BUILDING THE SUN4CAST SYSTEM

Improvements in Solar Power Forecasting

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The Sun4Cast System results from a research-to-operations project built on a value chain approach, benefiting electric utilities' customers, society, and the environment by improving state-of-the-science solar power forecasting capabilities.

This paper reports on the results of a public–private–academic collaboration to improve the state-of-the-science of solar power forecasting. Led by the National Center for Atmospheric Research (NCAR), the project applied a value chain approach to leverage the vision of the team members and progress toward the end goal of improving the economics of deploying solar energy (Haupt et al. 2016). This paper analyzes the collaborative design process, discusses the project results, and provides recommendations for "best practice" solar forecasting.

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Background. The use of solar power is increasing exponentially. In the United States, solar power has grown from 1.2 GW (0.1% of the electricity supply) in 2011 to more than 30 GW in 2016, largely because of the rapid decreases in the levelized cost of solar electricity production (LCOE[1]; Woodhouse et al. 2016). This solar usage is expected to continue to grow at similar rates for the foreseeable future. On a global basis, the International Energy Agency states, "Renewable energy will represent the largest single source of electricity growth over the next five years, driven by falling costs and aggressive expansion in emerging economies…Renewables hold [great

[1] LCOE accounts for the total life cycle cost of energy from project inception through decommissioning, including electricity generation.

promise] for affordably mitigating climate change and enhancing energy security" (www.iea.org/newsroom/news/2015/october/renewables-to-lead-world-power-market-growth-to-2020.html, accessed 8 December 2016).

Harvesting solar power relies on transforming the sun's energy in the form of irradiance into usable power. However, some of this energy is attenuated by atmospheric aerosols and clouds on its way to Earth's surface, decreasing the available irradiance depending on the atmospheric conditions. The variability of the available solar power becomes an important consideration for utilities as they maintain grid stability and plan for the following day's unit allocations.

Thus, as integration of solar power into the national electric grid rapidly increases, it becomes increasingly imperative to overcome the traditional forecasting challenges of this highly variable renewable resource. Solar power prediction is accomplished by different techniques for various time scales. Solar energy is particularly variable over space and time because of the myriad complexities caused by the dynamic evolution of clouds.

Variability of solar power. The variability of power output is greater with high penetrations of solar on the grid than with high penetrations of wind (Lew et al. 2012), illustrating a key challenge of solar power integration. A utility company's operating reserve requirements, which provide for rapid changes in matching system electric load, are determined by the response speed (ramp rate and start-up time), response duration, frequency of use (continuously or only during rare events), direction of change (up or down), and type of control mechanism (Ela et al. 2013). Traditionally, utilities have had to increase the amount of operating reserves to account for the variability of renewable energy. More recently, however, these operating reserves are being appropriately managed with accurate solar forecasts, as energy costs can be strategically minimized with knowledge of the short- and long-term variations in solar irradiance (Curtright and Apt 2008).

The quantification of temporal solar irradiance variability caused by the dynamic evolution of clouds has been extensively studied. Hinkelman et al. (2013, 2014) determined that cloud optical depth and cloud height are the best predictors of irradiance variability at 1-min time resolution. Gueymard and Wilcox (2011) analyzed the regional dependence of solar power and showed that greater variability tends to occur in coastal and mountainous areas, such as along the California coast, due to topography-induced microclimates.

The difficulties in predicting cloud cover at specific locations and times are well known, and a number of groups around the world are actively engaged in solar power forecasting research. Real-time solar power forecasting has been reviewed in recent publications, including Kleissl (2013), Troccoli et al. (2014), Dubus (2014), and Tuohy et al. (2015). Lorenz et al. (2014) review the extensive work of the team at the University of Oldenburg in Germany. The Australian initiative is ongoing (Davy and Troccoli 2012). Schroedter-Homscheidt et al. (2013) point out the need for improved aerosol forecasting for solar power prediction and discuss techniques leveraging European Centre for Medium-Range Weather Forecasts (ECMWF) chemistry forecasts.

The Sun4Cast project. This project was selected for funding by the Department of Energy's (DOE) SunShot Initiative as a "Public-Private-Academic Partnership to Advance Solar Power Forecasting." The goals of this project were to

- build a solar power forecasting system to advance the state-of-the-science through cutting-edge research;
- test the system with appropriate metrics for several geographically diverse, high-penetration solar utilities and independent system operators (ISOs); and
- disseminate the research results widely to raise the bar on solar power forecasting technology.

PROJECT PROGRESSION. *Beginning with the end in mind.* The first step of any project is assembling the right team to accomplish the goals, including identifying and engaging the stakeholders. Here, the end users are the electric utilities and system operators who make the decisions on unit allocation, energy trading, and real-time integration into the grid. Several utilities and ISOs were part of the process from the beginning and some others participated during portions of the project. It was important for the researchers to listen to their needs in planning the details of the system, how to bring it together, how to convey the output, and how to properly assess it to best help these end users. A second set of stakeholders is the commercial forecast providers who regularly communicate and transfer forecast results to the end users.

The scientists who performed the research and the software engineers who configured and built the system came from national laboratories and universities

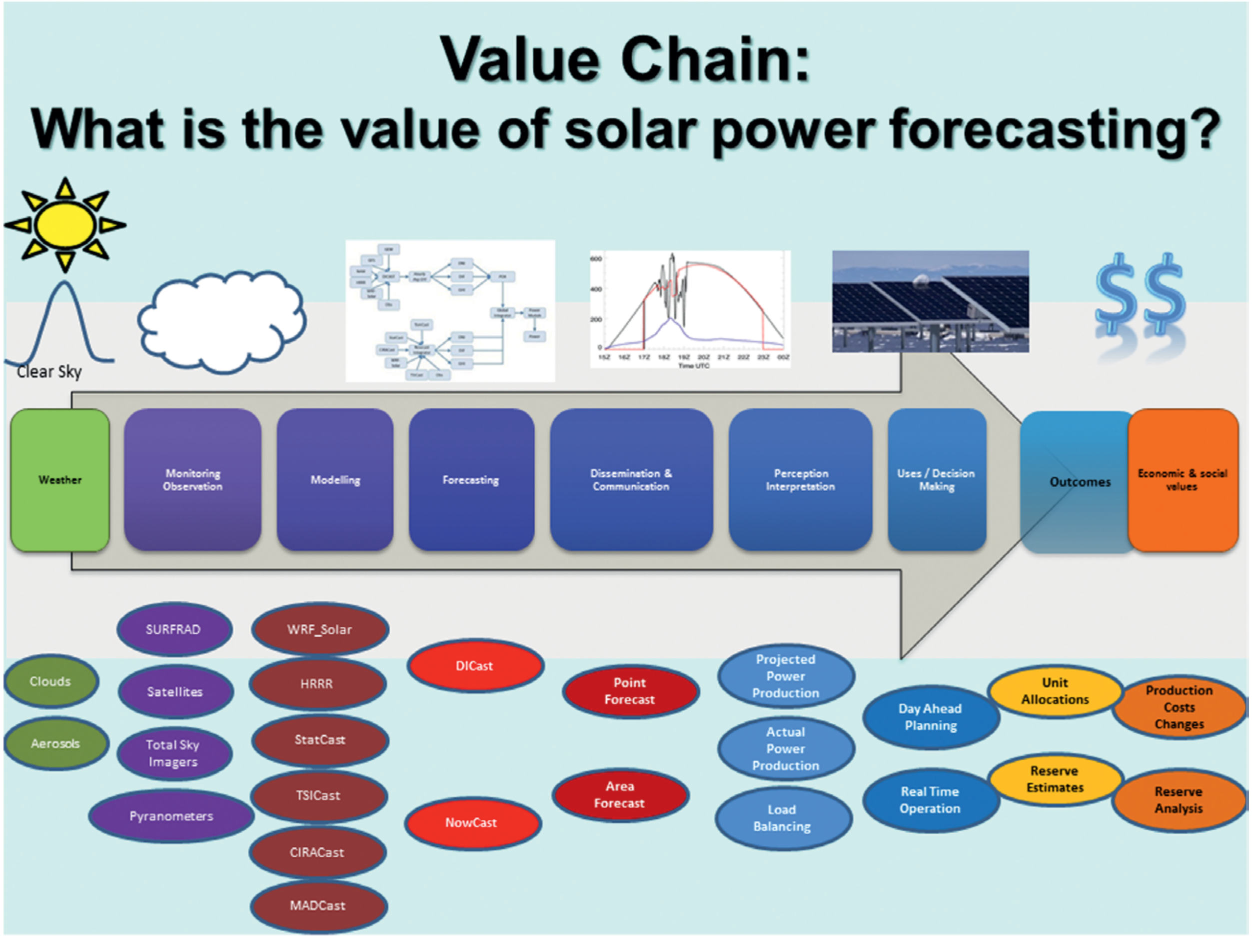

Fig. 1. Value chain implementing a weather decision support system for solar power. At the bottom are the components of the NCAR team's system that build toward providing an economic impact of this system.

that perform use-inspired research. The NCAR-led team was already immersed in solar forecasting research at the time of the award.

The first-year project workshop at NCAR was an opportunity to convene the entire team to think through how to integrate all of the research into a working Sun4Cast system. The workshop emphasized meeting the needs of the users. After an initial introduction to the project goals, the workshop commenced with a user panel of utility and ISO representatives to explain how they use forecasts and what they need in the forecast, as well as when it must be delivered to be most useful. We saw this session as "beginning with the end in mind" as a way to envision the project outcome. This began the process of conceptual modeling (see "Conceptual modeling" sidebar), which brought out ideas from the various stakeholders, and that the management team then synthesized into a working value chain (Fig. 1) that could guide the rest of the project. This approach, derived from social science, is rather novel for configuring and running scientific projects but proved to be quite effective for this large integrated project.

Metrics from the start. Another unique feature of this project is the development of metrics across SunShot teams through listening to stakeholder needs. Development of metrics was accomplished jointly with a collaborative team that included DOE SunShot Initiative leadership, the IBM Watt-Sun forecasting team (Utsler 2014), and National Oceanic and Atmospheric Administration (NOAA) team members, in addition to the Sun4Cast team. That group held several workshops that engaged end users. With that input and many team teleconferences, the group designed a table of proposed metrics (Table 1) for evaluating the system (Zhang et al. 2015; Jensen et al. 2016). In parallel, the NCAR Metrics team worked with our utility stakeholders and discussed methods of assessing the value provided by improved forecasting.

CONCEPTUAL MODELING

With the background provided by the stakeholders, time was devoted during the first-year project workshop to developing a shared conceptual model of the weather–solar power value chain. The group broke into five preassigned teams that mixed forecast users, providers, and researchers to develop mental models of the forecast value chain. The objectives of this exercise were team building, facilitating discussion, enhancing understanding across all participants in the project, building a qualitative model of the weather–solar power value chain, and explaining how research to improve forecasts will create value (Lazo 2017).

All team members were given general guidance to spend time "drawing" and discussing their own value chain, considering the following issues: What values, decisions, or outcomes do you think are important to end users and decision-makers? How does weather impact those decisions? How does weather information relate to those decisions? How would changes or improvements in weather forecasts change those outcomes? Who are the decision-makers? What are their needs, resources, and constraints? How do different "agents" in the value chain add value to information? What is the relevant forecast information? What if this project improved the relevant forecast by *x*%? What does an *x*% improvement mean? How does an *x*% improvement affect outcomes for weather forecast vendors, utilities, ISOs, and RTOs? This approach was quite successful for team building and enabled the group to come to a joint visualization of the project goals.

The team then delved deeper into the elements of the forecasting systems and determined how to fit them into one cohesive whole. Figure 1 illustrates a more complete vision that fits the value chain to the elements of the project. Breakout discussion groups were configured to bring together specific teams on the project. The project progressed with five primary teams that discussed their research and advances at least monthly. These teams were 1) metrics, 2) nowcasting, 3) numerical weather prediction, 4) engineering, and 5) management (including all team leads). This proved to be an effective way to manage the flow of the project.

THE SUN4CAST SYSTEM. The Sun4Cast system (Fig. 2) has two main forecast tracks: a nowcast track that forecasts at high temporal resolution extending to 6 h, the results of which are blended via the Nowcasting Expert System Integrator (NESI), and the Dynamic Integrated Forecast (DICast; Mahoney et al. 2012; Myers et al. 2011) track that forecasts at coarser temporal resolution out to several days based on numerical weather prediction (NWP). Both NESI and DICast apply a consensus forecasting approach, meaning that they blend and optimize multiple models to provide a better forecast than any of the models would produce alone. That is, they consider multiple input forecasts and weight those forecasts according to the recent observed skill of each input.

While this consensus forecasting approach has been applied to forecasting more common weather variables (e.g., air temperature), it had not previously been applied to solar irradiance forecasting in any significant way. Only recently have public forecast systems begun to use a consensus forecast approach, such as in the NOAA National Blend of Models (Gilbert et al. 2016). In the private sector, some companies employ a consensus approach, while others rely on a single-source model; much of this is proprietary.

Table 1. Consensus of metrics to be exercised in evaluating solar power forecasting systems.

	Model–reference comparison	Utility planning/operations support	
	Statistical information	Statistical	Economic/value
Base	BC1: distribution of forecast errors BC2: mean absolute error BC3: rmse BC4: standard deviation/variance BC5: Pearson's correlation coefficient BC6: categorical statistics for event BC7: frequency of superior performance	BP1: mean bias error BP2: skewness BP3: kurtosis BP4: 99th percentile	BV1: operating reserves analysis BV2: electricity production cost analysis
Enhanced	EC1: Kolmogorov–Smirnov test integral EC2: OVER metric EC3: Renyi entropy EC4: paired test for mean and variance EC5: performance diagram for continuous statistics	EP1: probability interval forecast evaluation EP2: Brier score EP3: receiver operator characteristic curve and area EP4: reliability diagram	EV1: electricity load payments analysis EV2: solar generation curtailment EV3: power trading impact P1: load forecast improvement P2: storage optimization

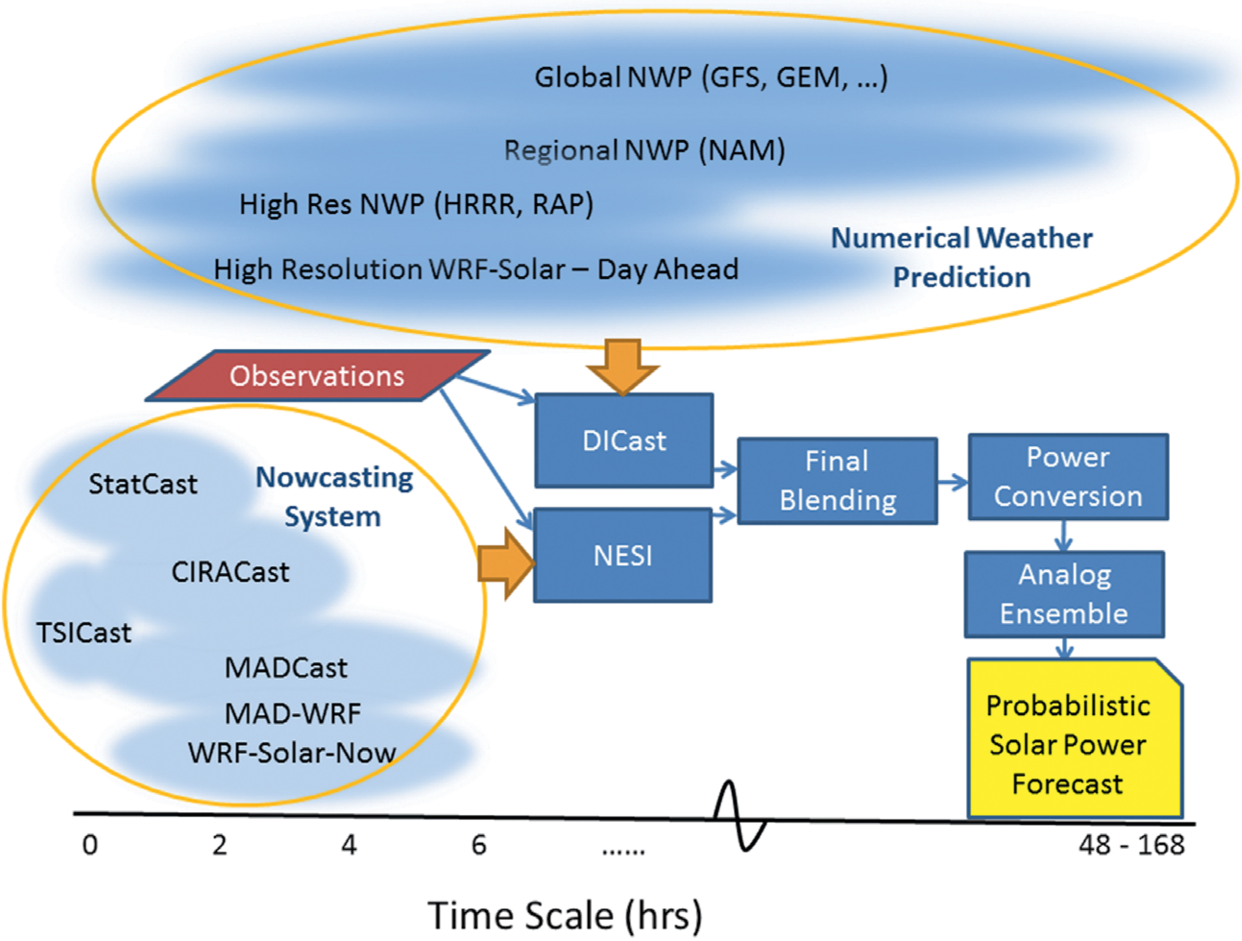

Fig. 2. Sun4Cast forecasting system predicts across scales. The fuzzy ovals roughly indicate the time scales of each component's forecast. Each component is discussed in the text.

Forecasts from Sun4Cast are provided every 15 min, extend to 72 h, and can be provided as far out as 168 h.

WRF-Solar: Improving NWP for irradiance forecasting. Most modern weather forecasting systems rely on NWP models for their base forecasts. Thus, a major emphasis of this project was on improving NWP by developing, testing, evaluating, and improving the solar configuration of the Weather Research and Forecasting (WRF) Model (WRF-Solar), the first NWP model specifically designed to meet the increasing demand for specialized forecast products for solar energy applications (Jiménez et al. 2016a,b). WRF-Solar is used in both the NESI and DICast systems.

An intercomparison of different global, multiscale, and mesoscale models' skill in forecasting solar irradiance performed by Perez et al. (2013) indicated that the ECMWF global model significantly outperforms the GFS-driven WRF Model across a wide range of sites. So far, this has been interpreted as partially being due to shortcomings in cloud modeling and data assimilation. It is also possible that the radiative transfer algorithms in the U.S. forecast models do not perform as well for this application. This hypothesis was confirmed by Ruiz-Arias et al. (2013) in the case of the WRF Model (Skamarock et al. 2008). That study highlighted biases in one frequently used radiation algorithm in WRF, as well as the need for improvement by adding aerosol data. In addition, cloud formation and dissipation needed to be improved. Thus, the project team made a variety of augmentations to the WRF Model to tailor it for solar power forecasting. Figure 3 depicts these WRF-Solar upgrades.

The first augmentation focused on improving the solar-tracking algorithm to account for deviations associated with the eccentricity of Earth's orbit and obliquity. Because solar energy applications require more frequent calls to the radiation package, inaccuracies in the solar position caused a nonnegligible error.

Second, WRF-Solar added the direct normal irradiance (DNI) and diffuse (DIF) components from

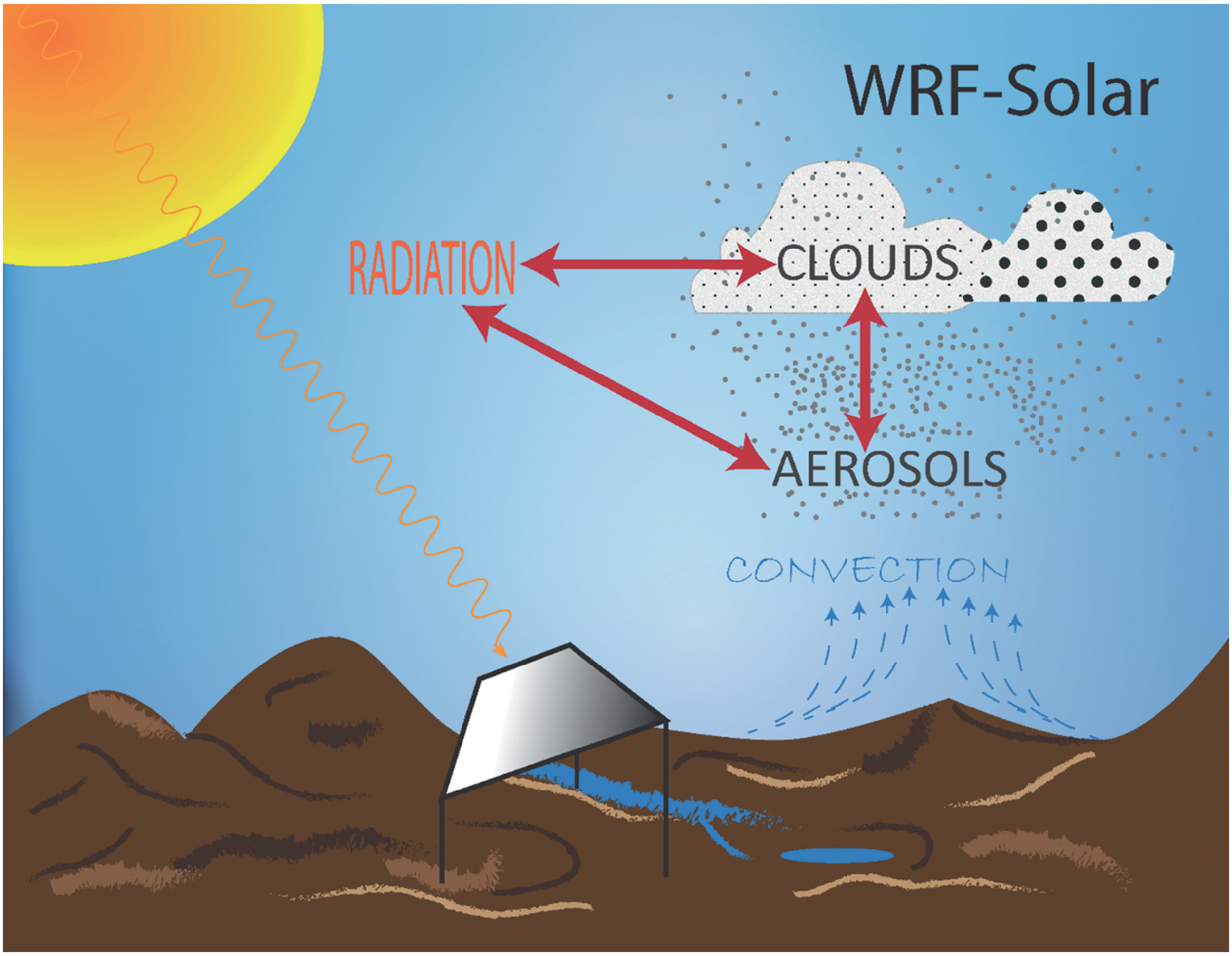

Fig. 3. Diagram showing the WRF-Solar augmentations that now include specific interactions between radiation, clouds, and aerosols.

the radiation parameterization to the model output in addition to global horizontal irradiance (GHI), parameterizing them when needed (Ruiz-Arias et al. 2010).

Third, efficient parameterizations were implemented either to interpolate the irradiance in between calls to the radiative transfer parameterization or to use a fast radiative transfer code that avoids computing three-dimensional heating rates but provides the surface irradiance (Xie et al. 2016).

Fourth, a new parameterization was developed to improve the representation of absorption and scattering of radiation by aerosols (aerosol direct effect), including allowing high spatiotemporal variability of aerosols. The treatment of aerosols (Ruiz-Arias et al. 2014) allows for the ingestion of aerosol optical properties with time stamps to accurately model the temporal variations in aerosol loading, permitting the ingested aerosol concentration to represent the aerosol optical properties in WRF-Solar. Jiménez et al. (2016b) examined the use of several different aerosol datasets and found improvement with dynamic input.

A fifth advance was to specify the interactions of the aerosols with the cloud microphysics, altering the cloud evolution and radiative properties (aerosol indirect effects). Traditionally, these effects have only been implemented in atmospheric chemistry models, which are significantly more computationally expensive than NWP models without detailed chemistry. WRF-Solar uses a simplified treatment of the aerosols (i.e., only two general aerosol species are allowed, specifically the nonhygroscopic ice-nucleating aerosols, which are dust particles, and the hygroscopic aerosols including sea salts, organic matter, and sulfates) that accounts for changes in the size of cloud hydrometeors to represent these aerosol indirect effects (Thompson and Eidhammer 2014) with a moderate increase in computational cost (~16%). The aerosols are advected by the model dynamics and the parameterization is linked to the WRF-Solar aerosol parameterization to provide a fully coupled representation of the cloud–aerosol–radiation system.

A sixth development accounts for the feedbacks that subgrid-scale clouds produce in shortwave irradiance, as implemented in a shallow cumulus parameterization (Deng et al. 2003, 2014). The scheme includes predictive equations for the subgrid-scale cloud water/ice content and the cloud fraction.

Finally, as described below, WRF-Solar was coupled with elements of a forefront satellite data assimilation model, which allows for the assimilation of infrared irradiances from satellites, resulting in an improved initialization of the cloud field that further increases the performance of short-range forecasts.

The Pennsylvania State University and the National Renewable Energy Laboratory (NREL) collaborated with NCAR in making these enhancements. NCAR responded to numerous requests to use beta versions of WRF-Solar. The community sees this as a way to advance the deployment of solar energy by enabling better forecasting of the irradiance resource. NCAR expects to further exercise and improve WRF-Solar in future projects.

Nowcasting systems. The shortest ranges of forecasts must leverage measurements that are available in real time, those from both ground-based sensors as well as satellite-mounted sensors. The shortest-range irradiance forecast (0–6 h) is supplied by the NESI system. The NESI system consists of several short-range forecasting systems: the Total Sky Imager Nowcast (TSICast; Peng et al. 2015), StatCast (McCandless et al. 2015, 2016a,b), the Cooperative Institute for Research in the Atmosphere (CIRA) Nowcast (CIRACast; Miller et al. 2012, 2017), the Multisensor Advection-Diffusion Nowcast (MADCast; Auligné 2014a,b; Descombes et al. 2014), WRF-Solar-Now, and MAD-WRF.

TSICast is a ground-based cloud imaging and tracking system that operates on the shortest time scale, with a latency of only a few minutes and forecasts that currently extend to approximately 15 min. This project facilitated research to develop and test model algorithms and improve the hardware and software so that new high-definition cameras deployed at multiple nearby locations facilitate the discernment of clouds at varying levels and advection according to the winds observed at those levels (Peng et al. 2015).

Pyranometers supply the in situ data for initializing StatCast. During the course of this project, short-range statistical forecasting was advanced by emphasizing regime-dependent forecasting, both implicitly through a regression tree approach and, more explicitly, by combining clustering techniques with artificial neural networks. These methods produce a substantial improvement in mean absolute error (MAE; from 15% to 50%) over short-range smart persistence forecasts (McCandless et al. 2015, 2016a,b). While multiple versions of StatCast were developed, in this article we focus on StatCast-Cubist (McCandless et al. 2015), which uses a hierarchical regression tree (the Cubist model; Quinlan 1992; Kuhn et al. 2012).

A second category of systems employs satellite imagery and uses that information to discern clouds and their motion, allowing the systems to project the clouds, and the resulting irradiance attenuation, in time. During this project, NOAA reduced satellite data latency while allowing the recovery of higher-resolution data. The CIRA team advanced cloud shadowing, parallax removal, and the implementation of better advecting winds at different altitudes (Miller et al. 2017). A second satellite-based system, MADCast, assimilates data from multiple satellite imagers and profilers to incorporate a cloud fraction for each grid column into the dynamic core of WRF (Auligné 2014a,b; Descombes et al. 2014). That model allows advection of the clouds directly via the WRF dynamics.

One issue with the satellite data assimilation methods described above is that they do not allow for cloud formation and dissipation, which is in the domain of NWP models. Thus, WRF-Solar (Jiménez et al. 2016a,b) was adapted for nowcasting, being run at lower resolution more frequently to fill the gap of time (between 1 and 6 h) where changes in the clouds are most likely (WRF-Solar-Now). Finally, as the project progressed, it became obvious that combining the advantages of WRF-Solar-Now with MADCast, which assimilates the current cloud observations and allows for cloud formation and dissipation via WRF-Solar-Now, and thus was born MAD-WRF (Haupt et al. 2016).

The nowcasting system evaluation (Haupt et al. 2016) revealed that each component has a "sweet spot" where it is most effective. For instance, the satellite-based method, CIRACast, provides the best initial state during partly cloudy conditions, although that may not carry through to clear or fully cloudy conditions. It does, however, provide value for forecasting short-range ramps due to changing cloud cover [see Figs. 5–8 in Haupt et al. (2016)]. Thus, the blending of the different nowcasting components produces an effective method of nowcasting.

System engineering–integration. Building the individual component models is necessary, but not sufficient, to supplying a high-quality solar power forecast. It is also critical to engineer a system that smoothly handles data input and output and effectively blends the results of each of the components. This engineered system must allow for missing observations or model results as well as allowing for "graceful degradation" when not all systems are performing optimally. Haupt and Kosović (2017) discuss the "big data" aspects of this system and how it brings observational data together with model data to produce a complete system.

NESI uses recent performance information to smartly blend the nowcast components by weighting the model contributions according to their historical performance at each lead time. Although this is currently accomplished using historical statistics, moving to a dynamically blended system in the future could prove advantageous.

The DICast system blends the output of NWP models, both WRF-Solar output as well as that from publicly available models, including NOAA's High Resolution Rapid Refresh (HRRR), the North American Mesoscale Forecast System (NAM), the Global Forecast System (GFS), and the Canadian Global Environmental Multiscale Model (GEM) for this project. This blending is accomplished by first correcting biases in the individual models, then by dynamically optimizing their weights for each lead time. Although DICast has shown a high degree of accuracy for other forecast variables (Myers et al. 2011), this project was the first time that the method was employed for irradiance forecasts. Development during the project included building algorithms to account for disparate model time frames and consideration of solar angle in blending the model output correctly. The DICast and nowcast systems must in turn be blended during the overlap periods.

At this point, the blended system forecasts irradiance; thus, it is then necessary to convert irradiance to power. This was accomplished by using a Cubist regression tree model (Kuhn et al. 2012) that was trained on historical irradiance and power observations. The advantage of this empirical approach to power conversion is that it can use GHI, DNI, or plane-of-array (POA) irradiance as long as these are used consistently. Furthermore, it can implicitly account for the specifics of solar panel installation (tilt angle, etc.) by training the power output directly to the observed input solar irradiance. This process inherently mitigates problems by not directly using any metadata, which is often inaccurate.

The last step in the forecast process applies the analog ensemble technique (AnEn; Delle Monache et al. 2011, 2013; Alessandrini et al. 2015, Haupt et al. 2016). AnEn searches the database for past forecasts most similar to the current forecast. It then forms a probability density function (pdf) of the observations that correspond to those historical forecasts. The mean of this pdf becomes the improved forecast and its spread quantifies the uncertainty. Thus, the AnEn both corrects the power forecast and provides probabilistic information for quantifying the uncertainty of the forecast. Again, this project was a first opportunity to exercise AnEn for solar power and it effectively quantified the uncertainty in the solar power forecasts with significantly lower computational cost than standard multisimulation model ensembles.

TESTING AND EVALUATING THE SYSTEM.

Quasi operationalization. The system was deployed in concert with the team partners as forecast systems came online. The full system was run in quasi-operational mode from January 2015 through March 2016. The partners in the project are located in a geographically diverse set of locations across the country—the eastern United States [Brookhaven National Laboratory (BNL)], central United States (Xcel Energy), and western United States [Sacramento Municipal Utility District (SMUD) and Southern California Edison (SCE)]—thus bolstering the robustness of the results.

Assessment. The verification system is based on NCAR's Model Evaluation Tools (MET; www.dtcenter.org/met/users/) package. Specifically, the Stat-Analysis tool is used to compute verification measures of irradiance and power, and the METViewer database and display system are used to aggregate the results. Several baselines are available for this evaluation, including persistence with knowledge of sky conditions and solar zenith angle (labeled "smart persistence") for nowcast components and publicly available NWP models for both the nowcast and DICast components. Here, we show a small sample of the results reported elsewhere (Haupt et al. 2016).

Day-ahead Assessment. DICast statistically blends NWP forecasts for the Sun4Cast system, providing the forecast beyond 6 h (although it also produces forecasts from time $t = 0$). Figure 4 indicates that when scores are aggregated over all partners' locations, including BNL, Xcel, SMUD, and SCE, the blended Sun4Cast and WRF-Solar systems perform better than the operational models for day-ahead forecasts. Statistical analysis through pairwise differences and bootstrapped confidence intervals indicates that these results are statistically significant at the 95% level for

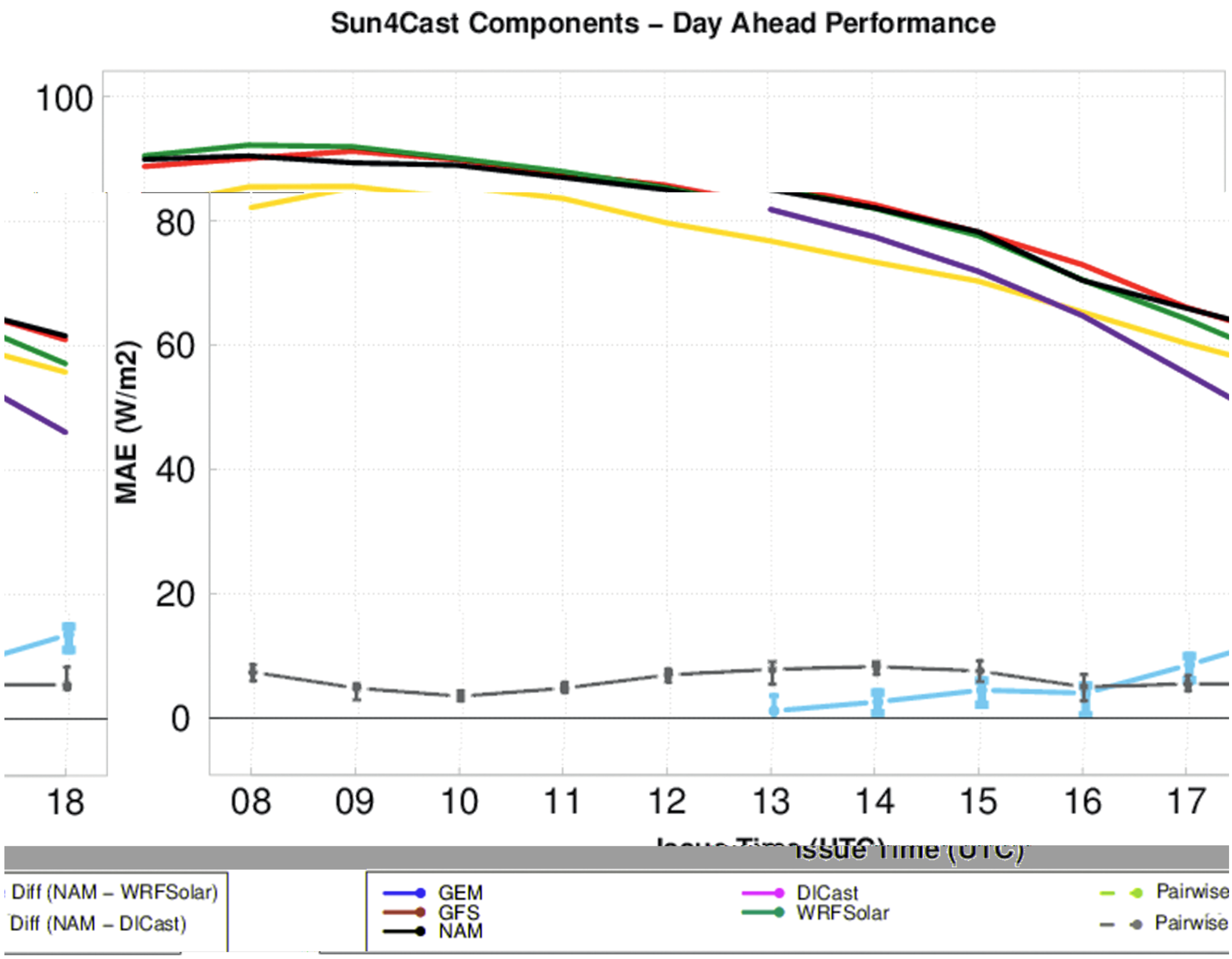

FIG. 4. MAE (W m^{-2}) for day-ahead forecasts from DICast components and the Sun4Cast system at all partner locations and under all sky conditions.

all issue times when NAM is compared to DICast, and all but the first issue time when NAM is compared to WRF-Solar. Figures 5–13 in Haupt et al. (2016) also indicate statistically significant results at all lead times.

NOWCAST ASSESSMENT. One purpose of exploring multiple nowcast components is that each one is potentially skillful for a different forecast horizon (lead time) and set of sky conditions. Figure 5 provides a measure of each model's skill when these scores are accumulated over the geographic regions for the entire 15-month evaluation period. The scores were aggregated over the hourly initialization times. It also shows the skill for clear, partly cloudy, and cloudy conditions. During clear conditions, only WRF-Solar-Now and the blended nowcast NESI outperform the smart persistence to 45 min (0.75 h). After this, all methods have lower MAEs than does smart persistence, with WRF-Solar-Now and CIRACast performing the best out through 2 h and WRF-Solar-Now and MAD-WRF through 3–6-h lead times. For partly cloudy and cloudy conditions, the performance of the components is much more variable, with NESI and MADCast providing the best forecasts during partly cloudy conditions and StatCast-Cubist and MAD-WRF giving the better forecasts during cloudy conditions. One can see oscillations in the blended models such as MAD-WRF and NESI as they switch the weighting from one model to another.

NOWCAST CASE STUDIES. To better understand the performance of the various nowcast components in specific situations, a series of intercomparison case studies was undertaken by Lee et al. (2017). The 15-min-average GHI predictions were compared against observations from seven pyranometers near Sacramento, California, that are owned and operated by SMUD. The GHI forecasts from several forecast models—StatCast-Cubist, CIRACast, MADCast, and four versions of WRF-Solar—were compared over

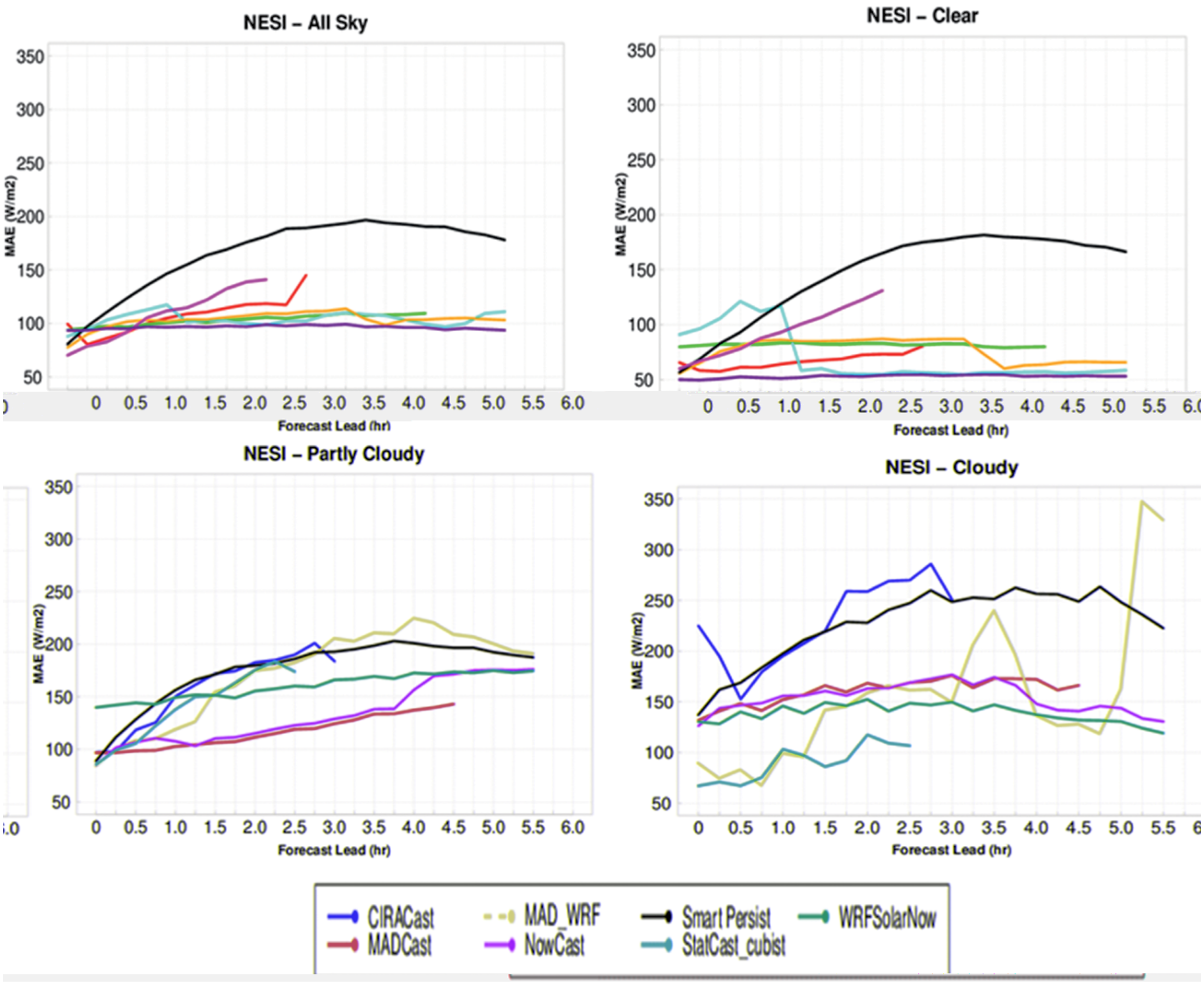

Fig. 5. MAE (W m^{-2}) for all nowcast components aggregated across (top left) all partners and all sky conditions, (top right) clear skies, (bottom left) partly cloudy skies, and (bottom right) cloudy sky conditions.

four case days with canonical sky-cover regimes (i.e., clear skies, morning stratocumulus, mix of clouds and sun, and overcast).

Statistical forecasting with StatCast-Cubist provided the best forecast under clear skies, because of the attenuation from typical aerosol loading already accounted for in its training dataset and the observations. StatCast typically had some of the lowest errors on all case days for the first 45–60 min. GHI forecast errors for longer lead times increased when clouds were present, however. Especially in cases when rapidly changing cloud cover led to reversing trends in GHI, this result is unsurprising.

The satellite-based forecasting methods CIRACast and MADCast also generally performed well at short lead times. Unsurprisingly, these methods struggled on days with rapid formation, growth, and decay of clouds after forecast initialization. Cloud fields predicted by MADCast are generally smoother than those from CIRACast, but the GHI variability is often grossly underestimated by MADCast.

NWP with WRF-Solar performed comparatively accurately for GHI predictions for all four cases. The best accuracy resulted when representing the aerosol direct effect using a high-resolution aerosol dataset and when representing the radiative effects of unresolved shallow cumulus clouds using the Deng et al. (2014) mass-flux scheme. Improving the treatment of aerosols made a noticeable difference during clear-sky conditions, while the shallow cumulus scheme substantially reduced the GHI forecast errors during periods of extensive cloud cover.

Assessment of probabilistic power forecasts. When the output of the power conversion module is compared to the measured power for five solar farms, mean absolute errors normalized to the percentage of capacity (MAPE) range from 1.3% to 4.4% with a median value of 2.1%, as discussed in more detail in Haupt et al. (2016).

The AnEn showed promising results for providing an ensemble-mean forecast and uncertainty quantification for GHI forecasts. Toward the end of the project, the technique was also applied to power forecasts for SMUD locations. The root-mean-square error (rmse) of the AnEn mean and Sun4Cast versus power measurements were assessed for the 0–72-h forecast. Overall, AnEn provides substantial improvement to the deterministic forecast as measured by rmse, MAE, and bias error. 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. A marked improvement was obvious in terms of Brier skill score (Wilks 2011) for probabilities of an exceedance of 50% of capacity (Haupt et al. 2016). The computed Brier skill score across all lead times was 0.55 [see Figs. 5–23 in Haupt et al. (2016)].

Economic valuation. Production cost modeling (PCM) approaches were used to assess the value of energy forecasts. PCM is used by utilities on an operational basis to determine the optimal system configuration (e.g., lowest cost) for the day-ahead time frame, given expected demand (load) while taking into consideration all other relevant factors (e.g., fuel costs, maintenance on facilities, transmission constraints). Martinez-Anido et al. (2016) used a PCM to derive value estimates for day-ahead solar power forecasting improvements for the New England Independent System Operator (ISO-NE) with varying solar power penetrations (4.5%, 9.0%, 13.5%, and 18.0%) and solar power forecasting improvements (25%, 50%, 75%, and 100%). Their analysis indicates that improved solar power forecasting reduces operational electricity generation costs. The benefits increase further with higher penetration levels and with larger forecast improvements.

An economic evaluation based on PCM for the Public Service Company of Colorado showed that a 50% improvement [see Fig. 5-5 in Haupt et al. (2016), which indicates a 45%–48% improvement over a year of the project] in day-ahead forecast accuracy will save their customers $819,200 in 2024 with the projected solar deployment for that year. Using econometrics, NCAR scaled this savings to the national level and showed that an annual expected savings for this 50% forecast error reduction ranges from $11 million in 2015 to $43 million expected in 2040 with increased solar deployment (Lazo et al. 2017). This amounts to $455 million in potential discounted savings over the 26-yr period of analysis (Haupt et al. 2016).

DISCUSSION. The DOE-funded Public-Private-Academic Partnership to Advance Solar Power Forecasting project functioned as a collaborative team, with each participant contributing to portions of the Sun4Cast Solar Power Forecasting System. The project began by seeking to understand industry needs in order to configure a system that meets those needs, based on characterizing the problems using a value chain approach. The end result is the Sun4Cast solar power forecasting system that has been thoroughly evaluated.

Recommendations for best-practice forecasting. A major goal of this project was to draw conclusions about the performance of each component system and make recommendations for best practices in configuring solar power forecasting systems. Some specific recommendations include the following:

- Blend component models or systems together. The forecasts from blended models/systems are invariably significantly better than those produced by a single model or approach, when evaluating the full time frame.
- Use an NWP model tuned for the purpose. Using WRF-Solar significantly improved the forecasting. Including high-resolution, high-quality aerosol datasets and a shallow cumulus scheme have proven especially beneficial.
- Include multiple NWP models. Blending multiple NWP models improves the forecasts for time scales from 3 h through the day-ahead forecast and beyond.
- Employ statistical learning methods trained on targeted in situ observations for short-range forecasting. StatCast trained using local pyranometer data was better than smart persistence, even at short time scales (15 min–3 h), and TSICast, which uses multiple sky imagers as well as statistical learning techniques, improved upon persistence for time ranges of less than 15 min.
- Use satellite-based cloud advection, being mindful of its challenges. For mountainous or coastal regions, it is necessary to include some model physics to account for stationary clouds as well as for cloud formation and dissipation. It is important to include the improvements related to correcting for shadowing and parallax as accomplished by CIRACast.
- Combine NWP with satellite data via assimilation for nowcasting. MAD-WRF runs quickly and pro-

duced the best forecast on the 1–6-h time scale.

- Include analog ensembles. AnEn both improves upon the deterministic blended forecasts and produces probabilistic predictions that are well calibrated.
- Develop an empirical power conversion method. Such methods are amenable to training using site-specific information, even when missing metadata. Artificial intelligence techniques are capable of predicting directly from an observation to a target value if historic training data are available.
- Perform verification with an enhanced series of metrics. Carefully chosen metrics allow for meaningful evaluation and tuning of both individual models and the entire system.
- Consider economic metrics of value to the user. Expand the use of PCM and reserves analysis to quantify and demonstrate the economic benefits of improvements to solar power forecasting.

Lessons learned. Typical of any real-world applied project, the team encountered several challenges. Chief among these issues was solar farm data availability and quality, which is a critical issue for any forecasting system. Addressing these issues would benefit researchers, practitioners, and the end users but would require some coordination or adoption of standards across the community. Additionally, historical data were often unavailable. Statistical learning and artificial intelligence methods require historical data for training the system, so where data do not exist, those techniques cannot be employed. Finally, because the atmosphere is a chaotic dynamical system, there are limits to the predictability that should be recognized in designing and assessing any forecast system. Although weather and climate forecasting is constantly improving, the sensitivity to initial conditions provides a theoretical limit on how well we can forecast for a particular time frame.

Leveraging the design process. The team demonstrated and evaluated a working Sun4Cast solar power prediction system that includes the multiple components described herein. The individual components and the overall Sun4Cast system were validated using the metrics developed toward the beginning of the project. The team met or exceeded most of the target values specified by the project sponsor, the DOE SunShot Initiative. Data streams from various model systems were made available to the forecasting partners, forecasts were regularly provided to the utility and ISO partners, and feedback from the partners was used to iteratively improve the forecasting models.

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

The team approach of infusing social science from the beginning to facilitate team building was widely successful. We believe that this approach of starting with the end in mind, listening to the end user, group mental-modeling exercises, and continued communication throughout a project can be leveraged for other large projects with many interacting parts.

Continuity and next steps. The team members have all grown in their research capabilities in solar energy and the collaborative research is expected to continue. Further improvements can be made and new applications of solar power as well as forecasting its output are continually appearing. A direct point of continuity is continued collaboration among the partners.

The details of the models are documented in Haupt et al. (2016) and individual journal papers describing each model, many of which are referenced herein. Many of the component models are open source and available from NCAR (see https://wiki.ucar.edu/display/Sun4Cast/Sun4Cast+Home).

Our utility and ISO partners provided feedback regarding their vision of the future of solar power forecasting. One partner commented, "the industry need is still there and it will only get larger as more distributed energy is connected to the grid." Another said that forecasts will be from "centralized regional transmission authority (RTO)/ISO/balancing authority (BA)-generated forecasts that will have multiple uses and at varying granularities." As a community, we must strive to continually provide improved forecasts in a form that will be appealing and beneficial to end users.

As the penetration of solar power continues to grow, solar power forecasting with systems such as Sun4Cast will provide key technologies that will make the economics more feasible, thus empowering greater 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.

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