

Sky Image-Based Photovoltaic Output Forecasting

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Introduction

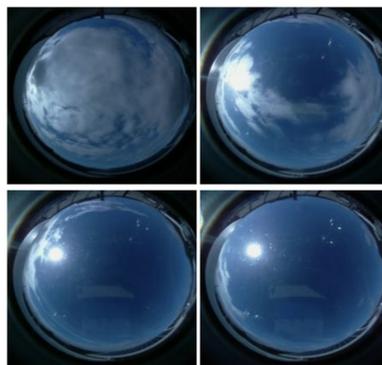
Solar energy has emerged as a promising renewable energy source. However, despite the expansion of solar infrastructure and the advancements in engineering, the integration of solar power generation systems into electric grids remains challenging owing to the variability associated with such systems.

Measuring solar irradiance, which is essentially the brightness of the sunlight at a given spot on the Earth, may serve as a useful tool for onsite PV power forecasting, in turn allowing better predictability with regards to power generation and higher penetration of solar power generation systems into the grid.

Dataset

We use ground-based sky images related to sunny, partially cloudy, and overcast sky conditions with the corresponding power measurements that were obtained from two rooftop PV systems at University of Wollongong, Australia for the signal processing based study.

We have 9000 images - 3000 obtained each day from 09/10/19 to 09/12/19. Since the image capturing and PV power measurement systems were decoupled, the sky images are captured at time intervals of 10 seconds while the PV output is obtained every 30 seconds. To fix this mismatch, linear interpolation was used.

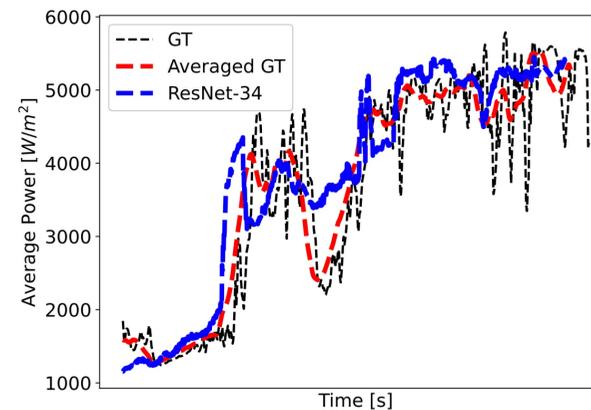


References

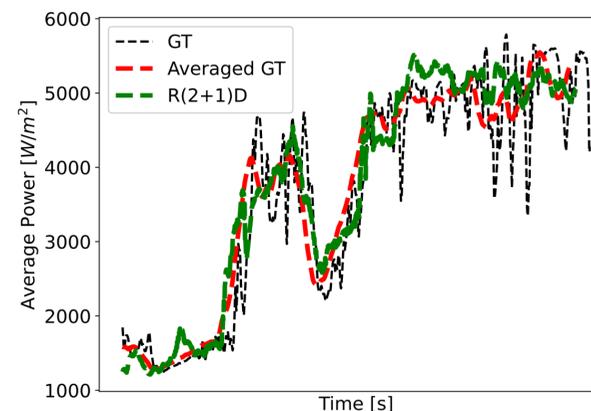
- [1] Duane; Agalgaonkar Ashish; Godaliyadda Roshan ; Ekanayake Parakrama; Perera Sarath ; Ekanayake Janaka Dissawa, Lasanthika; Robinson. Sky Images and PV Power Measurements for Irradiance Forecasting. <https://data.mendeley.com/datasets/cb8t8np9z3/2>, 2021.
- [2] Du Tran, Heng Wang, Lorenzo Torresani, Jamie Ray, Yann LeCun, and Manohar Paluri. A closer look at spatiotemporal convolutions for action recognition. In Proceedings of the IEEE conference on Computer Vision and Pattern Recognition, pages 6450–6459, 2018.

Experiments & Analysis

ResNet-34 Averaged Ground Truth vs Prediction



R(2+1)D-18 Averaged Ground Truth vs Prediction



Despite being over twice as computationally expensive as ResNet-34, the R(2+1)D model achieved an unremarkable increase in performance. This may have occurred because the size and scope of the dataset is not enough to squeeze our lower losses and higher accuracies from more complex residual CNN models.

R(2+1)D-18 and ResNet-34 Best Test Set Performance

| Model | RMSE [W/m ²] | Accuracy |
|-----------|--------------------------|----------|
| ResNet-34 | 408 | 67.81% |
| R(2+1)D | 377 | 72.65% |

The accuracy and RMSE achieved on the test set illustrates the minimal accuracy gains that we saw the R(2+1)D-18 model achieve over ResNet-34.

Methods

ResNet-18/34

The pretrained ResNet-18 and 34 models were modified to fit our specific use case. The output layer was altered to have a single one (from 1000). The first Conv2D layer was modified as these models were trained to take in individual images with 3 channels while our input contained a series of images ($n = 5/10/15$) making the input tensor dimension $3n \times L \times W$. The ResNet-34 architecture generated validation accuracies that were orders of magnitude higher than ResNet-18.

VideoNet: R(2+1)D

R(2+1)D introduces spatiotemporal convolutions as a middle ground between 2D models like ResNet-34 & computationally expensive 3D CNN models like R3D18. It explicitly factors each of the 3D convolutions into multiple 2D spatial convolutions followed by a one-dimensional temporal convolution.



Conclusions & Future Work

The best results are observed when predicting the average PV output over the next 5 to 10 mins using images from the previous 2.5 to 5 mins. Using images more than 5 mins prior to the point from which PV output must be predicted or trying to increase the forecast horizon to 15 mins leads to poor performance likely because of the high volatility of PV outputs i.e. their ability to rise or fall dramatically within a very short time frame.

Future work could involve attempts to achieve greater accuracy over forecast horizons higher than 10 mins by augmenting images with information about temperature, azimuth etc. In addition to this data, using optical flow to track cloud movement could also improve solar irradiance prediction.