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Development of a data-driven approach for the short-term prediction of solar power

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Short-term forecasting background

Computer vision-based approaches are expected to be useful to extract and exploit the spatial and temporal information of the dynamics of cloud movement, which causes the temporal variability of solar irradiance and solar power. Taking advantage of a growing number of meteorological inputs, data-driven approaches are being developed in order to improve short-term and intra-hourly irradiance forecasts.

Dataset

All-Sky-Imager (ASI): these images of the sky are taken from the ground by a webcam with a fisheye lens. A year's worth dataset is available with a photo taken once every 30s [2]. The images were preprocessed before training; rotation, masking, undistortion, resizing and greyscale.

Irradiance: the global horizontal irradiance (GHI) is measured on site [2]. The sequence of data is averaged over a minute before training.

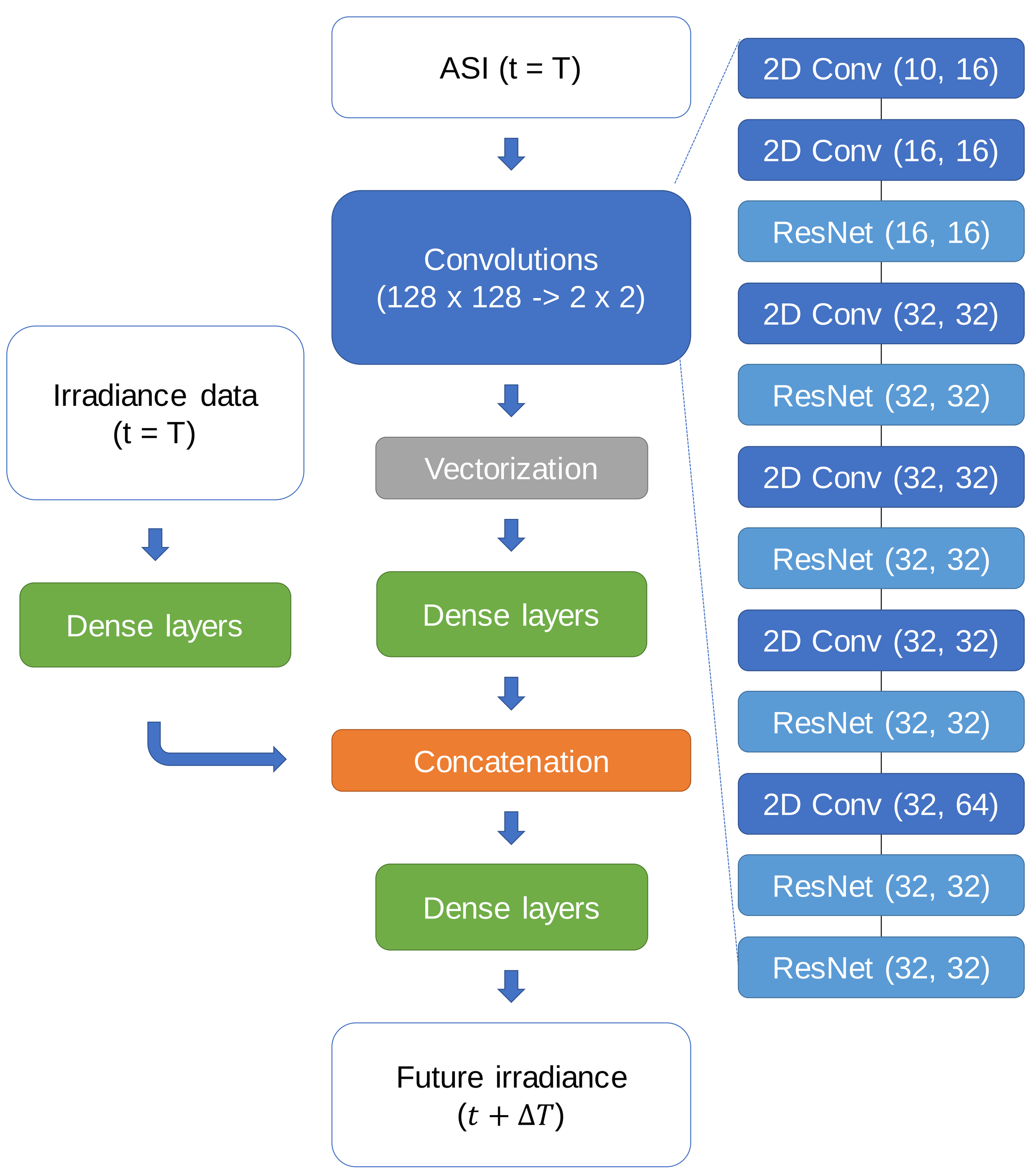

Fig.1: CNN architecture to forecast irradiance [1]

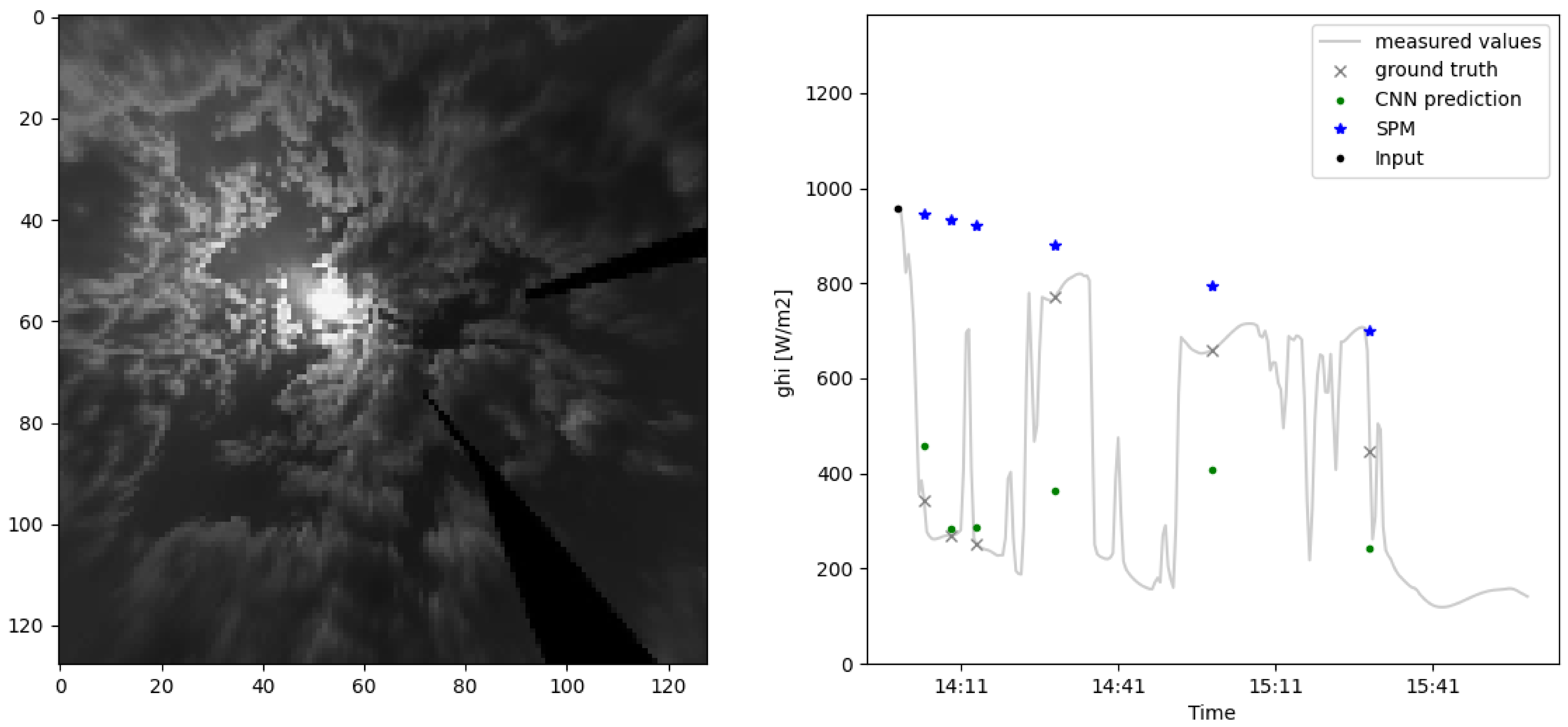

Fig.2: Example of how the CNN model and the SPM make 5 to 90 mins ahead predictions (6 points). ASI input (left) and the irradiance input and results for 30.05.2020 between 14:00 and 15:30 (right).

	RMSE [W/m2] (Forecasting skill [%])					
	5-min	10-min	15-min	30-min	60-min	90-min
SPM	128.4 (0 %)	145.1 (0 %)	152.2 (0 %)	159.9 (0 %)	150.9 (0 %)	166.8 (0 %)
CNN	105.7 (17.7 %)	117.0 (19.4 %)	124.2 (18.5 %)	134.6 (15.9 %)	137.3 (9.0 %)	148.3 (11.1 %)

$$\text{SPM}: \hat{y}(t+\Delta T) = \frac{y(t)\, y_{clr}(t+\Delta T)}{y_{clr}(t)}$$

$\hat{y}$: Future irradiance, y: Measured irradiance, y_{clr}: Irradiance from a clear sky model

$$\text{Forecasting skill} = \left(1 - \frac{RSME_{CNN}}{RSME_{SPM}}\right) \text{x } 100\ [\%]$$

Table.1: The forecasting skill metric using root mean square error is used and the results are compared with the smart persistence model (SPM).

Training & Testing

A convolutional neural network (CNN) is used as the image encoder for the machine learning architecture (Fig. 1). The training dataset contains 185,000 samples randomly selected from the year 2020 at the OLDON ASI station in Oldenburg, while the testing dataset contains 11,800 samples which are seven random days and are completely unseen by the model.

Results

To assess the performance of the model, the forecasting skill metric using root mean square error is used and the results are compared with the smart persistence model (SPM). Overall, the CNN model outperforms the reference model. Some ramp events are not well predicted.

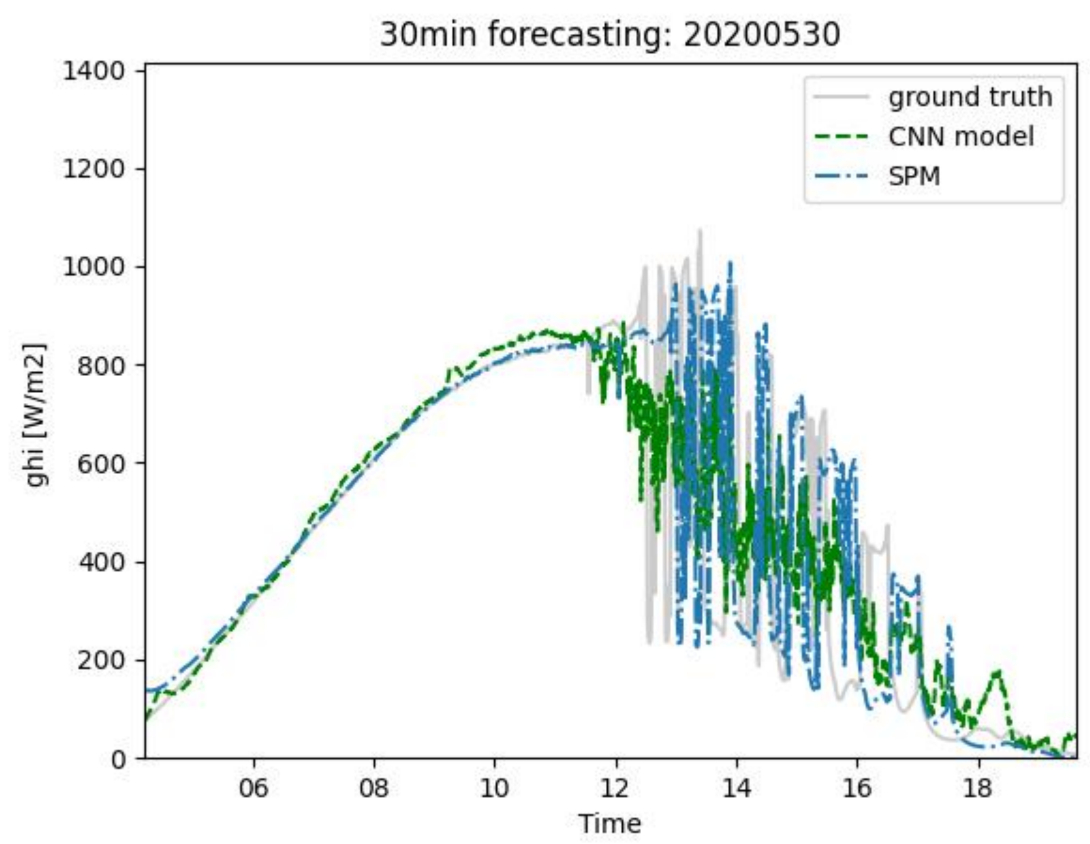

Fig. 3: A day plot of 30 mins predictions by the CNN model and the SPM

However, the CNN model makes a good prediction for $t + \Delta T$ solely from one ASI and irradiance data.

Outlook

To further improve the forecasting skills of longer forecasting horizons, we are currently working on feeding satellite imagery, e.g. cloud index, as an additional input variable.

References:
[1] Paletta, Q., Arbod, G., Lasenby, J., 2021. Benchmarking of deep learning irradiance forecasting models from sky images – An indepth analysis. Solar Energy 224, 855–867.
[2] Schmidt, T., Stührenberg, J., Schellhorn, M., Blum, N., Lezaca Galeano, J., Hammer, A., von Bremen, L., Schroedter-Homscheidt, M., 2023. Solar irradiance nowcasting based on a network of all sky imagers: the value of high-resolution data on variability information. EMS Annual Meeting 2023, 03.-08. Sep. 2023, Bratislava, Slowakei.

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