Robust satellite derived solar irradiance nowcasting with spatio-temporal neural networks

DESTINATION EARTH

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Purpose & Goals

→ Solar irradiance nowcasts required for PV power output estimation
→ Satellite derived irradiance data enables large area forecasts
→ Efficient near-real-time nowcasts with spatio-temproal neural network
→ Robustness to missing frames due to loss or delay

Outlook

→ Operationalization as Singularity container (DE330 Phase 2 WP12)
→ Introduction of further features while maintaining near-real-time availability

DATA & CHALLENGES

Data:

- Solar irradiance –DSSF[1] (3km^2 (sub nadir), 15min)
- Orographic component – elevation map[2]
- Temporal components (day/year, minute/day)

➢ 12T x 256W x 64H x 6C (primary use case: Austria)

Challenges:

- Missing and delayed irradiance frames in near-real-time context – Model robustness

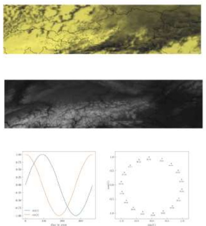

Figure 1: Sample of dataset (Austria): DSSF, elevation map and cyclically encoded timestamp features

MODEL: IrradPhyDNet

The spatio-temporal neural network IrradPhyDNet is the result of a comparative evaluation of convolutional-recurrent model architectures and cell designs. It contains a two-branch architecture similar to PhyDNet[3], a "physical" branch utilizing a modified variant of PhyDNet´s PhyCell and a "residual" branch based on an adaptation of IrradianceNet[4].

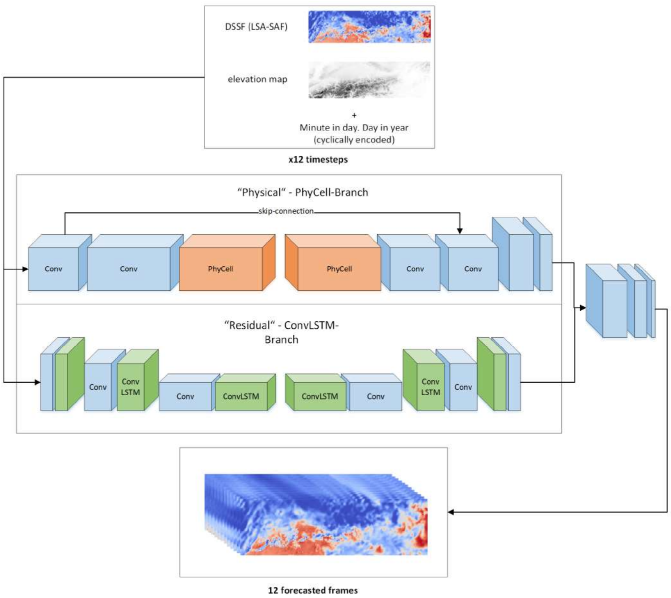

Figure 2: Architecture of IrradPhyDNet, default dataset Austria with max. 3h-lead time in 15min intervals

TRAINABLE ROBUSTNESS: Timestep-Dropout

➢ **Robustness as an alternative to ad-hoc interpolation**

Technique:

Probability-based zeroing/dropping of dynamic timestep-grids (here irradiance) during training. Static and timestamp features are not zeroed.

$$\forall T \in X : f(T) = \begin{cases} 0_{T_{m*n}} & \text{if } p < c \\ \mathrm{T} & \text{else} \end{cases}$$

X : sample of 12 timesteps T
T : spatial timestep of shape $m * n$
c : constant threshold
p : pseudo-random number drawn from $U([0.0, 1.0])$

RESULTS: Extremes case study (DE330 Phase 1 WP8)

The timeframe of interest for this case study was 11-12.06.2019, encompassing a thunderstorm over Denmark. IrradPhyDNet´s forecast results were compared with, among other methods, Harmonie in 750m spatial resolution (runs at 0:00 and 12:00). The nowcasts were evaluated with two different lead times (1h and 2h). Ground truth measurements were taken from 21 GLORAD stations.

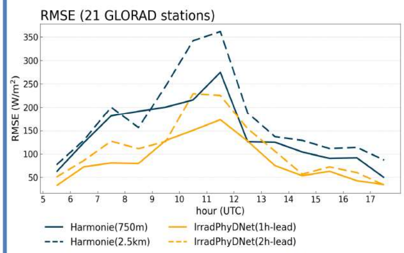

Figure 3: IrradPhyDNet and Haromnie forecasts validated against GLORAD stations, 12.06.2019

The forecasts from IrradPhyDNet with either lead-time achieve a competitive accuracy. 1h-lead performs better over the whole solar day, except for first hour of 750m-Harmonie´s 12:00-forecast, despite its coarser resolution.

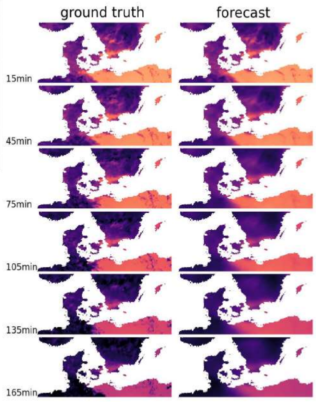

Figure 4: IrradPhyDNet and DSSF ground truth, 06.12.2019 12:15-15:00 UTC (cropped to 30 min interval)

RESULTS: Timestep-Dropout

Robustness pre-tests

Broad pre-test results from a multi-model study showed the largest benefit of Timestep-Dropout at 0.3 (30% chance of an irradiance frame being zeroed/dropped).

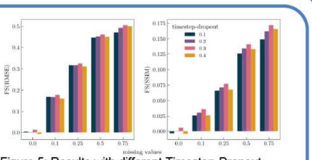

Figure 5: Results with different Timestep-Dropout ratios, Forecast Skill relative to regularly trained models

Timestep-Dropout training improved robustness on all evaluated models, with two models (IrradPhyDNet and PhyDNet-dual) remaining more accurate than Persistence when not receiving any irradiance data

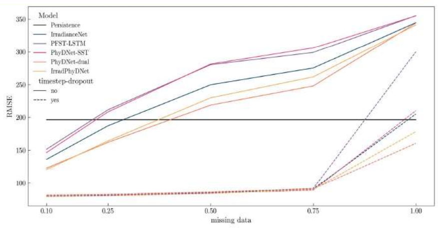

Figure 6: Timestep-Dropout trained models evaluated on a range of missing data ratios, 2021 (2000 random samples), Persistence (naïve) kept constant with 1 frame

ADDED VALUE

✓ Single irradiance satellite-data-product sufficient for viable forecasts
✓ Issues with missing data largely recoverable with Timestep-Dropout
✓ Light-weight NN-nowcasts able to compete with NWP forecasts

1 MDSSFTD (LSA-207) provided by LSA-SAF, ©2020 EUMETSAT
2 EU Digital Elevation Model provided by Copernicus

3 Guen, V. L., & Thome, N. 2020. Disentangling physical dynamics from unknown factors for unsupervised video prediction. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 11474-11484).
4 Nielsen, A.H., Iosifidis, A., Karstoft, H., 2021. IrradianceNet: Spatiotemporal deep learning model for satellite-derived solar irradiance short- term forecasting. Solar Energy 228, 659–669.