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Benchmarking Accuracy and Variability in Intra-Hour Solar Irradiance Forecasts from Satellite and Ground Observations

Summary

In recent years, there has been a growing need for more accurate forecasts of hourly solar irradiance to enable the seamless integration of high shares of solar energy into electricity grids. In particular, under highly variable conditions where cloud dynamics lead to significant fluctuations in solar irradiance, improved forecasting of short-term generation is required. In this study, various forecasting models were compared for site-specific applications such as commercial PV power plant management. The models utilize combinations of local ground-based measurement data from all-sky imagers and pyranometers, as well as cloud cover information from satellites. The benchmark focuses on the ability to provide accurate forecasts at minute intervals for a period of up to 30 minutes, as well as to predict fluctuations in solar irradiance over the next 30 minutes. The results demonstrate the strong performance of purely data-driven models in terms of root mean square error; however, significant differences are observed in their ability to correctly predict fluctuations in solar irradiance.

Keywords: Solar irradiance forecasting, PV Power, Data driven models, All-Sky Imagers, Satellite-based forecasting

Field of application for the findings: PV power forecasting, grid integration

Addressed audience: PV plant operators, Energy traders, Forecast providers

1. Aim and Approach

This benchmark aims to compare various short-term solar irradiance forecast models for the intra-hour range in terms of providing accurate forecasts along with solar irradiance variability. Data driven models tend to smooth solar irradiance forecasts in highly variable conditions in order to reduce the root-mean-square-error (RMSE). RMSE increases rapidly when forecasts provide a wrong timing ("double penalty") and amplitudes of solar ramps. Smoothing is preferred if a precise timing on minute-scale is not possible to predict by a model or not needed for an application, on the other hand information on the variability of the solar radiation is lost.

The benchmark builds up on two previous studies conducted on a dataset from the Eye2Sky network from August 2020 (Lezaca, 2023; Nouri, 2025). The test site is located in northwestern Germany (53°8´46.96´´N, 8°13´2.41´´E). This site is part of the unique Eye2Sky ASI cloud monitoring network, which consists of 30 ASIs and 12 irradiance measurement stations distributed across an area of approximately 10,000 km² (Schmidt, 2025). The parameter selected for the benchmark is global horizontal irradiance (GHI)

The models analysed can be classified based on the data sources and the modelling approach (architecture) they use (Table 1).

Table 1: Overview of the models used in this benchmark.

Model Name	Data source	Architecture	Reference
PERSISTENCE	Ground observations		
ASI_NET	All-Sky Imager Network Eye2Sky	Semi-physical	Blum, 2022
SAT	Satellite nowcasts	Cloud-Motion Vectors	Hammer, 2015
LSTM	ASI_NET + Satellite nowcast	Blending	Lezaca, 2023
ASI-CNN	1 All-Sky Imager + Ground obs.	Convolutional Neural Network	In preparation
ASI-TF	1 All-Sky Imager + Ground obs.	Transformer	Fabel, 2024
ASI-TF+SAT+ PERSISTENCE	Persistence + ASI-TF + Satellite nowcast	Blending	Nouri, 2025

Persistence forecasts based on the latest readings from the local sensor are used as a reference. These forecasts are scaled with clear sky irradiance to account for the diurnal variation of the sun position.

The ASI_NET forecasts are based on a model developed by Blum (2022) and comprises of 13 All-Sky Imager in the Eye2Sky network. The model iprovides maps of solar irradiance for the whole city of Oldenburg (approx. 12km x 12km) allowing for forecasts at any point of the map. The products are based on estimations of cloud distributions, transmittance, height and velocity from each single ASI. It can be considered as a semi-physical model as it translates the current cloud distribution into spatial distributions of surface solar irradiance. The solar irradiance is calibrated with onsite measurements from the measurement stations used in this study (Blum, 2022).

The SAT model uses images from Meteosat Second Generation (MSG) and a cloud-motion vector approach to estimate future cloud conditions (Hammer, 2015). Its temporal resolution is 15 minutes and forecasts have been interpolated to minutely data for this benchmark.

The LSTM model blends forecasts from the two aforementioned models into a single model (Lezaca, 2023).

The ASI-CNN model uses a Convolutional Neural Network to estimate future irradiance conditions on the site of interest incorporating latest ASI images and onsite ground measurements.

The ASI-TF model produces multi-step solar irradiance forecasts through a dual-branch transformer architecture. One branch processes time-series data, including past irradiance and sun position, while the other extracts spatiotemporal features from all-sky imagery. The resulting feature representations are fused and passed to a multi-layer perceptron to predict irradiance (Fabel, 2024).

The ASI-TF+SAT+PERSISTENCE model blends forecasts from the aforementioned ASI-TF model, satellite-based forecasts (SAT) and persistence, via a post-processing regression approach (Nouri, 2025).

For the benchmark, traditional error metrics like the Root Mean Square Error (RMSE) at each single forecast lead time have been evaluated.

Moreover, the variability index VI was computed for each forecast up to 30 minutes ahead. It is defined as the ratio of the "length" of the measured 1-min-average GHI curve over time to the "length" of a reference clear-sky GHI curve (Stein, 2012). In order to put both forecast errors and forecast variability in relation, the average forecast RMSE (of each 1 to 30 minute-ahead forecast) and average VI has been computed.

2. Results and conclusions

For this abstract we focus on results of RMSE and variability evaluations.

RMSE statistics (Figure 1) show that all models except for SAT and ASI-CNN in the first minutes outperform persistence as expected. The SAT model can be seen as as baseline. It is designed to provide forecasts on a global scale and has not been calibrated using measurements from the test site. The ASI_NET model (as well as the other ASI-based forecasts) is calibrated with local data and therefore has low RMSE for the first minutes but shows high RMSE on longer time horizons. The blending of both SAT and ASI_NET in the LSTM model makes use of the advantages of both models on the very short (ASI_NET) and longer horizons (SAT). These results have been demonstrated by Lezaca (2023). Lowest RMSE is reached by the ASI-TF model (Fabel, 2024) and the superior blending model that combines it with satellite-based and persistence forecasts. These results have been emphasized by Nouri (2025). Notably, the ASI-TF model was trained on data from southern Spain but evaluated in northern Germany, indicating robust generalization across regions with substantially different climatic and atmospheric conditions. The RMSE of the ASI-CNN is enhanced in the first minutes but reaches comparable values for longer horizons (15-30 minutes).

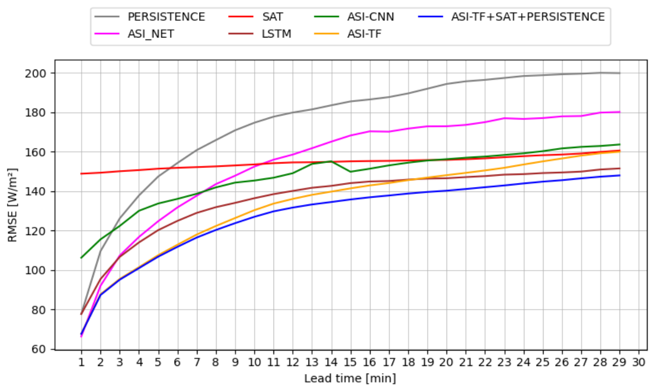

Figure 1: Average variability indices of all forecasts for each models vs. the overall RMSE of the 30 minute ahead forecasts.

The variability statistics reveal that the ASI_NET, the LSTM and the ASI-CNN model show significantly higher variability metrics than the ASI-TF, SAT and the blending of both with persistence model (Figure 2). However, the minutely variability of the measurements in the 30 minutes window is still much higher than predicted by any of the forecasts (Average ~22). These findings highlight that nowcasting models generally tend to smooth their forecasts and are rarely able to reproduce the ground-based variability information. For data driven models, the usage of persistence and objective functions that minimize RMSE are suppressing variability information.

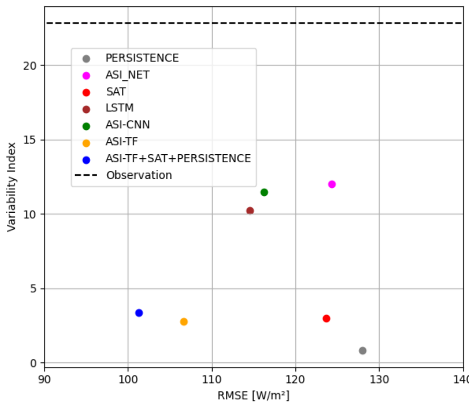

Figure 2: Root mean square error (RMSE) of all forecast models vs. VIforecastforecast lead time.

The benchmarking study highlights how the differences in model architecture and selection of data sources for nowcasting influences the irradiance forecasts at different forecast horizons and the capability of providing high accuracy as well as consistent variability information.

For the full conference contribution, the benchmarking will be extended to include the latest model developments, including generative approaches with potentially enhanced capabilities for representing irradiance variability. The evaluation will be conducted over longer and more recent data periods and across multiple sites. In addition, the analysis will incorporate additional performance metrics and condition-specific discretization.

3. References

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