# Benchmark Solar Power Forecasts

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## Summary

- DOE EERE SETO Solar Forecasting 2 funding opportunity supports 8 teams working to improve solar power forecasts and their application to grid management.
- **Our team is creating a framework to fairly and transparently evaluate solar power forecasts**. The framework will support the 7 other DOE funded teams and the broader solar forecast community.
- Benchmark solar power forecasts support forecast evaluations:
  - Benchmark forecasts help stakeholders understand the added value of a research effort or commercial product.
  - The Forecast Skill metric requires a benchmark forecast.
  - Benchmark forecasts may help researchers diagnose model strengths and weaknesses.
- The evaluations will be performed by the open source *Solar Forecast Arbiter*.
- **The Solar Forecast Arbiter will contain a benchmark forecast capability** and will support user-supplied benchmarks.
- **See solarforecastarbiter.org** for project details, to sign up for the mailing list, and to join the Stakeholder Committee (open to all).
- Please give us your thoughts on benchmark solar forecasts!

## Benchmark Forecast Attributes

We suggest that all benchmark forecasts should have the following attributes:

- Available throughout the U.S.
- Freely accessible or easily implemented
- Provide quantities of interest to both forecast users and providers
- Stakeholder buy-in

For Solar Forecasting 2 teams, additional attributes may include:

- Forecast method should be published before the Solar Forecasting 2 project kick-off date (July 1, 2018)
- Represent the state of the art of solar forecast modeling

Some attributes are subjective. For example, a researcher experienced with WRF and that has access to a high performance computer may find WRF Solar to be “easily implemented”. Other users may define “easily implemented” as persistence of a measured value. A stakeholder suggestion is that ”easily implemented” means that a researcher can download and run a python package within 30 minutes. As another example, both WRF Solar v1.2 and WRF v4.0 were published before the kick-off date. However, the value of improved WRF physics may be best understood when benchmarked against a new version of WRF that merges WRF Solar v1.2 and WRF v4.0.

## 1 Hour – 7 Days Ahead Benchmarks

The Solar Forecast Arbiter will contain a benchmark solar forecast capability based on NOAA operational weather models (GFS, NAM, RAP, HRRR). Challenges include:

- Inconsistent variable availability
- Short period of record (POR) for easily accessible archival datasets
- Handling average and instantaneous values
- Imprecise solar position calculations
- Lack of GHI, DNI, or DHI data
- Efficient queries for timeseries from specific points

When modeled irradiance is insufficient (due to e.g. solar position, time resolution, data availability), we suggest following Larson (2016) to calculate GHI from cloud cover forecasts:

```
ghi = (offset + (1 - offset) * (1 - cloud_cover)) * ghi_clear
```

where `offset=0.35`, `cloud_cover` is the total cloud cover, and `ghi_clear` is determined by a climatological clear sky model. The DISC model can then used to calculate DNI and DHI. This approach was used to benchmark a commercial forecast trial in 2016 and a regional WRF model in Holmgren (2017). Examples of this approach are shown below.

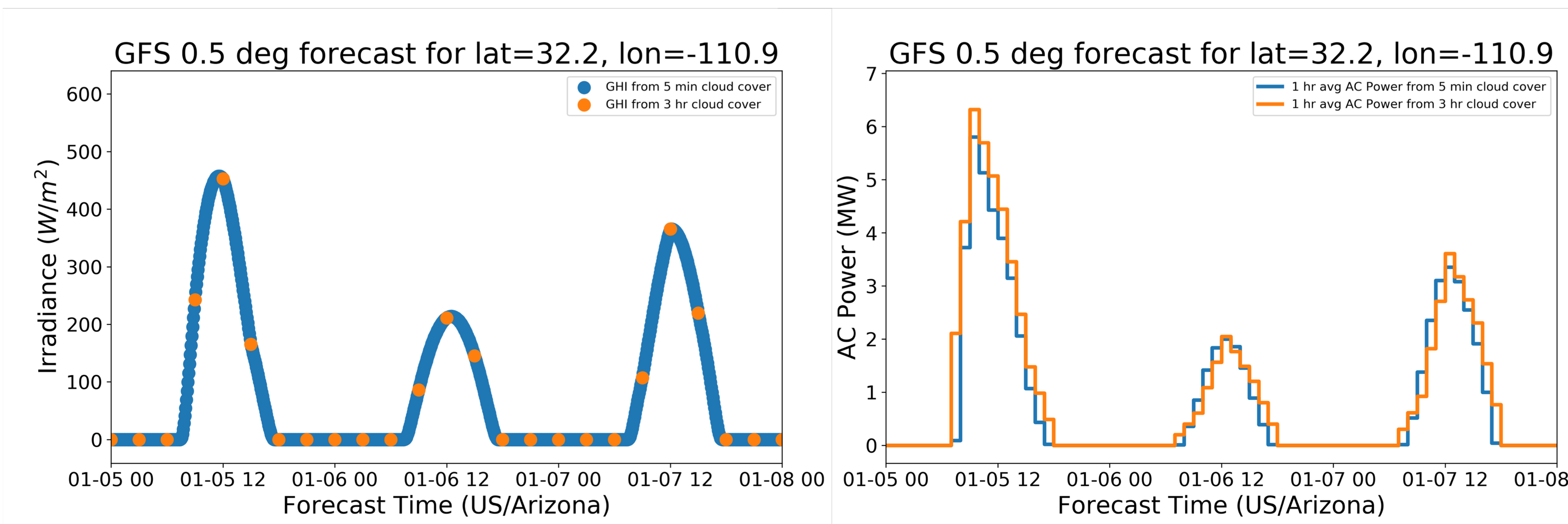


**Figure 1**. 3 days of GHI and AC Power forecasts derived from GFS total cloud cover variable following methods of Larson (2016). **Left**: 3 hour resolution irradiance (orange dots) derived directly from 3 hour resolution cloud cover and 5 minute resolution irradiance (blue dots) derived from 3 hour cloud cover linearly interpolated to 5 minute resolution. **Right**: Hourly average AC Power for a simulated single axis tracker using 3 hour (orange) or 5 minute (blue) irradiance inputs to the power model. 3 hour power is linearly interpolated to hourly resolution. The 3 hour power interpolated to hourly power predicts significantly more generation during the hours near sunrise and sunset. Similar issues can be seen when using hourly instantaneous irradiance data to calculate hourly average power. The power model uses the open source pvlib python library described in Holmgren (2018).

User-supplied benchmark forecasts may help researchers more accurately determine the improvements to the most sophisticated models. A challenge with this approach is determining the rules for when a user-supplied benchmark may be used and when a standard benchmark should be used.

## Intrahour Benchmarks

We envision supporting several intrahour benchmark forecast methods:

- Persistence of measured value
- Persistence accounting for solar position (sometimes known as smart persistence)
- ARMA model fitted to site-specific data

The most appropriate benchmark may depend on the evaluation scenario. Persistence accounting for solar position requires system metadata or historical generation data to create a clear sky model. An open question is if the Solar Forecast Arbiter should include a benchmark method that blends one or more NWP models with an intrahour forecast method.

## Net Load Benchmarks

The Solar Forecast Arbiter will support evaluations of net load forecasts. Several definitions of net load exist. The Solar Forecast Arbiter will support net load benchmarks that account for behind the meter (BTM) PV and metered PV, but not other renewables.

✓ net load = true demand – BTM PV – metered PV
✓ net load = true demand – BTM PV
X net load = true demand – all renewables

The benchmark forecast may comprise a regression of load on weather variables.

## Probabilistic Benchmarks

The Solar Forecast Arbiter will support evaluations of probabilistic forecasts. We seek stakeholder feedback on the best approach for probabilistic benchmark solar forecasts. Input data may include:

- Global Ensemble Forecast System (GEFS) cloud cover
- HRRR Ensemble irradiance or cloud cover
- Historical data

Challenges include data management, defining a fair method for converting input ensemble data into a calibrated probabilistic forecast, and assessment.

## References

- Larson, Nonnenmacher, and Coimbra (2016). Day-ahead forecasting of solar power output from photovoltaic plants in the American Southwest. *Renewable Energy*, 91, 11. DOI: 10.1016/j.renene.2016.01.039
- Holmgren, Lorenzo, and Hansen (2017). A Comparison of PV Power Forecasts Using PVLib-Python. *2017 IEEE 44th Photovoltaics Specialists Conference*. DOI: 10.5281/zenodo.1400857
- Holmgren, Hansen, and Mikofski (2018). pvlib python: a python package for modeling solar energy systems. *Journal of Open Source Software,* 3(29), 884. DOI: 10.21105/joss.00884