plenty of room for advancement. This Public-Private-Academic Partnership has been working to fill the gaps in the research and then use the research results to build a functioning, seamless SunCast™ forecasting system.

Project Objectives:

The goal of this project was to build a solar power forecasting system that advances the state-of-the-science through cutting edge research and to test it in several high penetration solar utilities and ISOs with geographic and climatological diversity, using appropriate metrics, and to disseminate the research results widely to raise the bar on solar power forecasting technology. Achieving this goal has brought seminal advances in the state of cloud forecasting, and thus, solar irradiance and power forecasting, as well as integrating that power into the grid and assessing the resulting value. The project has advanced the ability to integrate solar energy into the power mix more efficiently, economically, and reliably. We have documented the economic savings of improved solar power forecasting. Thus, the results of this project stand to advance greater penetration of renewable energy.

Project Results and Discussion: The SunCast Solar Forecasting System

System Overview

The team has demonstrated and evaluated a working SunCast™ solar power prediction system that includes the multiple components described herein, including WRF-Solar™, multiple models from national centers, TSICast, CIRACast, and MADCast, MADWRF, as well as statistical models. The individual components and the overall SunCast™ system have been validated using the metrics developed at the beginning of the project. The team has met or exceeded target values specified in most of the milestone tables in the statement of work to DOE. Data streams from various model systems have been made available to the forecasting partners, forecasts were regularly provided to the utility and ISO partners, and feedback from the partners were incorporated into the forecasting models.

The team employed a holistic philosophy in configuring the system, thinking of it in terms of a value chain (Figure 1). A pictorial representation of how the component modules would have to fit into the system is shown in Figure 2, which illustrates our view of how these Nowcasting and NWP systems work together to produce a seamless forecast across scales. They are blended via complex systems engineering (Figure 3), dealing with Big Data issues (Haupt and Kosovic 2015, 2016), including high data volume; variety of types of data, ranging from point observations through very large output of gridded NWP forecasts; must be dealt with in real-time arriving sporadically from multiple sources; highly complex; high variability; and of mixed veracity, which requires large amounts of quality control.

Although these issues are challenging, the prospects for enhanced application are promising. As more solar energy is brought into the energy grid, the need for accurate forecasts grows. This demand for continually improving forecasts provides interesting research topics for our atmospheric scientists and software engineers. Here we blend a mix of physical models with artificial intelligence methods to blend the two in order to produce an improved forecasting system.

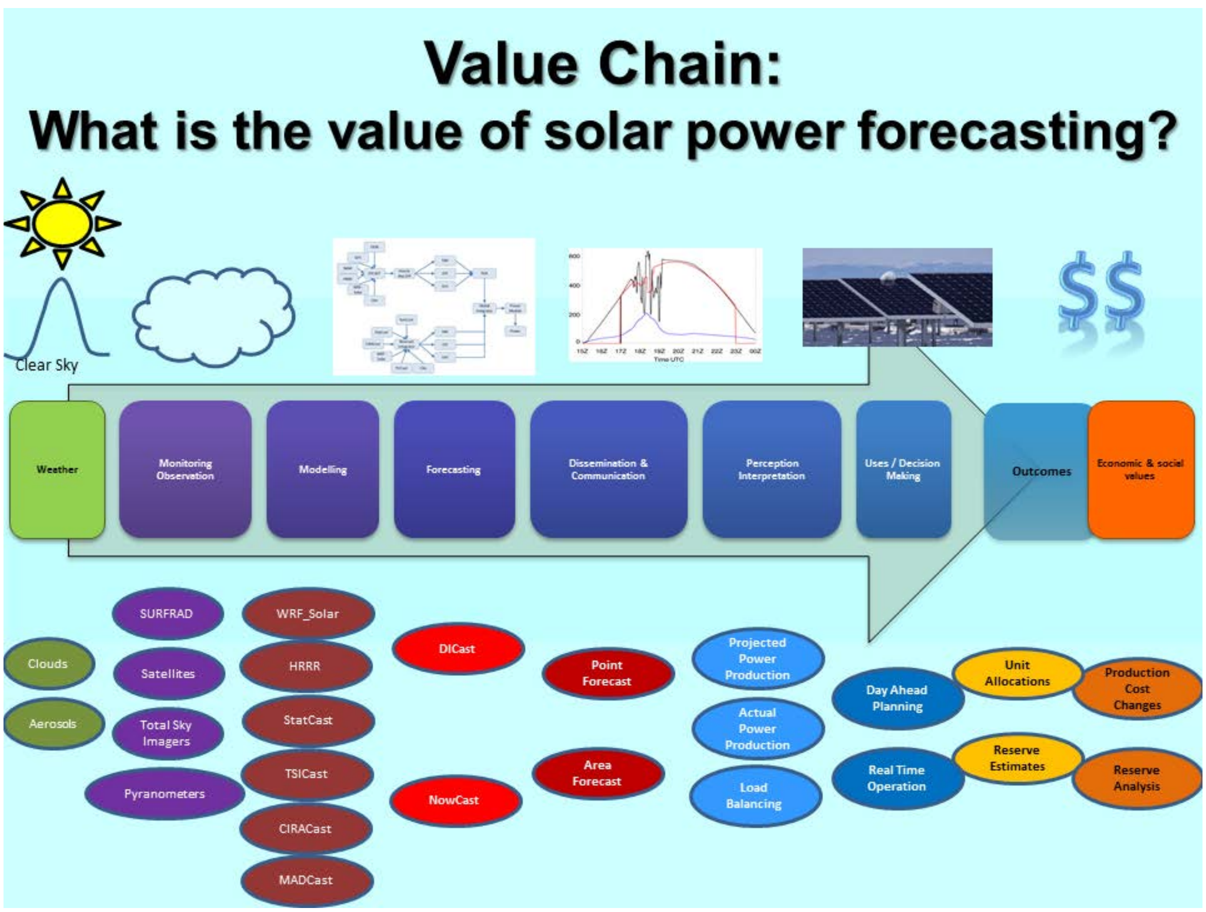

Figure 1. Value chain of implementing a weather decision support system for solar power. At the bottom are the components of the NCAR team's system that build toward providing an economic impact of this system.

The engineered SunCast™ system (Figure 3) has two main forecast tracks: a Nowcast track that forecasts at high temporal resolution out to 6 hours, and a DICast® track that forecasts at coarser temporal resolution out several days. Both of these modules apply a consensus forecasting approach. That is, they consider multiple inputs and perform a forecast integration that takes advantage of the strengths of each input. While the consensus forecasting approach has been applied to forecasting more common weather variables (e.g., air temperature), in the past it had not previously been applied to solar irradiance forecasting in any significant way. No other public systems use a consensus forecasting approach. In the private sector, some companies may use a consensus approach, while others rely on a single-source model; much of this is proprietary and not disseminated. Forecasts are provided every 15 min out to 72 h and can be provided as far out as 168 h.

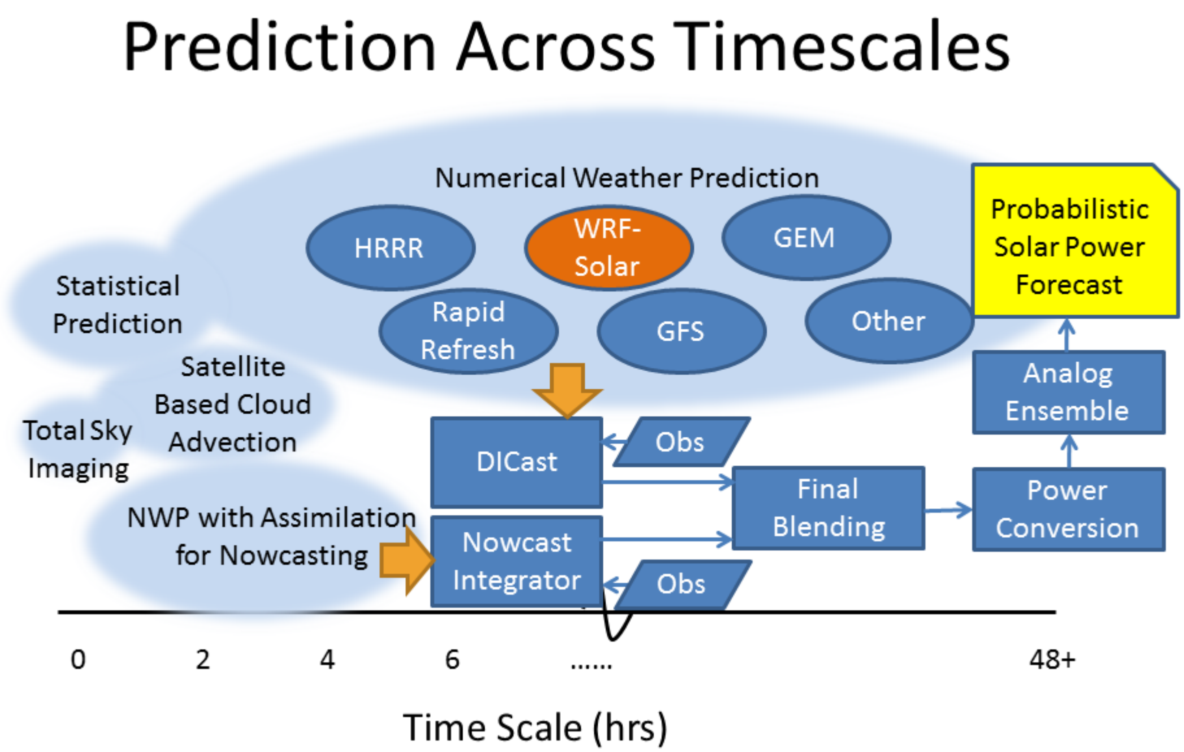

Figure 2. SunCast™ forecasting system predicts across scales.

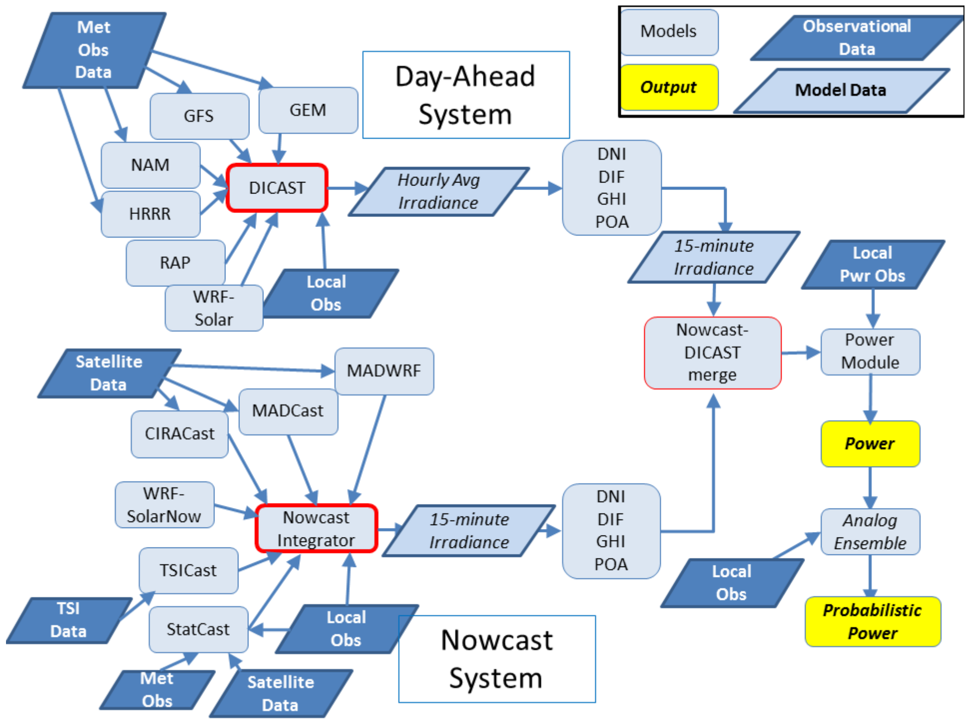

Figure 3. The engineered SunCast™ system.

Nowcast System

TSICast

BNL deployed 25 pyranometers in the Long Island Solar Farm (LISF) as shown in Figure 4 to measure the surface solar irradiance. These sensors measure the GHI in real-time. The measurements, which are recorded every 10 sec, are synchronized with the TSI observations. The variations in zenith angle and the diurnal and seasonal patterns are also recorded in the raw GHI measurements, and therefore bias our subsequent irradiance forecast models. To mitigate this bias, we normalized each radiation value to a clear-sky index Kt during model training and testing. Letting GHI^t be the raw GHI measured at time t and GHI^t_{clear} be the corresponding clear-sky estimate, the clear-sky index Kt is calculated as follows:

$$Kt = \frac{GHI\ Observed\ at\ the\ Surface}{GHI\ at\ the\ Top\ of\ the\ Atmosphere} \tag{1}$$

where Kt ranges from 0 to 1. However, its maximum value can be greater than one due to the cloud enhancement caused by diffuse sunlight.

Among the techniques of tracking the motions of clouds, block matching and optical flow (OF) are applied widely to various types of imagery, including ground-based cameras and satellites. Block-matching techniques take a collection of pixels (i.e., a block) as a tracking unit, have the ability to utilize information from multiple areas, and therefore are sufficiently robust to both image noise and brightness variations within images. If the underlying motions consist of only translational velocity, and do not involve shearing and stretching, a block-matching approach can faithfully represent the true movements of clouds (Huang et al. 2011). Optical flow models originate in the field of computer vision, where motion tracking is usually resolved by estimating the pixel-wise distribution of prominent velocities of brightness/texture patterns on an image. In general, an OF method can obtain dense motion vectors at the granularity of a pixel, and was proven to be quite effective in detecting cloud motions in satellite images (Corpetti et al. 2008).

BNL developed a new hybrid approach that integrates the block-matching (BM) method and the variational OF model, and uses the former method to guide/refine the latter one. This new model encompasses three main steps: (1) extracting a cloud mask, and generating cloud blocks via bottom-up merging and detecting block-wise motions; (2) identifying dominant motion patterns from detected motion vectors; and (3) estimating optical flow using our new formulation and refining based on multiple motion filters. This design recognizes that the vectors detected by the BM and the OF models are actually inter-dependent. For optimal results, they should be integrated into the same framework to ensure mutual enhancement.

Furthermore, we increased the range of the state-of-the-art ground-based prediction system from the level of one minute to 10-15 minutes, depending on the speed at which the clouds are moving. This work includes three components: 1) a robust algorithm to detect the identical piece of cloud across different views of the TSI cameras, and recover its height information, and to track clouds across different time frames of the same camera and calculate its motion; 2) an intelligent cluster algorithm to identify different cloud layers and regimes that are based on information streams from multiple TSIs; and 3) a stitching algorithm to expand the field of view by concatenating multiple images from different cameras, and to handle the challenges of stitching images based on ambiguously defined features, such as cloud heights, borders, shapes, and textures.

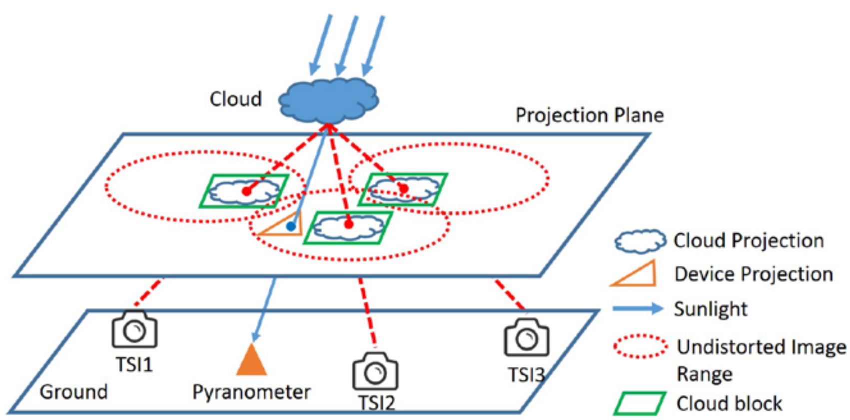

Figure 4. Overview of three-TSI tracking.

With the development of various imaging systems and growing interests in image-based solar forecasts, there is an urgent need to provide reliable approaches to extract cloud information and to build irradiance models from sky images. BNL extracted cloud spatial-temporal information and investigated a series of image analysis modules for a complete forecast system, including image preprocessing, motion tracking, multi-camera integration, and multi-layer determination in various types of sky images. To improve the robustness of image-based prediction and extend the forecasting range, our work integrates heterogeneous image datasets and ensembles a series of cloud tracking and prediction algorithms, each of which has its own strength and weakness in different cloud conditions and prediction periods. BNL's most significant contributions include:

1. BNL developed a cloud detection pipeline that utilizes a supervised classifier and abnormal image correction based on histogram equalization. This research significantly improved the accuracy of extracting cloud mask and attained improved performance in various cloud types, weather conditions, and lighting patterns.
2. On the basis of previous work of tracking clouds in sky imagery, BNL designed a hybrid model of cloud motion tracking that combines block-matching and optical flow. The new model is able to determine local deformations of clouds, to extract cloud layers with dominant motion patterns, and to remove noise from the resulting motion field with customized motion filters.
3. BNL designed a comprehensive framework of cloud image simulations and generated synthetic image sequences using motion models and Gaussian noise. The simulated image is used for the evaluation of motion tracking models under different simulations, e.g., with cloud deformation and corrupted images.
4. BNL devised a short-term solar forecast system utilizing ground-based sky cameras. The system adopts multi-angle observations to undertake the task of cloud tracking based on spatial and temporal correlation and provides a pipeline to detect multi-layer motions via clustering. The robust feature extraction and irradiance models are then vetted for real production forecasts. Compared with single-camera models, the proposed system significantly enlarges the field of view, enables 3-D cloud tracking, and obtains more accurate forecasts.

Compared with single-camera models, TSICast significantly enlarges the field of view, enables 3-D cloud tracking, and obtains more accurate forecasts. As is shown in Figure 5, TSICast improves on GHI persistence forecasts[2] by an average of 25-30% in the 5-15 minute range, and by 30-40% in the 1-5 minute range, in testing performed for the network of 25 pyranometers at BNL.

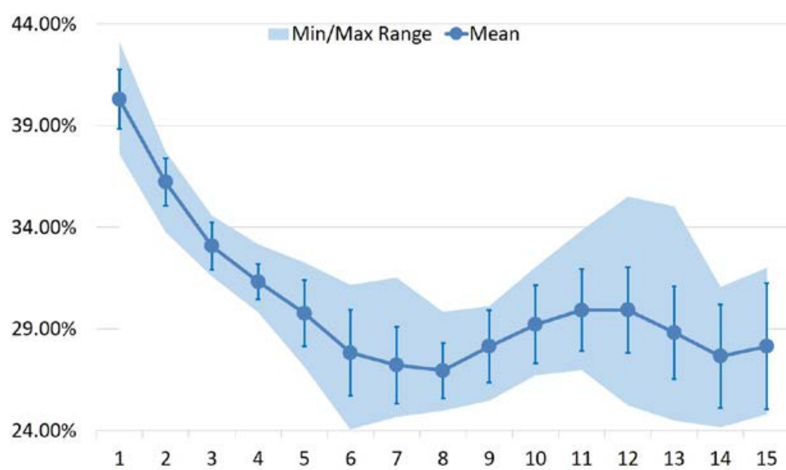

Figure 5. Improvements in the MAE ratio achieved by the non-linear SVRrbf model in comparison with the GHI persistent model on all available data. The Min/Max bounds represent the range of the percent improvement values for all 25 stations.

[2] This is the only use of straight GHI persistence as a baseline for comparison in this document. This is appropriate for the very short timeframe represented in the TSICast forecast. All other short-range comparisons are to Smart Persistence, defined on p. 14.

Statistical Characterization and StatCast

University of Washington studied statistical variability for different cloud properties as observed by satellite data. To be useful predictors of solar irradiance variability, the cloud properties not only need to be independent of each other but also correlated with the variations. In Figure 6 we plot the 95th percentile points for the populations of 1-minute averaged total hemispherical irradiances falling in a given cloud height, fraction, or optical depth bin. As seen earlier, cloud optical depth, which directly determines transmittance, has a clear, though not one-to-one, relationship with variability. Surprisingly, cloud fraction does not. We would expect broken clouds to lead to higher variability, but cloud fraction depends only on the total cloud amount, not brokenness. Another measure of brokenness should probably be sought. The surprising result of this analysis is that cloud top height exhibits a nearly linear relationship to the 95th percentile of an irradiance distribution function, indicating that it would be a good criterion from which to estimate irradiance variability.

NCAR has developed, built, and tested several versions of Statcast. StatCast forecasts the clearness index, Kt, as defined in Eq. (1) above. The inclusion of regime dependence was inspired by initial experiments with data that divided a time series into clear, cloudy, and partly cloudy days.

The four current versions of StatCast include:

1. StatCast-Persistence (Kt-persistence) –The model assumes that Kt persists from the previous time step. This results in a model that recognizes the changes in solar angle, but assumes persistence of atmospheric constituents and clouds. This is sometimes called "smart persistence" and is used in much of the rest of the assessment as a baseline.
2. StatCast-Cubist – This version of StatCast uses the Cubist model regression tree to train on historical data, then predicts in real-time. Compared to StatCast-Persistence, StatCast-Cubist yielded improvements of generally 35-50% in terms of MAPE at all lead times on clear days, and 10-50% on cloudy days, with improvements getting larger with increasing lead time, as compared to Smart Persistence.
3. Regime-Dependent StatCast (RD-ANN-KtCC) – RD-StatCast uses a k-means clustering method to separate instances into cloud regimes, then applies an artificial neural network (ANN) to each regime separately. StatCast-RD frequently improve upon StatCast-Persistence by generally 15-25% for lead times of 1-3 hours.
4. Regime-Dependent StatCast incorporating Satellite Data (RD-ANN-GKtCC) – Based on the third version, this most advanced version of StatCast also includes data from the GOES-East satellite to determine cloud state. This version generally performs better than version 3 if there are sufficient data. If not, this method tends to overfit the data.

Results of the methods are compared in Figure 7 for all forecast lead times at the Sacramento Municipal Utility District (SMUD) sites. As expected, the forecast error increases as the forecast lead time increases. The only method that generally performs worse than clearness index persistence is the RD-ANN-GCT method that uses the GOES-East derived cloud types as the regime classification method. At the 15-min lead time, the RD-ANN-KtCC, RD-ANN-GKtCC, ANN-ALL, and clearness index persistence all show similar errors. However, at the 60-min and longer lead times, the RD-ANN-KtCC, RD-ANN-GKtCC, and ANN-ALL all show improvement over the clearness index persistence, as shown by the larger MAE of the clearness index forecasts.

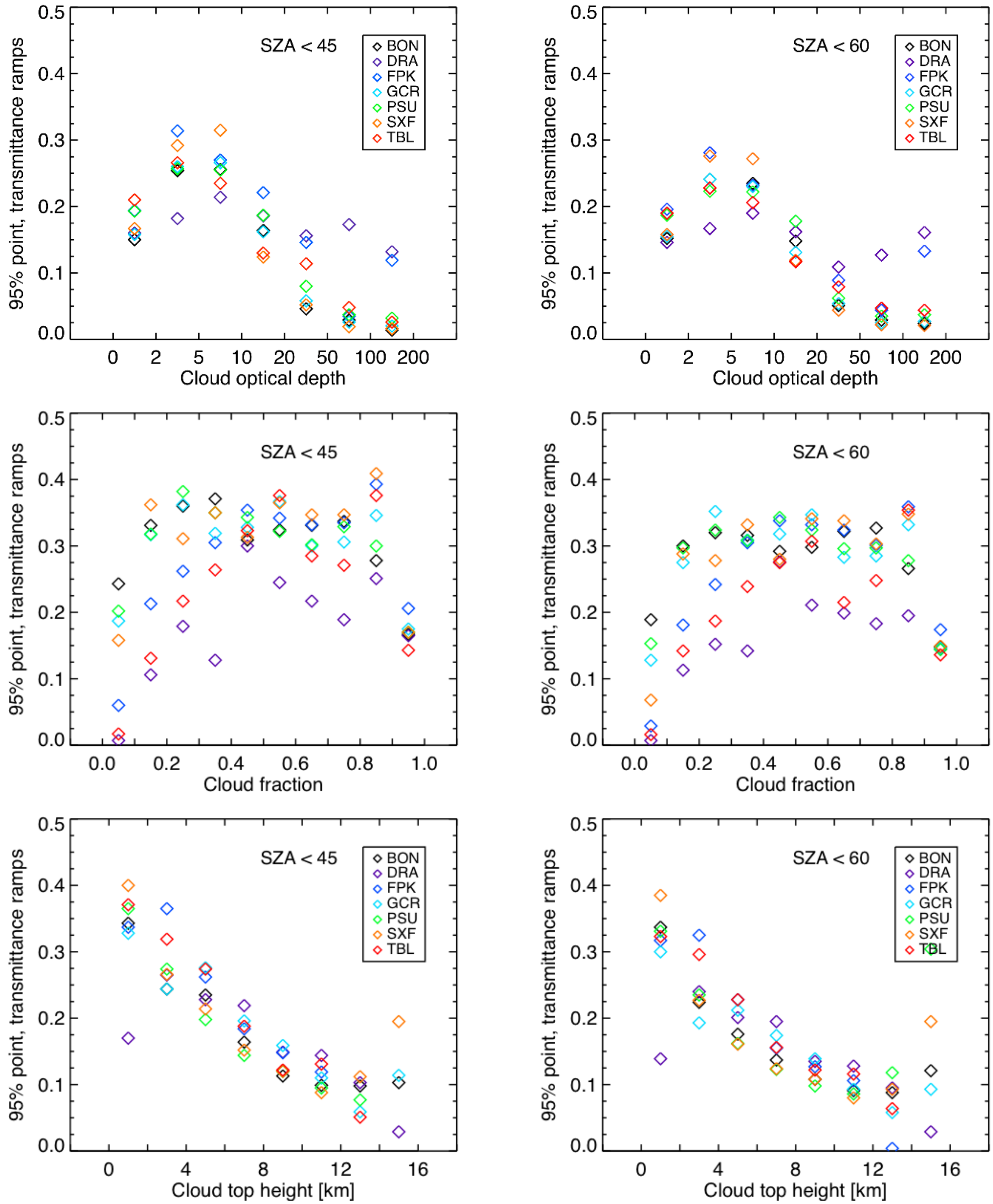

Figure 6. 95th percentile points in 1-min average transmittance difference distributions as a function of location and cloud optical depth (top), fraction (middle), and height (bottom). Plots in the left (right) column include only times of day with solar zenith *angles (angle between the sun and the vertical) less than 45° (60°). The colors refer to specific SURFRAD (SURface RADiation) network sites for which they were compared. Sites include Bondville, IL (BND), Desert Rock, NV (DRA), Fort Peck, MT (FPK), Goodwin Creek, MS (GCM), Penn State Univ, PA (PSU), Sioux Falls, SD (SXF), and Table Mountain, CO (TBL)*

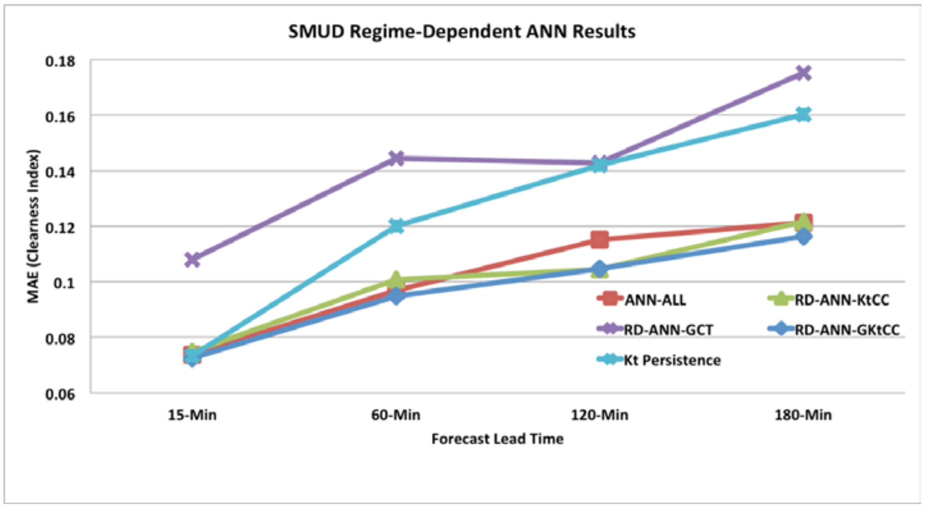

Figure 7. MAE as a function of lead time for all methods of the satellite determined cloudy instances for the SMUD sites. The method that performs best in the majority of the forecast lead-times is the RD-ANN-GKtCC method.

The method that generally performs best is RD-ANN-GKtCC method, which exploits the GOES-East data in both the k-means clustering and ANN. This work is reported in more detail in McCandless et al. (2015, 2016a,b).

CIRACast

Additionally, elements of the CIRACast algorithm were adapted to other components of the blended forecast algorithm. These components, which serve as deliverables for the project, include the adaptation of the shadow-casting and parallax correction components of the satellite algorithm, which, respectively, compute and correct for the location of cloud shadows derived from retrieved cloud-top properties and solar geometry, and the satellite geometry of observation. These two components were provided as source code to the WRF-Solar™ team and integrated successfully into that component's forecast ability. Additionally, CIRACast was adapted to work within the larger DICast® forecasting system, making the algorithm more readily ingestible by various forecast sources. Graphing and imagery code to aid in the analysis of satellite-derived forecasts were also developed during the course of the project.

To further improve accuracy, work was begun on a blended forecast wind guidance, utilizing cloud-motion vector (CMV) winds in concert with NWP guidance to identify stationary cloud features. As CMV wind products are designed to identify significant wind features, it was found late in the project that stationary cloud features were often filtered out from the CMV analysis, complicating the ability to identify and utilize CMV-derived wind fields using off-the-shelf CMV analyses. Continued work on identification and quantification of near-stationary wind vectors using satellite observations, to be used in concert with NWP guidance to improve cloud advection, will continue outside of the scope of this project.

As seen in Figure 8, relative MAE values of GHI forecasts computed for the Desert Rock, NV SURFRAD site was 9.6% (beating the project target error rate of 10% for "simple" sites), and

21.8% for Table Mountain, CO (not shown - nearly achieving the project target error rate of 20% for "complex" sites).

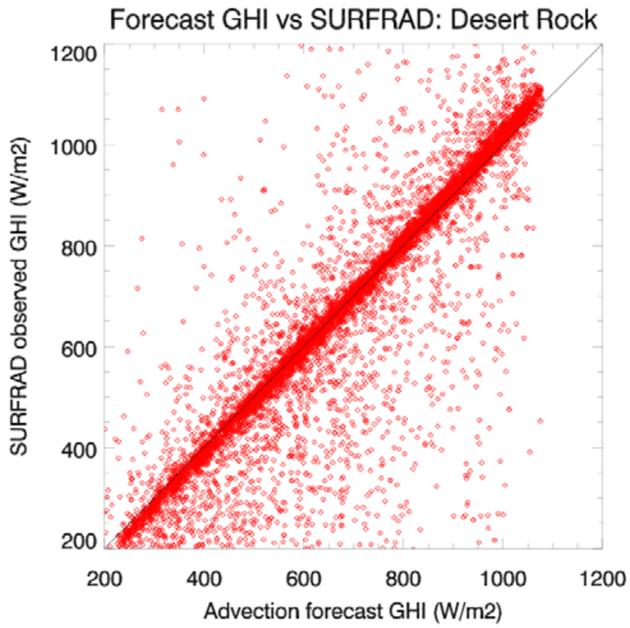

Figure 8. Scatter plot of forecasted GHI vs. observed GHI for the Desert Rock, NV, SURFRAD site. Forecasts are for the period between January and December 2014. Relative MAE for the period is 9.6%.

MADCast

The Multisensor Advection-Diffusion NowCast (MADCast) is a new model designed for the analysis and short-term forecasting of clouds (Auligné 2014a,b; Descombes et al. 2014). The following description is inspired by Descombes et al. (2014), where the interested reader is referred to for further technical details of MADCast.

The cloud analysis is based on retrievals of multiple infrared (IR) sensors using the multivariate minimum residual (MMR) scheme (Auligné 2014a,b). MMR has been implemented in the Gridpoint Statistical Interpolation system (GSI; Kleist et al., 2009). GSI provides three-dimensional cloud fields that are subsequently advected and diffused by a modified version of the Weather Research and Forecasting model (WRF; Skamarock et al. 2008). Finally, the predicted cloud field is used to diagnose the surface irradiances completing the short-term forecast.

The fundamental piece of the cloud retrieval process is the MMR scheme (Auligné 2014a,b). The MMR scheme has been implemented in the GSI data assimilation system. GSI produces the cloud analysis consisting in a three-dimensional cloud fraction. This cloud fraction retrieval is performed following these steps:

- Calculate infrared radiance using WRF and the Community Radiative Transfer Model (CRTM; Han et al. 2006) under the clear sky hypothesis.
- Compute the departures between the satellite radiances and WRF for multiple channels sensitive to different altitudes in the atmosphere.

- Apply the MMR scheme to the departures to solve a variational problem (similar to a 1D-Var approach) in order to retrieve a cloud fraction profile from the satellite fields of view.
- Interpolate the cloud fraction profiles from the satellite fields-of-view to the model grid points. Specific procedures are used to optimally combine the information of sounders and imagers in order to exploit their different horizontal and vertical resolutions.

The cloud retrieval has been implemented successfully for a number of IR instruments on board of polar-orbiting and geostationary platforms. These instruments include AIRS, IASI, CrIS, MODIS, GOES-Imager, GOES-Sounder, FY-2D VISSR, Himawari-7 MTSAT-2, METEOSAT-10 SEVIRI. The AIRS, IASI and CrIS radiances are available from the National Centers for Environmental Prediction (NCEP).

The last step in the MADCast forecast is to combine the clear sky irradiances and the three-dimensional cloud fraction from WRF into surface irradiances valid for all sky conditions. This requires some assumptions about how the clouds attenuate the shortwave radiation. In principle, clouds at different heights may have different hydrometeors and can lead to different cloud extinction properties. This makes estimation of the cloud extinction properties to be a challenge.

WRF-Solar-Now

The WRF-Solar™-Now quasi-operational forecast started in September 2014. The model provides a 6-hour forecast over CONUS with a 9-km horizontal grid spacing. The model is run every hour using forecast data from the NOAA (National Oceanic and Atmospheric Administration) Rapid Refresh (RAP) model (Weygandt et al. 2011) to create the initial and boundary conditions. The model is initialized with the 3-hour forecast from RAP, which allows us to have the forecast available around 40 min before the initial time of the simulation (equivalent to 40-min negative latency). The output is recorded every 15 min and it is an input to the nowcasting integrator.

WRF-Solar™-Now uses the solar augmentations that were available at the beginning of the quasi-operational forecasts. These include an improved solar tracking algorithm, output direct and diffuse components, and time series every model time step at sites with surface irradiance available for evaluation of the model performance. The aerosols are represented using a monthly climatology and thus avoiding the increase in the computational cost associated with the advection of aerosols. An important WRF-Solar™ augmentation for nowcasting needs, the feedback of unresolved clouds, was not available at the beginning of the quasi-operational period and thus was not activated.

Data from the quasi-operational forecast was used to investigate the added value of MADCast with respect to the WRF-Solar™-Now system. The RMSE as a function of the lead time calculated with the four months of quasi-operational runs from December 2014 to March 2015 for the GHI from MADCast and WRF-Solar™-Now are shown in Figure 9. Results summarize statistics over fourteen sites over the contiguous U.S. (7 SURFRAD sites and 7 Integrated Surface Irradiance Study [ISIS] sites). MADCast RMSE shows a steady increase as a function of the lead time. On the contrary, the RMSE of WRF-Solar™ shows larger values at the beginning of the forecast with near steady values after 1 h 30 min. At 1 h 30 min both models show similar RMSE. This indicates that, on average, MADCast forecast is superior to WRF-Solar-Nowcast during the first hour and a half.

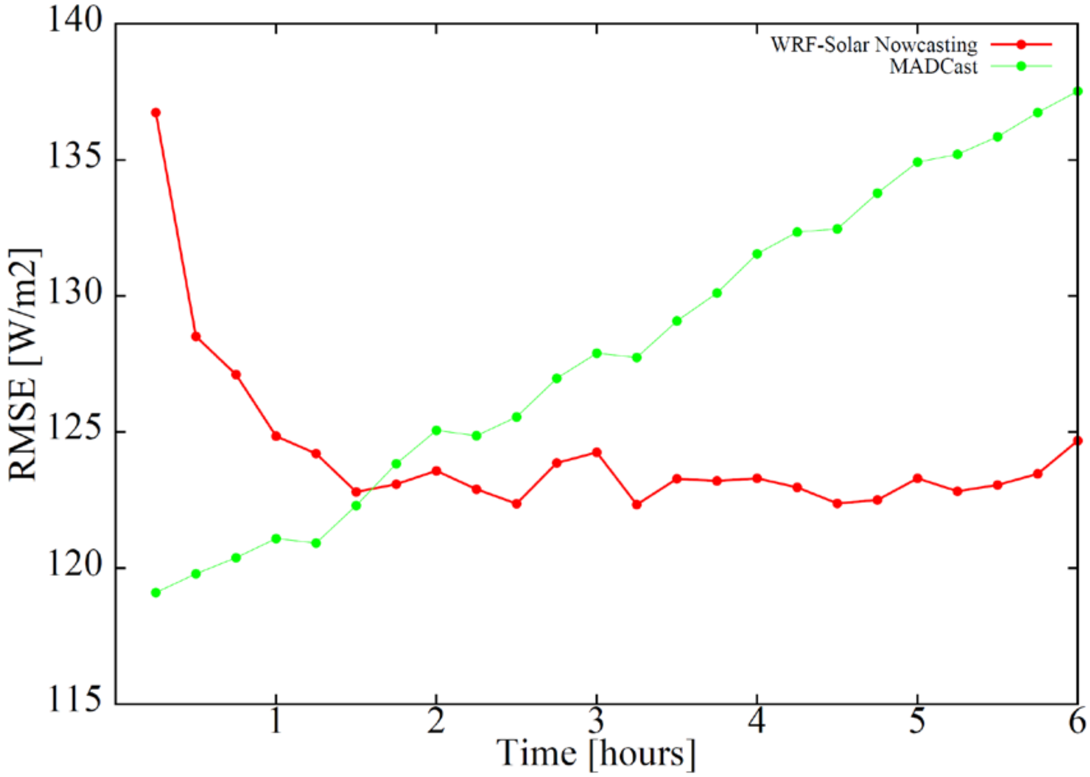

Figure 9. MADCast (green) and WRF-Solar™ Nowcasting (red) RMSE of the GHI as a function of the lead time.

The added value of MADCast in the short-term forecast Figure 9 indicates the potential of the model for nowcasting applications.

MAD-WRF

The two nowcasting systems, MADCast and WRF-Solar-Nowcasting, have been coupled to form MAD-WRF in order to exploit desirable and compatible characteristics of each system. MADCast assimilates infrared irradiances from different satellite platforms to infer the presence of clouds. The assimilated cloud fraction is subsequently advected and diffused, with simplified model physics, in order to provide the cloud forecasts. Once the forecast is completed, assumptions are made on how the clouds attenuate the clear sky radiation in order to obtain the irradiance forecasts. WRF-Solar™ does not assimilate clouds, but has better physical packages to represent microphysics and the interaction of clouds with radiation. The coupled system therefore takes advantage of the data assimilation from MADCast and the better physics of WRF-Solar™.

There are three fundamental aspects that need to be considered to couple the models:

- First, the definition of the cloud fraction from MADCast is different than the WRF-Solar™ definition, which is the conventional definition for any NWP model. In MADCast, the cloud fraction of each grid volume represents the contribution to the 2-D cloud fraction (vertically integrated) that do not overlap with other grid volumes in the same vertical column. On the contrary, the cloud fraction in NWP models is defined as the fraction of a given grid volume that has clouds. In order to use the assimilated cloud fraction in the coupled system (MAD-WRF), the MADCast cloud fraction needs to be converted to the NWP definition.

- Second, MADCast provides no information about the cloud water and ice mixing ratios that need to be specified in order to compute the shortwave radiative transfer.
- The third aspect is to consolidate the two sets of cloud fractions and cloud mixing ratios from MADCast and WRF-Solar-Nowcasting in order to provide one single set to the shortwave radiation package. This consolidation should take into account the better performance of MADCast during the beginning of the forecasts. Having consistent cloud fractions and mixing ratios and a strategy to consolidate the two sets are the fundamental components of the coupled MAD-WRF nowcasting system.

The cloud fraction from MADCast is converted to the NWP definition, assuming that the clouds are homogeneous. The first step is to calculate the 2-D cloud fraction from MADCast. This is straightforward given the MADCast definition. One just needs to add the cloud fractions of a given vertical column and repeat the process for each column. Assuming that the clouds are homogeneous implies that the 2-D cloud fraction is the cloud fraction of each grid volume that has clouds. In order to suppress the tendency of MADCast to produce clouds that reach the ground, a threshold has been imposed to classify the grid volumes into clear and cloudy. Figure 10 shows a conceptual diagram to illustrate this process.

The cloud and ice mixing ratios were specified with the assumption that the clouds are warm and homogeneous. Hence, we neglect the contribution of ice in the shortwave radiative transfer and impose the same cloud water mixing ratio for all the grid volumes identified as cloudy.

The two sets of cloud fractions and cloud mixing ratios were merged based on our experience with the quasi-operational runs performed with MADCast and WRF-Solar-Nowcasting. The analysis of four months of forecasts, from December 2014 to March 2015, indicates that MADCast is, on the mean, superior to WRF-Solar-Nowcasting during the first 1.5 h of the simulation). After that point WRF-Solar-Nowcasting is usually superior to MADCast. Based on these empirical results, the cloud fraction and mixing ratios from MADCast are imposed during 0-1 h; the two sets are averaged from 1-1.5 h, and the set from WRF-Solar-Nowcasting is imposed after 1.5 h.

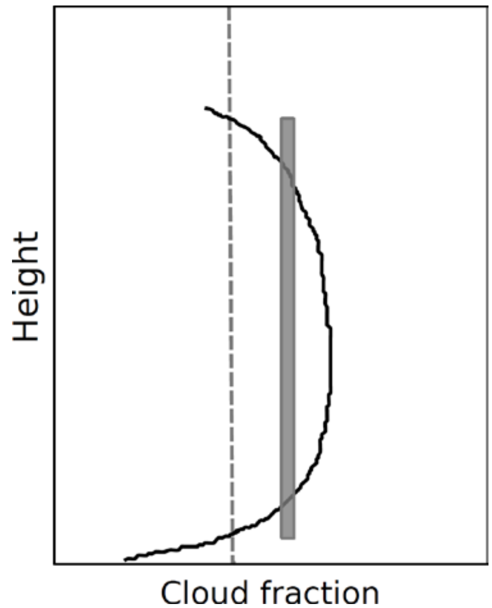

Figure 10. Conceptual diagram showing the cloud fraction from MADCast (black line) and its conversion to the NWP cloud fraction (gray rectangle). The threshold in the cloud fraction is also shown (gray dashed line).

Case Study Comparison

To better understand the performance of the various SunCast™ components in specific situations, a series of inter-comparison case studies was undertaken by NCAR. Four case days were chosen for the region near Sacramento, California. These four case days represent canonical cloud cover regimes of the region, and thus test forecast systems that predict GHI. Fifteen-minute average GHI predictions were compared against observations from seven pyranometers owned and operated by the SMUD. Results indicate that each forecast system has its own strengths and weaknesses in the various regimes, times of day, and forecast lead times. The specific components of SunCast™ that were used in the case studies were StatCast-Cubist, CIRACast, MADCast, and four configurations of WRF-Solar Nowcasting. Results are shown in the accompanying NCAR Technical Note.

WRF-Solar™

The primary enhancements that set WRF-Solar™ apart from the standard WRF NWP model include improved representation of the aerosol-radiation feedback, incorporation of cloud-aerosol interactions, and improved representation of cloud-radiation feedbacks, in addition to improving the handling of the solar position/equation of time calculation and making all three irradiance components (GHI, DNI, DIF) available for output every model time step as desired. These improvements have led to greatly reduced errors in GHI predictions. Figure 11 highlights this well for all the SURFRAD sites, where, for clear skies, errors in GHI predictions from WRF-Solar™ improved upon standard WRF by a remarkable 40-60%.

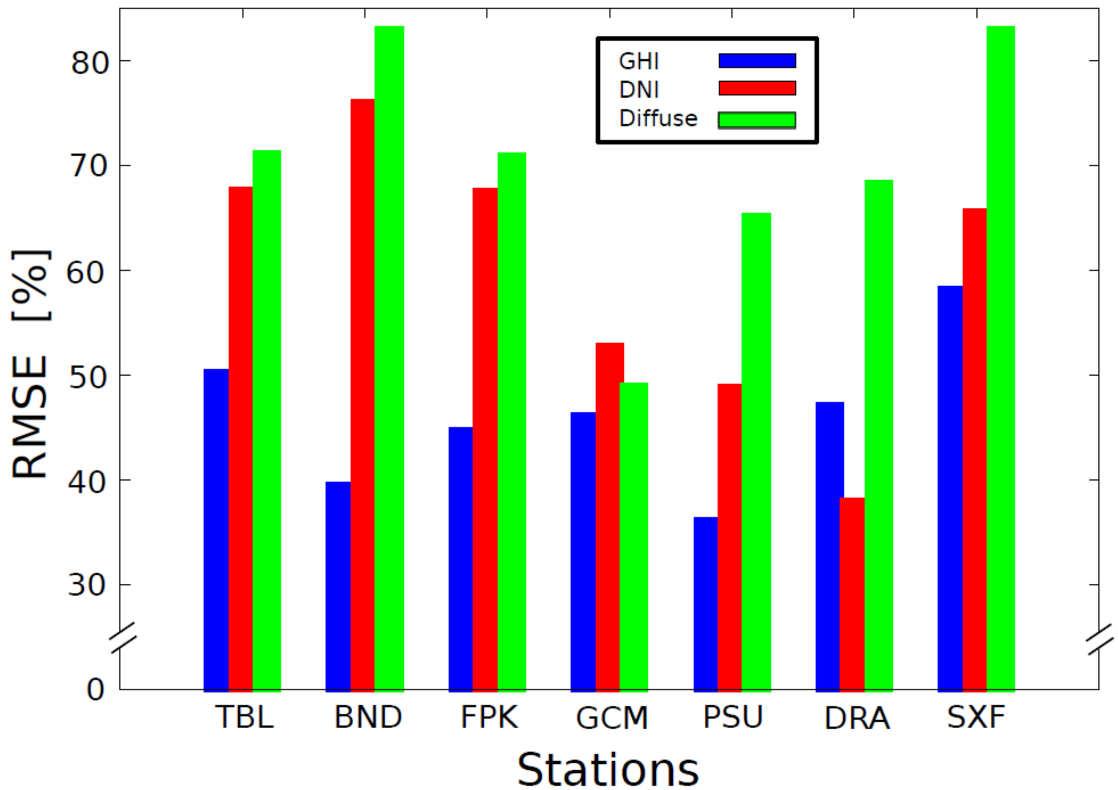

Figure 11. Improvements introduced by WRF-Solar™ (experiment GEOS5-AOD) in the estimations of the clear-sky surface irradiance components at the SURFRAD sites. The standard WRF simulations are used as a baseline for comparison. Stations are as defined in the caption to Figure 6.

System Engineering

The overarching concept for the SunCast™ system is to blend various forecasting models to provide a best consensus-based forecast over all timeframes. Using multiple models is an important part of this concept and is a "best practices" approach to modern meteorological prediction. Figure 3 displays the engineered system that blends Nowcast components as well as NWP via DICast®. The Nowcast blender takes uses statistics from historical operation of the components and trains weights in a nowcasting expert system integrator. The DICast® system used in SunCast™ combines forecasts from multiple numerical weather prediction (NWP) models in an optimal way to produce tuned irradiance forecasts at specific locations and forecast projections. The system uses a history of observations and model runs to determine the performance of each model, then weighs each model based on its relative performance. The resultant integrated forecast produces lower error characteristics than if one used the best-performing individual model over the time period. These two systems are then blended, interpolating hours 3-6 linearly, then we use an empirical power conversion method to convert the irradiance predictions to power, and finally apply an analog ensemble (AnEn) approach to further tune the forecast as well as to estimate its uncertainty. The AnEn module decreased RMSE by 17% over the blended SunCast™ power forecasts and provided skill in the probabilistic forecast with a Brier Skill Score of 0.55 (see assessment below). In addition, we have also developed a Gridded Atmospheric Forecast System (GRAFS) in parallel, leveraging cost share funds.

SunCast™ Assessment

A full assessment of SunCast™ is presented in the accompanying NCAR Technical Note. Here we focus on the metrics specific to Budget Period 4.

Several baselines are available for this evaluation, including persistence with knowledge of sky condition for NowCast components (Smart Persistence) and publically available numerical weather prediction (NWP) models for both the NowCast and DICast® components. Table 9 provides details describing the baselines.

As shown in Table 1, the publically available NWP baselines that were evaluated included the North American Mesoscale model (NAM), the Global Forecast System (GFS), the Global Environment Multiscale Model (GEM), and the High Resolution Rapid Refresh (HRRR). The HRRR is run at two locations: NOAA's National Centers for Environmental Predication (NCEP) and NOAA's Earth System Research Laboratory's Global Systems Division (GSD). The HRRR run at NCEP is the publically available operational model and is based on WRFv3.5.1 (similar to WRF-std baseline). The HRRR run at GSD is the development version in preparation for transition to operations in the next few months and includes many of the advancements in the WRF-Solar™ package as well as other developments.

Table 1. Characteristics of baselines for metrics evaluation.

Baseline	Abbrev-iation	Comparison with:	Fcst available	Comments
Smart Persistence based on initial StatCast	SmartP	NowCast	0-6 hr with 15 min increment	Requires past irradiance obs; when not available, constant clearness index of 0.6 used in lieu of obs. See NowCast section for complete description.
Standard Version of WRF	WRF-std	NowCast and DICast	0-48 hr	WRF version 3.5.1 with WRF solar development removed
Power Obs	Obs	Power Conversion	0-72 hr	Observations from partner locations
Publically available NWP	NAM	NowCast and DICast	0-72 hr	North American Model - Available via NOAA/NCEP - 12 km -– hourly
	GFS	DICast	0-72 hr	Global Forecast System - Available via NOAA/NCEP - 0.25 deg (~30 km) – 3 hourly
	GEM	DICast	0-72 hr	Global Environmental Multiscale Model - Available via Environment Canada – 25km – 3 hourly
	HRRR	NowCast	0-15hr	High Resolution Rapid Refresh - Available via NOAA/NCEP – 3 km -– hourly
	HRRRx	NowCast	0-15hr	High Resolution Rapid Refresh development model (NCEP refers to is as HRRRx) Available via NOAA/GSD – includes WRF-Solar improvements – 3 km - hourly

One purpose of exploring multiple nowcast components is that each one is potentially skillful for a different forecast horizon (lead time) and sky condition. Understanding the strengths and weaknesses of each system can lead to development of an expertly blended system. Figure 12 provides a synopsis of skill based on Mean Absolute Error (MAE) for many of the Nowcast components (except TSICast) during BP3 and BP4, stratified by sky condition. Sky condition was determined using the cloudiness index derived by StatCast Smart Persistence using the Clearness Index parameter. Cloudiness index >=0.6 was considered clear skies; values <= 0.2 were considered cloudy and everything in between was identified as partly cloudy. In Figure 12, the MAEs for clear sky conditions are generally smaller than those for cloudy and partly cloudy skies. The skill of smart persistence in all sky conditions is slightly smaller in BP4 versus BP3, very likely because the forecast conditions during an El Nino year can be more challenging to predict. Results depicted in Figure 12 are summarized in Table 2. In general, all components have larger improvements over smart persistence for clear conditions than for cloudy conditions. TSICast and MADCast showed positive improvements between BP3 and BP4 while StatCast and CIRACast showed less skill and WRF-Solar-Now showed no improvement between BP3 and BP4. The comparison between budget periods was performed during the winter months; Figure 13 provides a more complete picture of seasonal performance for partly cloudy conditions for one of the partners, SMUD. For these data, MAE tends to be smaller during summer months.

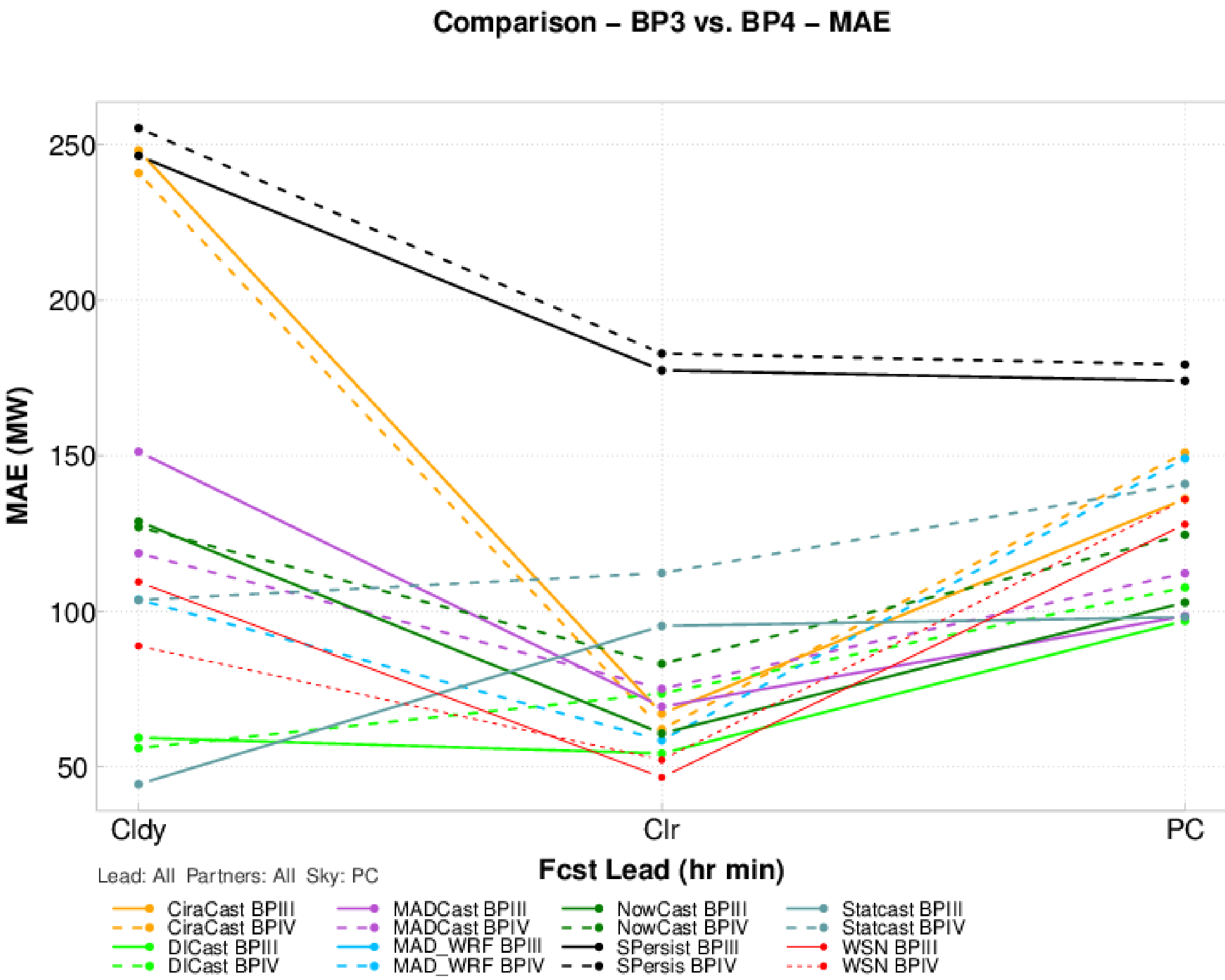

Figure 12. Median MAE for NowCast components stratified by sky condition. Scores for BP3 are denoted by a solid line and 2015 label in legend, and are aggregated over Jan, Feb and Mar 2015. Scores for BP4 are denoted by the dashed lines and 2016 labeled in the legend.

Table 2. Median MAE improvement in percent of NowCast components versus smart persistence for Clear and Partly Cloudy/Cloudy sky (Cldy) conditions stratified by budget period. Percent change between BP3 and BP4 is also identified.

	BP3			BP4			% Change		
Component	**Clear**	**Cldy**	**All**	**Clear**	**Cldy**	**All**	**Clear**	**Cldy**	**All**
StatCast	46.2	61.9	55.1	38.5	37.4	37.1	-16.6	-39.4	-20.9
TSICast*	-	-	29.0	-	-	34.0	-	-	17.0
CIRACast	62.1	16.5	45.9	66.0	12.8	36.3	6.2	-21.9	-8.3
MADCast	60.9	40.1	48.9	58.9	43.8	50.3	-3.2	9.3	2.8
WRFSolarNow	73.7	40.7	55.9	71.4	42.4	55.6	-3.1	4.19	-0.5

* TSICast was a higher frequency forecast that did not contribute directly to the NowCast blended system. It was evaluated separately and hence only evaluated for all sky conditions.

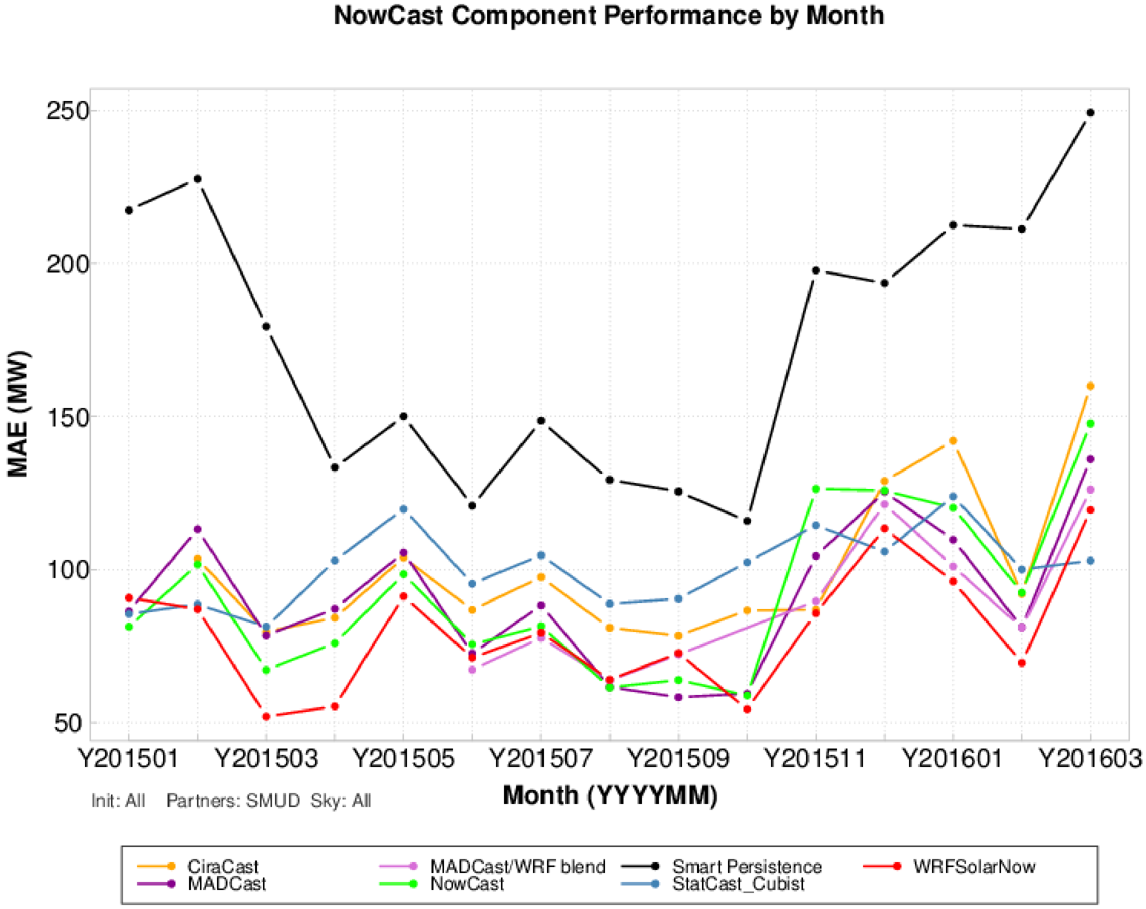

Figure 13. Median MAE for SMUD stratified by month.

TSICast provides one-minute forecasts out to 12-15 minutes depending on the weather conditions. The MAE values for TSICast provided in Table 3 indicate the largest errors are for the 14-minute forecasts, with an MAE of 64.1 W/m^2.The forecasts were evaluated using the Verification library within the R statistics package. The Bias, RMSE, and Skewness listed in Table 3 represent the first, second and third moments of the error distribution. The inner-quartile range (IQR) represents the distance between the 25th and 75th percentile of the distribution. The MAE at 15 minutes from the NowCast system for Smart Persistence was 97.3 W/m^2. Using this value as the baseline, the percent improvement of TSICast over Smart Persistence is 34%.

Table 3. Scores for TSICast error distribution including, Bias (or Mean Error), Mean Absolute Error, Root Mean Square Error, Inner Quartile Range, Maximum Value, Minimum Value, and Skewness. Units for all scores are W/m2.

Lead Min.	Bias	MAE	RMSE	IQR	Max	Min	Skewness
0	-7.4	35.8	94.3	10.38	1042.8	-1636.4	-0.41
2	-6.6	43.0	104.2	18.4	1064.6	-2170	-0.23
4	-6.1	48.4	111.0	26.8	1073.5	-1639.68	-0.14
6	-7.7	52.6	116.0	34.3	1105.5	-2192	-0.25
8	-8.9	57.2	121.1	41.4	1113.5	-1662.97	-0.18
10	-9.3	60.8	125.2	48.3	1147.7	-1636.4	-0.21
12	-9.0	63.0	126.7	54	1132.8	-2170	-0.20
14	-8.8	64.1	124.8	61.2	1134.9	-1639.68	-0.28

WRF-Solar™ configurations for both the Nowcasting system, extending out to 6 hours and the day-ahead system, extending from 6-48 hours, were evaluated and compared with several state-of-the-science models. The publicly available NWP baselines that were evaluated included the North American Mesoscale model (NAM), the Global Forecast System (GFS), the Global Environment Multiscale Model (GEM), and the High Resolution Rapid Refresh (HRRR). During BP3 and BP4, median percent improvement by WRF-Solar™ over HRRR during the first 15 hours of the forecasts for cloudy and partly cloudy conditions were 7.9 and 8.8% respectively, which represents an 11% improvement from BP3 to BP4. For longer forecast leads, the comparison must be made using NAM as the baseline because HRRR does not extend this far out. Scores were -2.7% and -0.3% improvement respectively for BP3 and BP4. While these scores are fairly similar, the improvement between budget periods reflects an 89% improvement (i.e., a decrease in negative skill) during BP4, which was shown to be statistically significant.

For the power conversion module, test values for five farms range from MAE values of 1.3 to 4.4 normalized to capacity (also known as MAPE) were reported with a median value of 2.1%. During BP3, median MAPE was 2.9% of capacity for three farms. This represents a 27% improvement in power conversion from BP3 to BP4. These comparisons are discussed in more detail in the accompanying NCAR Technical Note (Haupt et al. 2016).

The Analog Ensemble (AnEn) showed promising results for providing an ensemble mean forecast and uncertainty quantification for GHI forecasts. During BP4, the technique was also applied to power forecasts for SMUD locations. In Figure 14, the RMSE of the AnEn mean and SunCast™ versus power measurements are plotted versus the 0-72 h forecast lead for an example application. Overall AnEn provides Substantial improvement to the deterministic forecast as measured by RMSE, MAE and Bias. Improvements in power forecasts are similar to those reported for GHI forecasts with a median improvement of 17% in RMSE. Probabilistic forecasts were also computed for 10, 25, 50, 75 and 90% exceedance of power capacity. Results using other probability measures such as Brier Scores and Probability Interval Evaluation are presented in the SunCast Technical Note (Haupt et al. 2016). The specific questions and examples of usage of the measures are defined in the Metrics Technical Note (Jensen et al., 2016) published as part of this project as well. The Probability Interval Evaluation is a new metric developed for this project and establishes the frequency with which the observations fall within a user-specified probability interval (e.g. the likelihood that the power or GHI will fall within an 80% window). The Brier score evaluates how accurate the probability forecast is through the computation of the mean-square error. Lower Brier scores indicate better performance. Figure 15 shows the performance in terms of Brier Score of AnEn (black) and SunCast™ (red) for the computed thresholds. It indicates a marked improvement (lower values for AnEn in black) in Brier Score for probabilities of an exceedance of 50% of capacity. The computed Brier Skill score across all lead times is 0.55.

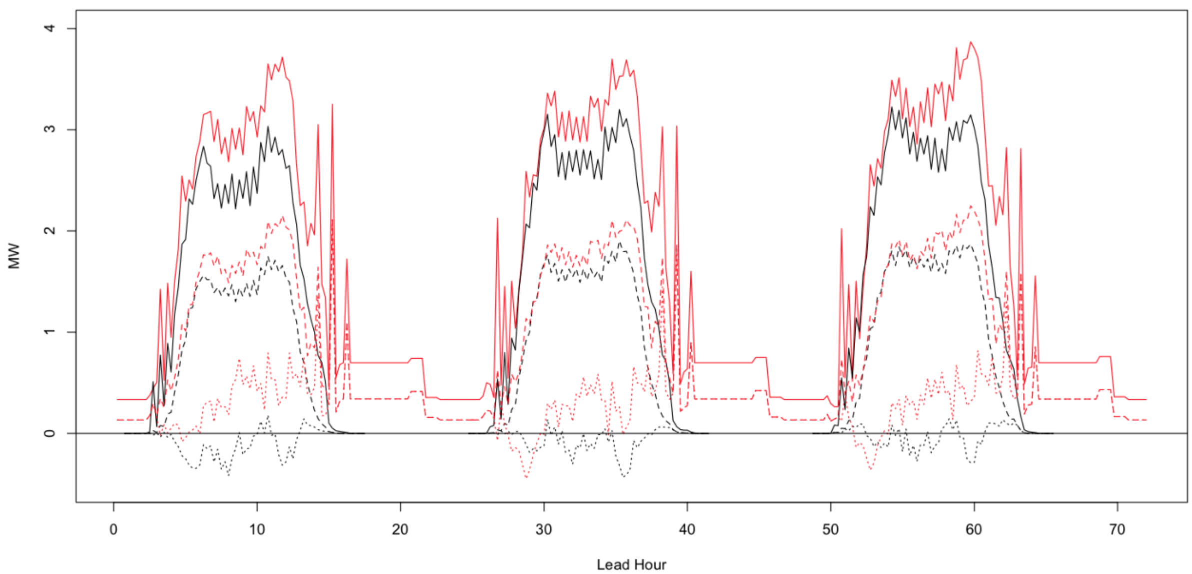

Figure 14. RMSE (solid), MAE (dashed), and bias (dotted) for AnEn Mean (black) and SunCast™ (red) systems.

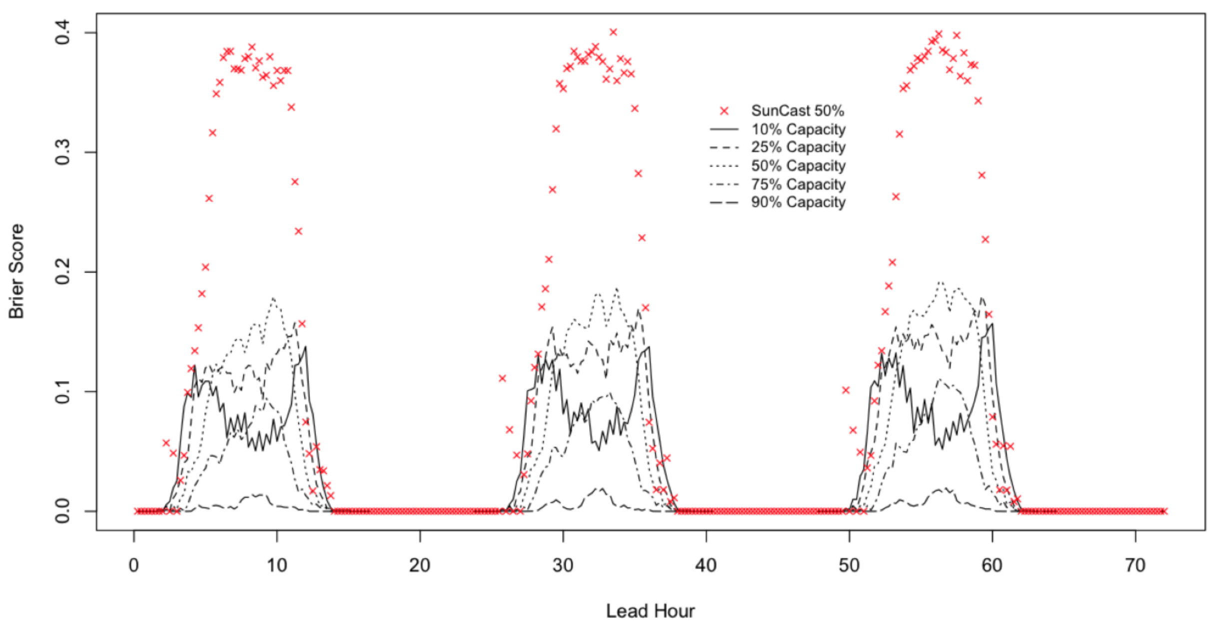

Figure 15. Brier Score of AnEn Mean (black) and SunCast™ (red) systems for probability of exceeding 10% (solid), 25% (dashed), 50% (dotted), 75% (dash-dot) and 90% (long dash) of capacity for a plant.

The previous analysis is only a fraction of what has been presented in the technical report (Haupt et al. 2016) and is provided to support the measured values and findings in the Milestone Table 4.1 in the BP4 SOPO. Table 4 replicates this table and summarizes the findings. Several goals in Milestone 4.1 were not met, including 4.1.1 (StatCast improvement), 4.1.3a (CIRACast improvement), 4.1.3b (MADCast improvement), and 4.1.3c (WRF-Solar-Now improvement). Several factors could be the cause of lack of improvements, including that the project may have reached the limits of predictability (less likely), the weather scenario became more challenging between BP3 and BP4 (highly likely), and that it is difficult to improve when the project is required to stop work due to contracting issues during budget period reviews. The larger errors for Smart Persistence during February and March 2016 over those same months in 2015, shown in Figure 13, suggest that the lack of improvement in BP4 of all four cloud-based components may be caused by less predictable weather, and hence cloud regimes due to the influence of El Nino. Additionally, while components like StatCast were enhanced with what was believed to be improvements to the algorithms during BP4 (the regime dependent versions of StatCast), there was little time to test in a deployment for an entire 15 months and assess if improvements indeed added value. We hope to complete these comparisons as part of future projects.

The milestones for task 4.2 included comparing the cutting edge WRF-Solar™ and blended SunCast™ system to currently available NWP. The comparison requires computing improvement from BP3 to BP4 and requires a full year of forecasts for the comparison. A truly clean comparison is difficult to achieve because the evaluation of BP3 covered Jan-May 2015 and this project ends prior to May 2016. To minimize the overlap, the 1 year period of comparison for BP4 consisted of April 2015 to March 2016. Improvements in MAE and RMSE for hourly forecasts of WRF-Solar™-Now, WRF-Solar™, and SunCast™ were computed using the NAM as the baseline, as it was the one with the lowest MAE and RMSE for all sky conditions over all initializations and geographic regions. Results are reported in Table 5 and show that while there was no improvement in scores between BP3 and BP4, the blended SunCast™ forecast outperformed NAM by as much as 17.5% in MAE and 15% in RMSE. Values from Table 5 are then used to support the measured values and finding in Milestone Table 4.4 in the BP4 SOPO. Table 6 replicates this table and summarizes the finds. Table 7 presents the summary metrics.

Table 4. Summary of Milestones, Metrics and Success Values for BP4 Task 4.1.

Milestone	Metric	Success Value	Measured Value	Assessment Tool	Goal Met?	Supporting Data (pg. #)
4.1.1	Improvement in a statistical model for short term solar power forecasting (StatCast) at SMUD sites.	Reduce MAE achieved in BP3 by at least 10% for cloudy conditions	-39%	% improvement over smart persistence	No	Table 5.2.2
4.1.2	Assessment of advective cloud variability based on TSI and other optical imaging (TSICast)	Reduce MAE achieved in BP3 by at least 10%	17%	% improvement over smart persistence	Yes	Table 5.2.4
4.1.3a	Demonstrate satellite-based prediction and assimilation of satellite data (CIRACast)	Reduce MAE achieved in BP3 by at least 10%	-8.3%	% improvement over smart persistence	No	Table 5.2.2
4.1.3.b	Evaluate the short range rapid-update WRF solar forecasting system (MADCast)	Reduce MAE achieved in BP3 by at least 10%	2.8%	% improvement over smart persistence	No	Table 5.2.2
4.1.3.c	Evaluate the nowcast configuration of the WRF solar forecasting system (WRF-Solar™Now)	Reduce MAE achieved in BP3 by at least 10%	-0.5%	% improvement over smart persistence	No	Table 5.2.2
4.1.4	Demonstrate improvement in WRF-Solar™ irradiance prediction	Document improvement for cloudy conditions due to new shallow convection scheme.	11% with HRRR base-line 89% with NAM base-line	WRF-standard (HRRR where forecasts available, then NAM)	Yes Yes	Previous Paragraph Previous Paragraph
4.1.5	Evaluate performance of final empirical power conversion using more complete data sets for 6 month period	Reduce MAE achieved in BP3 by at least 10%	27%	Within x% MAE of observed power	Yes	Previous paragraphs and Table 41 in Section 4
4.1.6	Assess AnEn results in real-time system operations for power forecasts	RMSE >= DICast Value Brier Skill Score to evaluate probabilistic predictions of AnEn computed with power converted DICAST system as reference > 0.10	17% de-crease 0.55	AnEn provides a new capability, i.e., uncertainty quantification (i.e., resolution and reliability of probabilistic predictions	Yes Yes	Figure 5.2.3 Figure 5.2.4

Table 5. Median MAE and RMSE improvement (%) of WRFSolar, WRFSolarNow and SunCast™ blended system versus the best performing publically available model, NAM, for all sky conditions and stratified by budget period. Percent change between BP3 and BP4 is also identified.

	BP3		BP4		% Change	
Component	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**
WRF-Solar™-Now	-14.7	-10.5	-31.3	-25.6	-112.6	-142.5
WRF-Solar™	-2.4	-8.8	-4.0	-4.0	-64.2	54.8
SunCast™	17.5	15.0	12.3	11.4	-29.6	-24.0

Table 6. Summary of Milestones, Metrics and Success Values for BP4 Task 4.2.

Mile-stone	**Metric Definition**	**Success Value**	**Measured Value**	**Assessment Tool**	**Goal Met?**	**Supporting Data (pg. #)**
4.2.2	Compare WRF-Solar™ results in target regions to publically available models for 1 year period	Reduce MAE achieved in BP3 by at least 20%	-112.5%	% improvement over NAM The target values will be tested at multiple locations with very diverse weather conditions	No	Table 5.2.6
4.2.2.b	Compare WRF-Solar™-Now results in target regions to publically available models	Reduce by at least 10%, the MAE at multiple initialization times over BP3.	-64.2%	% improvement over best single state of the art NWP model that has the lowest MAE	No	Table 5.2.6
4.2.3.b	Assess quality of blended forecasts for 1 year period.	Reduce RMSE achieved in BP3 by at least 10%	-24.0%	% improvement over best single model	No	Table 5.2.6

Table 7. Summary of Milestones, Metrics and Success Values for BP4 Task 4.3.

Mile-stone	Metric Definition	Success Value	Measured Value	Assessment Tool	Goal Met?	Supporting Data (pg. #)
4.3.0	Improvement as specified in the target values for all the metrics determined in BP1-Activity A	As specified in Task 1.1 – BP1	Yes	Section 5.2 of Tech Report	Yes	Target values set by DOE significantly greater than those set in Task 1.1 BP1
4.3.1	Complete and summarize results	25 metrics	At least 25 metrics used between this report and the Tech Report	Provide assessment of at least 90% of the metrics	Yes	Section 5.2 of Tech Report Section 5.2 of Tech Report
4.3.2	Evaluate decision makers' use of base and new forecast information in realistic decision-making situations	4 users	Confirmed with Xcel, MDA, GWC, SMUD are using. Some others have worked on it less.	Determine that at least 4 users are making use of forecasts, document the exact nature of the use of the forecasts, and provide a clear list, description, and quantitative case study analysis of the decisions that are being taken /modified by each user as a result of using these forecasts.	Yes	Chapter 6 of Tech Report.
4.3.3	Determine economic assessments value of the solar power forecasting system to the utilities and ISOs	$$ saved by applying forecasts	$470Million by 2040 with 50% reduction in MAE	Production cost modeling	Yes	Table 5.3 and Section 5.3 of Tech Report

Economic Valuation

A full report of the economic valuation is provided in the NCAR Technical Note (Haupt et al. 2016). The economic evaluation based on Production Cost Modeling in the Public Service Company of Colorado (PSCo) showed that the observed 50% improvement in forecast accuracy (beginning at 20% error and declining to 10% error, as was observed for the Xcel Energy forecasts) will save their customers $819,200 with the projected MW deployment for 2024.

While the PSCo analysis is unique in that each utility is unique, we use the results from this analysis to suggest aggregate national values for solar power forecast error reduction. The Energy Information Administration (EIA) projects increased solar energy generation growing at 6.8% annually from 2013 to 2020 (Energy Information Administration, 2015; Table A.16). By 2040 solar energy (measured as net summer generation) is projected to be 110.1 billion kilowatt hours (up from 18.5B KWh in 2013). This would then represent 13.56% of all generation in 2040 compared to 3.8% in 2013 (as per EIA 2015). Figure 16 plots the EIA projections for solar power generation indicating a steady increase over the next 25 years.

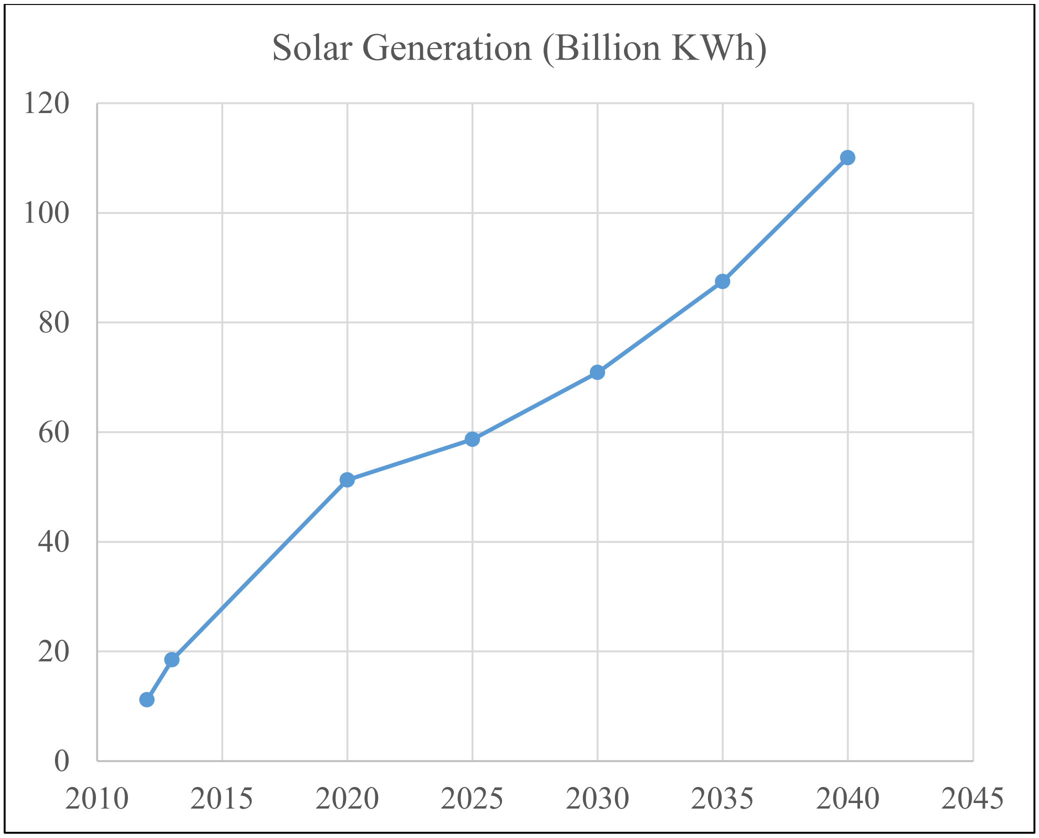

Figure 16. Projected Solar Generation (Source EIA 2015, Table A.16).

Using EIA projections of solar power generation and per MWh savings for forecast error reduction from the baseline analysis we generate order of magnitude estimates of the national value of improved (50% error reduction) solar power forecasts. Using the Billion KWh projections from EIA and an a baseline percent absolute error of 20% (the mean error used in the current time analysis, we calculate total annual forecast error in terms of MWh. Assuming a 50% reduction in MAE through the solar power forecast improvement program this gives an estimate of the reduction on total forecast error (in MWh). Multiplying this by the per MWh savings estimated from the regression model ($3.94 avoided generation cost per MWh reduction in forecast error) we generate annual national benefit estimates as indicated in Table 8.

Table 8. Aggregation to National Benefit Estimates							
Solar Photovoltaic	2012	2013	2020	2025	2030	2035	2040
Billion KWh	11.2	18.5	51.3	58.7	70.9	87.5	110.1
MWh	11,200,000	18,500,000	51,300,000	58,700,000	70,900,000	87,500,000	110,100,000
20% Absolute Error (MWh)	2,240,000	3,700,000	10,260,000	11,740,000	14,180,000	17,500,000	22,020,000
10% Absolute Error (MWh)	1,120,000	1,850,000	5,130,000	5,870,000	7,090,000	8,750,000	11,010,000
$/GW Error Reduction	$3.94	$3.94	$3.94	$3.94	$3.94	$3.94	$3.94
Benefit	$4,408,197	$7,281,397	$20,191,116	$23,103,674	$27,905,460	$34,439,038	$43,334,149

Recognizing, as noted, that this is order of magnitude, there are several caveats to this national aggregate benefit estimate. First we note that the EIA generation projections are for summer generation which is likely peak generation for solar power and thus we may be overstating annual total power generation. As noted in Martinez-Anido et al. (2016) and in our analysis, benefits are not linearly related to penetration levels whereas the current analysis does not account for this. The benefits also depends on baseline levels of error and future levels as well as adoption of forecasting improvements and we have not assessed these on national levels (i.e., assuming PSCo is nationally representative).

Also as indicated in Martinez-Anido et al., with a 13.5% level of solar penetration and 50% forecast improvement generated roughly $13M in benefits. Given those results, the current aggregation to national benefits may even be an underestimate.

Finally we note that the benefits from a research program to improve solar forecasting are ongoing. While there are likely also ongoing costs for observation, modeling, and forecast systems we do not have an estimate of those in order to develop benefit-cost estimates. As indicated in Table 9, extrapolating between the years indicated in the EIA projections, using a 3% rate of discount[3], and a 26-year analysis timeline starting in 2015, we develop an estimate of the present value of benefits from the forecast improvements of $455M in production cost savings.

[3] The discount rate of 3% reflects a relatively conservative approach to discounting given federally suggested nominal rates of 3.2% on 20 year and 3.5% on 30 year projects as per Office of Management and Budget (OMB) Circular A-94 Appendix C. Revised November 2015. (https://www.whitehouse.gov/omb/circulars_a094/a94_appx-c). Real rates of 1.2% and 1.4 % on 20 and 30 year projects may be more applicable for this analysis which implicitly assumes real values. Using a 3% rate of discount will thus provide a lower current value estimate and thus not overstate program benefits.

Table 9. Present Value of National Benefits			
Year	Current Value Benefit	Discount Rate 3%	Present Value Benefit
2015	10,969,888	1.000	10,969,888
2016	12,814,133	0.971	12,440,906
2017	14,658,379	0.943	13,816,928
2018	16,502,625	0.915	15,102,239
2019	18,346,870	0.888	16,300,956
2020	20,191,116	0.863	17,417,034
2021	20,773,627	0.837	17,397,586
2022	21,356,139	0.813	17,364,495
2023	21,938,651	0.789	17,318,574
2024	22,521,163	0.766	17,260,596
2025	23,103,674	0.744	17,191,303
2026	24,064,031	0.722	17,384,368
2027	25,024,389	0.701	17,551,603
2028	25,984,746	0.681	17,694,347
2029	26,945,103	0.661	17,813,887
2030	27,905,460	0.642	17,911,453
2031	29,212,176	0.623	18,204,062
2032	30,518,891	0.605	18,464,431
2033	31,825,607	0.587	18,694,190
2034	33,132,322	0.570	18,894,900
2035	34,439,038	0.554	19,068,060
2036	36,218,060	0.538	19,468,992
2037	37,997,082	0.522	19,830,392
2038	39,776,104	0.507	20,154,224
2039	41,555,127	0.492	20,442,369
2040	43,334,149	0.478	20,696,631
	Present Value Total Benefits		454,854,415

Significant Accomplishments and Conclusions:

The team has demonstrated and evaluated a working SunCast™ solar power prediction system that includes the multiple components described herein, including WRF-Solar™, multiple models from national centers, TSICast, CIRACast, and MADCast, MADWRF, as well as statistical models. The individual components and the overall SunCast™ system have been validated using the metrics developed at the beginning of the project. The team has met or exceeded target values specified in most of the milestone tables in the statement of work to DOE. Data streams from various model systems have been made available to the forecasting partners, forecasts were regularly provided to the utility and ISO partners, and feedback from the partners were incorporated into the forecasting models.

The SunCast™ system (Figure 3) has two main forecast tracks: a Nowcast track that forecasts at high temporal resolution out to 6 hours, and a DICast® track that forecasts at coarser temporal resolution out several days. Both these modules apply a consensus forecasting approach. That is, they consider multiple inputs and perform a forecast integration that takes advantage of the strengths of each input. While the consensus forecasting approach has been applied to forecasting more common weather variables (e.g., air temperature), in the past it had not previously been applied to solar irradiance forecasting in any significant way. No other public systems use a consensus forecasting approach. In the private sector, some companies may use a consensus approach, while others rely on a single-source model; much of this is proprietary and not disseminated. Forecasts are provided every 15 min to 6 h, then hourly out to 72 h and can be provided as far out as 168 h.

The team continued to conduct transformative research in statistical forecasting, advective/dynamic short-range forecasting, nowcasting with real-time data assimilation, satellite techniques and data assimilation for solar forecasting, numerical weather prediction with the WRF-Solar™ model (including cloud physics parameterization, convective parameterization, clear-sky aerosol estimation, and radiative transfer modeling), radiation-to-power conversion, and uncertainty quantification.

Publications and Results of Project:

Students Funded

Tyler McCandless, 2013-2015: **Dissertation:** Artificial Intelligence Techniques for Short-Range Solar Irradiance Prediction, Dissertation in Meteorology, The Pennsylvania State University.
David John Gagne, 2014-2016: **Dissertation:** Improved Forecasting of Economically Impactful Weather with Integrated Data-Driven and Physics-Based Methods, University of Oklahoma, expected Aug. 2016.
Zhenzhou Peng 2011-2016 **Dissertation:** Multi-source Image Integration Towards Solar Forecast
Hao Huang 2009-2014 (Co-Advise with Professor Hong Qin), **Dissertation:** A Scalable Physics-based Data Modeling Framework to Unsupervised High-Dimensional Data Mining, **First Employment:** Research Scientist at General Electric Global Research
Jin Xu 2012-2015.

Book Chapters

Haupt, S.E., P.A. Jiménez, J.A. Lee, and B. Kosovic, 2016: Principles of Meteorology and Numerical Weather Prediction, in Renewable Energy Forecasting: From Models to Applications, G. Kariniotakis, Ed., Elsevier, London, UK. Submitted and in review.
Miller, S.D., A.K. Heidinger, and M. Sengupta, 2013: Physically-Based Satellite Methods. Chapter 3, *Solar Energy Forecasting and Resource Assessment,* J. Kleissl, Ed. ISBN 9780123971777

Technical Reports

Haupt, S.E., B. Kosovic, T. Jensen, J. Lee, P. Jimenez, J. Lazo, J. Cowie, T. McCandless, J. Pearson, G. Weiner, S. Alessandrini, L. Delle Monache, D. Yu, Z. Peng, D. Huang, J. Heiser, S. Yoo, P. Kalb, S. Miller, M. Rogers, and L. Hinkleman, 2016: The SunCast Solar Power Forecasting System: The Results of the Public-Private-Academic Partnership to Advance Solar Power Forecasting. NCAR Technical Report TN-526+STR.

Jensen, T.L, T.L. Fowler, B.G. Brown, J. Lazo, S.E. Haupt. 2016: Metrics for evaluation of solar energy forecasts. NCAR Technical Report TN-527+STR.

Journal Papers

Alessandrini, S., L Delle Monache, S Sperati, and G Cervone, 2015: Solar forecasting with an analog ensemble. Applied Energy 157, 95–110.

Auligné, T., 2014a: Multivariate Minimum Residual Method for Cloud Retrieval. Part I: Theoretical Aspects and Simulated Observations Experiments. *Mon. Wea. Rev.*, **142**, 4383 – 4398.

Auligné, T., 2014b: Multivariate Minimum Residual Method for Cloud Retrieval. Part II: Real Observations Experiments. *Mon. Wea. Rev.*, **142**, 4399 - 4415.

Davo', F., Alessandrini, S., Sperati, S., and Delle Monache, L., 2016. A Principal component analysis for regional wind and solar power forecasting. Conditionally accepted.

Descombes, G., T. Auligné, H.-C. Lin, D. Xu, C. Schwartz and F. Vandenberghe, 2014: *Multi-sensor Advection Diffusion nowCast (MADCast) for cloud analysis and short-term prediction*. NCAR Tech. Rep. TN-509STR. 21 pp.

Haupt, S.E. and B. Kosovic, 2016: Variable Generation Power Forecasting as a Big Data Problem, submitted to IEEE Transactions on Sustainable Energy.

Jiménez, P. A., J. P. Hacker, J. Dudhia, S. E. Haupt, J. A. Ruiz-Arias, C. A. G. and G. Thompson, T. Eidhammer, and A. Deng, 2016a: WRF-Solar™: An augmented NWP model for solar power prediction. Model description and clear sky assessment. Bull. of the Amer. Met. Soc., (In press.).

Jiménez, P. A., S. Alessandrini, S. E. Haupt, A. Deng, B. Kosovic, J. A. Lee, and L. Delle Monache, 2016b: The role of unresolved clouds on short-range global horizontal irradiance predictability. *Mon. Wea. Rev.*, accepted.

Lee, J. A., S. E. Haupt, P. A. Jiménez, T. C. McCandless, M. A. Rogers, and S. D. Miller, 2016: Solar energy nowcasting case studies near Sacramento. *Wea. Forecast.*, submitted.

McCandless, T.C., G.S. Young, S.E. Haupt, and L.M Hinkelman, 2016b: Regime-Dependent Short-Range Solar Irradiance Forecasting, submitted to *Journal of Applied Meteorology and Climatology,* accepted.

McCandless, T.C., S.E. Haupt, and G.S. Young, 2016a: A Regime-Dependent Artificial Neural Network Technique for Short-Range Solar Irradiance Forecasting, *Applied Energy,* **89**, 351-359.

McCandless, T.C., S.E. Haupt, and G.S. Young, 2015: A Model Tree Approach to Forecasting Solar Irradiance Variability, *Solar Energy,* **120**, 514-524. DOI:10.1016/j.solener.2015.07.0200038-092X

Miller, S.D., M.A. Rogers, J.M. Haynes, and M. Sengupta, 2016: A Satellite-Initialized Model-Advected Scheme for Short-Term Solar Energy Forecasting. In preparation for *Solar Forecasting* 2016.

Peng, Z., D. Yu, D. Huang, J. Heiser, S. Yoo, P. Kalb, 2015: 3D cloud detection and tracking system for solar forecast using multiple sky imagers", *Solar Energy*, **118**, pp. 496-512.

Peng, Z., D. Yu, D. Huang, J. Heiser, S. Yoo, P. Kalb, 2016: A Hybrid Approach to Estimate the Complex Motions of Clouds in Sky Images, *Solar Energy*, *under review*.

Ruiz-Arias, J. A., J. Dudhia, and C. A. Gueymard, 2014: A simple parameterization of the shortwave aerosol optical properties for surface direct and diffuse irradiances assessment in a numerical weather model. *Geoesci. Model Dev.*, 7, 1159–1174.

Sperati, S Alessandrini, P Pinson, G Kariniotakis, 2015: The "Weather Intelligence for Renewable Energies" Benchmarking Exercise on Short-Term Forecasting of Wind and Solar Power Generation. Energies, 8(9), 9594-9619.

Sperati, S., Alessandrini, S., and Delle Monache, L., 2016: An application of the ECMWF Ensemble Prediction System for short-term solar power forecasting Solar Energy. Conditionally accepted.

Thompson, G., and T. Eidhammer, 2014: A study of aerosol impacts on clouds and precipitation development in a large winter cyclone. *J. Atmos. Sci.*, 71, 3636–3658.

Xie, Y., M. Sengupta, and J. Dudhia, 2016: A Fast All-sky Radiation Model for Solar Applications (FARMS): Algorithm and performance evaluation. Solar Energy (Under review).

Xu, D., Auligné T., Huang X.-Y., 2015: A Validation of the Multivariate and Minimum Residual Method for Cloud Retrieval Using Radiance from Multiple Satellites. *Advances in Atmospheric Sciences*, **32**, 349-362. doi: 10.1007/s00376-014-3258-5

Conference and Workshop Presentations

Alessandrini, S., 2015: Solar Forecasting with an Analog Ensemble, Solar Power International, Anaheim, CA.

Alessandrini, S., L Delle Monache, S Haupt, 2015: An Application of an Analog Ensemble for Short-Term Solar Power Forecasting, AMS annual meeting, Phoenix (AZ).

Alessandrini, S., 2014: The WIRE solar & wind forecasting benchmark exercise, Renewable Energies Forecasting - State of the art & challenges for the future "WIRE" final workshop, Paris, France. (invited presentation)

Auligné, T., 2014a: Multivariate Minimum Residual Method for Cloud Retrieval. Part I: Theoretical Aspects and Simulated Observations Experiments. *Mon. Wea. Rev.*, **142**, 4383 – 4398.

Auligné, T., 2014b: Multivariate Minimum Residual Method for Cloud Retrieval. Part II: Real Observations Experiments. *Mon. Wea. Rev.*, **142**, 4399 - 4415.

Delle Monache, L., S. Alessandrini, G. Cervone, C. Junk, D. Rife, J. Ma, S. Sperati, S.E. Haupt, T. Brummet, P. Prestopnik, G. Wiener, J. Nielsen, S. Hawkins, 2015: The Analog Ensemble for Renewable Energy Applications: An Overview. International Conference on Energy and Meteorology, Boulder, CO, June 25.

Deng, A., B. Gaudet, J. Dudhia, and K. Alapaty, 2014: Implementation and evaluation of a new shallow convection scheme in WRF. *26th Conf. on Wea. Anal. and Forecast./22nd Conf. on Numer. Wea. Pred.* at the *94th Amer. Meteor. Soc. Annual Meeting*, Atlanta, GA, 2-6 Feb

2014. Preprint available at https://ams.confex.com/ams/94Annual/webprogram/Paper236925.html.

Descombes, G., T. Auligné, H.-C. Lin, D. Xu, C. Schwartz and F. Vandenberghe, 2014: *Multi-sensor Advection Diffusion nowCast (MADCast) for cloud analysis and short-term prediction*. NCAR Tech. Rep. TN-509STR. 21 pp.

Gagne, D.J., S.E. Haupt, S. Linden, and G. Wiener, 2016: An Evaluation of Statistical Learning Methods for Gridded Solar Irradiance Forecasting, Joint Session between 14th Conference on Artificial and Computational Intelligence and its Applications to the Environmental Sciences and Seventh Conference on Weather, Climate, Water, and the New Energy Economy, AMS Annual Meeting, New Orleans, LA, Jan. 12.

Gagne, D.J., Haupt, S.E., Linden, S., Williams, J.K., McGovern, A., Wiener, G., Lee, J.A., and T.C. McCandless, 2015: Scaling Machine Learning Models to Produce High Resolution Gridded Solar Power Forecasts. *13th Conference on Artificial Intelligence: The Last Mile: Methods and Technologies for Delivering Custom Weather, Water, and Climate Information to Everyone in the World*, Phoenix, AZ, Amer. Meteor. Soc. T.J.1.1

Gagne, D.J., S.E. Haupt, S. Linden, G. Wiener, 2015: A Community Gridded Atmospheric Forecast System for Calibrated Solar Irradiance. International Conference on Energy and Meteorology, Boulder, CO, June 24.

Gagne, D.J., S.E. Haupt, S. Linden, J.K. Williams, A. McGovern, G. Wiener, J.A. Lee, and T.C. McCandless, 2015: Scaling Machine Learning Models to Produce High Resolution Gridded Solar Power Forecasts, 13th Conference on Artificial Intelligence, AMS Annual Meeting, Phoenix, AZ, Jan. 7.

Haupt, S.E., 2016: Comparison of Solar Power Forecasting Techniques, Joint Session between 14th Conference on Artificial and Computational Intelligence and its Applications to the Environmental Sciences and Seventh Conference on Weather, Climate, Water, and the New Energy Economy, AMS Annual Meeting, New Orleans, LA, Jan. 12.

Haupt, S.E., 2016: Integrating and Operationalizing Renewable Energy Forecasts: It Takes a Community, Seventh Conference on Weather, Climate, Water, and the New Energy Economy, AMS Annual Meeting, New Orleans, LA, Jan. 11.

Haupt, S.E. and B. Kosovic, 2015: Big Data and Machine Learning for Applied Weather Forecasts: Forecasting Solar Power for Utility Operations, IEEE Symposium Series on Computational Intelligence, Capetown, South Africa, December 9. Fully reviewed paper.

Haupt, S.E., 2015: The SunCast™ Solar Power Forecasting Decision Support System, American Solar Energy Society Conference, State College, PA, July 28.

Haupt, S.E., S. Drobot, T. Jensen, 2015: The SunCast™ Solar Power Forecasting System. International Conference on Energy and Meteorology, Boulder, CO, June 23.

Haupt, S.E., 2015: Renewable Energy Needs, Rapid Update Analysis/Nowcasting Workshop, NOAA ESRL, Boulder, CO, June, 4.

Haupt, S.E., 2015: NCAR's Solar Power Forecasting Research, California Utility Forecasting Meeting, Folsom, CA, April 29 (invited).

Haupt, S.E., 2015: Counting on Solar Production: Advances in Forecasting, Utility Solar Conference of the Solar Electric Power Association, San Diego, CA, April 28 (invited).

Haupt, S.E., 2015: Solar Power Forecasting: SunCast™ and GRAFS, Utility Variable Generation Integration Group Forecasting Workshop, Lakewood, CO, Feb. 19, 2015.

Haupt, S.E., 2015: The SunCast™ Solar Power Forecasting System, Joint Session between Sixth Conference on Weather, Climate, and the New Energy Economy and 13th Conference on Artificial Intelligence, AMS Annual Meeting, Phoenix, AZ, Jan. 7.

Haupt, S.E., B. Kosovic, and S. Drobot, 2014: Advances in Solar Power Forecasting, Fall Meeting of the American Geophysical Union, San Francisco, CA, Dec. 15.

Haupt, S.E. and S. Drobot, 2014: New Irradiance Models for Solar Energy, Solar 2014 sponsored by the American Solar Energy Society, San Francisco, CA, July 7. (full paper).

Haupt, S.E. and S. Drobot, 2014: A Public-Private-Academic Partnership to Advance Solar Power Forecasting, SunShot Summit, Anaheim, CA, May 20. Invited Poster Presentation and Review.

Haupt, S.E., 2014: Renewable Energy, UCAR Research and Partnership Meeting, Boulder, CO, April 22.

Haupt, S.E., 2014: NCAR-led SunShot Solar Forecasting Project, Utility Variable Generation Forecasting Workshop, Tuscon, AZ, Feb. 26. Invited Panel Presentation.

Haupt, S.E., 2014: Advances in Predicting Solar Power for Utilities, Fifth Conference on Weather, Climate, and the New Energy Economy, AMS Annual Meeting, Atlanta, GA, Feb. 6.

Haupt, S.E., 2014: Using Artificial Intelligence to Inform Physical/Dynamical Models, 12th Conference on Artificial and Computational Intelligence and its Applications to the Environmental Sciences, Invited Panel Presentation, Feb. 3. Invited Panel Presentation.

Haupt, S.E., 2013: A Public-Private-Academic Partnership to Advance Solar Power Forecasting, International Conference on Energy and Meteorology, Toulouse, France, June 25.

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Jimenez, P., S. Alessandrini, S.E. Haupt, and A. Deng, 2016: Accounting for the Effects of Unresolved Clouds in the Shortwave Irradiance Forecast of the WRF-Solar™ Model to Improve Solar Power Forecasts, Seventh Conference on Weather, Climate, Water, and the New Energy Economy, AMS Annual Meeting, New Orleans, LA, Jan. 11.

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McCandless, T. C., 2014: SunCast™ Solar Irradiance Prediction and Statistical Short-term Solar Irradiance Prediction. Seminar at Aerospace Corporation, Pasadena, CA,October 25.**Pearson, J.M.,** Haupt, S.E., Jensen, T.L., Burghardt, C., McCandless, T.C., Brummet, T., and S. Dettling, 2015: Predicting Distributed Solar Power Production for Utilities. Sixth Conference on Weather, Climate, and the New Energy Economy: Short-Range Forecasting Modeling for Solar Electric Generation, Phoenix, AZ, Amer. Meteor. Soc. 4.2.

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Xu, J., S. Yoo, D. Yu, H. Huang, D. Huang, J.Heiser, and P. Kalb, Solar Irradiance Forecasting using Multi-layer Cloud Tracking and Numerical Weather Prediction, the 29th Symposium On Applied Computing (SAC'15), Salamanca, Spain.

Short Courses and Workshop Presentations

Haupt, S.E., 2016: Short-range Weather Forecasting (hours to days) for Energy Applications. WMO-WEMC-GFCS Summer Course on Climate and Energy, Norwich, UK, July 5.

Haupt, S.E., 2016: Applications of Computational Intelligence to Enable Renewable Energy, Ph.D. Course, Trento, Italy, May 9-13.

Haupt, S.E., 2015: Short-range Weather Forecasting (hours to days) for Energy Applications. International Conference on Energy and Meteorology Pre-Conference Seminar, Boulder, CO, June 22.

Haupt, S.E., 2015: Introduction to Probabilistic Forecasting, Utility Variable Generation Integration Group Tutorial on Stochastic Forecasting Methods and Applications, Lakewood, CO, Feb. 18, 2015.

Haupt, S.E., 2014: NCAR's Research including Renewable Energy, Kuwait Institute for Scientific Research presents Workshop on Solar Resource Assessment, Kuwait City, Nov. 17, 2014.

Haupt, S.E., 2013: Meteorological Forecasting I: Some Basic Considerations for Atmospheric Modeling, COST Weather Intelligence for Renewable Energy Summer School, Montegut, France, July 1, 2013.

Haupt, S.E., 2013: Meteorological Forecasting II: Predicting Atmospheric Realizations: Dealing with Uncertainty in Applied Meteorology, COST Weather Intelligence for Renewable Energy Summer School, Montegut, France, July 1, 2013.

Haupt, S.E., 2013: What is your mental model of using meteorological uncertainty information for energy? Workshop on Uncertainty in Meteorology for the Energy Sector, Preconference Seminar, International Conference on Energy and Meteorology, Toulouse, France, June 24.

Haupt, S.E., 2013: How can we better facilitate using meteorological uncertainty information for energy? Workshop on Uncertainty in Meteorology for the Energy Sector, Preconference Seminar, International Conference on Energy and Meteorology, Toulouse, France, June 24.

Path Forward:

This project has been built on leveraging a network of experts in all aspects of solar power forecasting to develop, build, deploy, assess, and test the SunCast™ System in a wide variety of locations and climatologies. Thus, we have brought together university and laboratory researchers, software engineers skilled in Big Data issues, utility and ISO personnel, and forecast providers to assess and help us to iteratively improve the system. As described in the introduction (Chapter 1 of NCAR Tech Note), the kick-off workshop and second year workshop were effective in cementing the collaborations and allow time for deep exchange of ideas. This project has fostered a host of networks (see Section 6.3 of NCAR Tech Note - Haupt et al. 2016) and many inquiries from around the world about the SunCast™ system. We expect to have opportunities to deploy the full system or components of it in various places.

WRF-Solar™ has been a substantial advance in the state-of-the-science of NWP for renewable energy forecasting. NCAR has had numerous requests for the beta-versions of the code and we have communicated with teams from around the world who are anxious to deploy and test WRF-Solar™ for solar power forecasting (see section 6.3 of the NCAR Tech Note). Many of the advances have already become part of the most recent WRF releases.

An addendum to this report is a full wiki on the released code that has been developed as part of this project. These codes will allow wide access to major portions of the software developed with DOE funds. NCAR plans to make these codes more widely available under a project to make digital resources available to the community.

Finally, the results of this project are becoming archived in the peer-review literature as detailed above. Our testing of many types of models and applying the metrics developed as part of this project have resulted in a series of recommendations for best-practice solar power forecasting. Some specific recommendations include:

- It is best to blend various component models or systems together. The forecast from blended models/systems is invariably significantly better than those produced by a single model or approach.
- Use a base NWP model tuned for the purpose. We found very significant improvements in forecasting by employing WRF-Solar™.
- Including multiple NWP models improve the blended forecast for time scales from 3 h through the day-ahead forecast and beyond.
- It is possible to improve upon persistence, even at the very short-range by using methods trained on targeted *in situ* observations. StatCast trained to employ pyranometer data was better than persistence, even at short time scales (15 min to 3 h) and TSICast, which uses multiple sky imagers improved upon persistence in the time range less than 15 min.
- Satellite based cloud advection is useful, but tricky. For regions near the mountains or along coasts, it is necessary to include some model physics to account for stationary clouds as well as cloud formation and dissipation. It is important to include the improvements related to correcting for shadowing and parallax as accomplished by CIRA.
- NWP can be combined with satellite data via assimilation to produce a fast-running, short-range (0-6 h) forecast that is helpful for nowcasting (see MAD-WRF, Section 2.4). This produced the best forecast on the 1-6 h time scale.
- The analog ensemble approach is helpful for both improving on the deterministic blended forecast as well as for producing a probabilistic prediction that is well calibrated.
- An empirical power conversion method is amenable to training site-specific information, even when missing metadata. Artificial intelligence techniques are capable of predicting directly from an observation to a target value as long as historic training data is available.
- An enhanced series of metrics is helpful for evaluating and tuning individual models as well as the entire system.

Finally, we asked our utility and ISO partners where they see solar power forecasting going in the future and some comments include:

- "…the industry need is still there and it will only get larger as more distributed energy is connected to the grid."
- [Forecasts will be from] "centralized RTO/ISO/BA generated forecasts that will have multiple uses and at varying granularities."

This project has served to advance the state-of-the-science of solar power forecasting as originally planned. The team that worked on the project included some of the best-known researchers in the field. The team worked extremely synergistically and produced demonstrably better models than existed previously, blended the models to produce improved consensus forecasts, and used forefront postprocessing methods to further correct the models as well as convert the irradiance forecasts to power and provide probabilistic forecast information to the utility and ISO partners. Although challenges were encountered, the team worked to rise above those and complete the project admirably. The SunCast™ system and its component models have been thoroughly assessed using a full range of metrics, some of which were specifically derived for this project. An economic evaluation estimated saving in one particular service region, which were then scaled up to estimate a substantial potential for savings across the US as more solar power is deployed in the future.

Thus, as the capacity of solar power grows, solar power forecasting with systems like SunCast™ will provide enabling technologies that will make the economics more feasible, empowering more solar power deployment. Such enhanced deployment has the potential to improve air quality, mitigate climate change, improve energy security, and provide enhanced employment opportunities throughout the renewable energy sector.

The team members have all grown in our research capabilities in solar energy and the collaborative research is expected to continue. A direct point of continuity is continued collaboration among the partners. For instance, the SunCast™ system is fully deployed operationally for Xcel Energy's Public Service of Colorado for their commercial solar plants, delivered by Global Weather Corporation. Xcel, PSCo, and GWC are all partners in this project. MDA Federal reports that they are also assuming portions of the systems from this project as part of their forecasting system. As reported above, WRF-Solar™ has been widely tested and many of its component modules are already part of the public WRF release and being used too widely to document. In addition, NCAR plans to continue to advance the SunCast™ system in regions throughout the world with wide partnerships. A specific partnership that is in the process of starting is between NCAR, BNL, and the Electric Power Research Institute (EPRI). That project, led by EPRI, will deploy sky imagers over New York City and provide forecasts using SunCast™ systems to utilities in New York. We expect additional collaborations to continue.

In summary, this project not only advanced the state-of-the-science through cutting edge research, but on a grander scale, it enabled a host of partnerships that are in the process improving the economics of solar energy and advancing its deployment.

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