Transition Into Solar Elevation Angle Domain for Photovoltaic Power Generation Forecasting

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Introduction

In modern society, electricity plays a very important role. It could be said that society is addicted to it. Nowadays, it is hard to imagine life without access to energy. Therefore, the blackout has become a major threat with the potential to cause significant consequences [1]. Unfortunately, fossil fuels on which the power system is currently based lead to environmental pollution. Moreover, their resources are limited. To counteract these effects, we have started an energy transition [2], which is based on Renewable Energy Sources (RES). However, RES have their limitations. The main obstacle is the difficulty in predicting the power. In other words, RES produce as much energy as is delivered from the sun or wind.

Justification

The production of photovoltaic installation is dependent on the amount of energy that is delivered to the panels. Whereas the power delivered depends on the sun's position and weather. Different types of weather allow energy to pass or block some amount of it.

$$sin(\alpha) = sin(L)sin(\delta) + cos(L)cos(\delta)cos(HRA) \quad (1)$$

The sun's position over the horizon (elevation angle) can be calculated according to the equation 1. The yearly trajectory of the sun's elevation is presented in Figure 1. During the year, the most characteristic days can be distinguished. These are the summer solstice, winter solstice, and two equinoxes. Figure 2 compares the sun's altitude on those specific days.

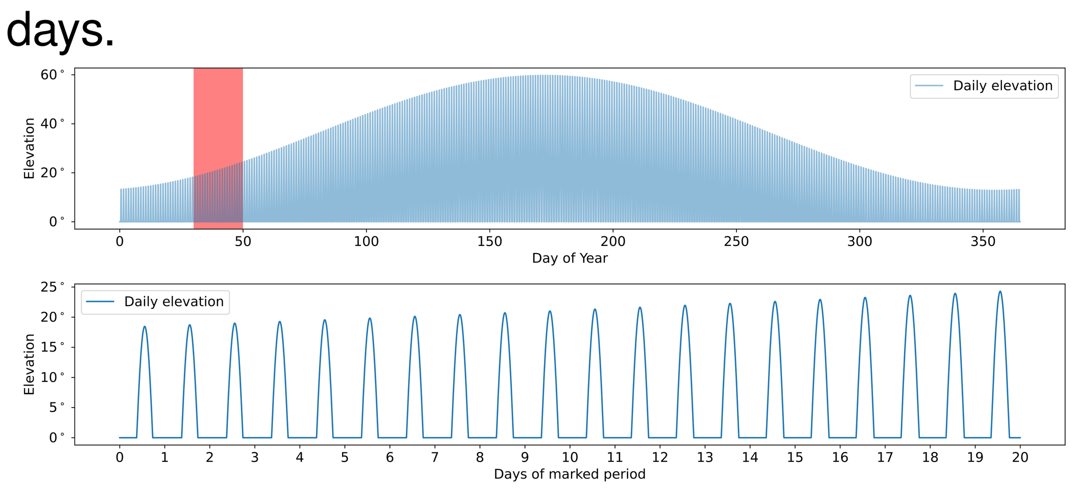

Figure 1: Elevation angle during the year (top) and a closer look for red marked rage (bottom) for a location with a latitude of 53.671^o.

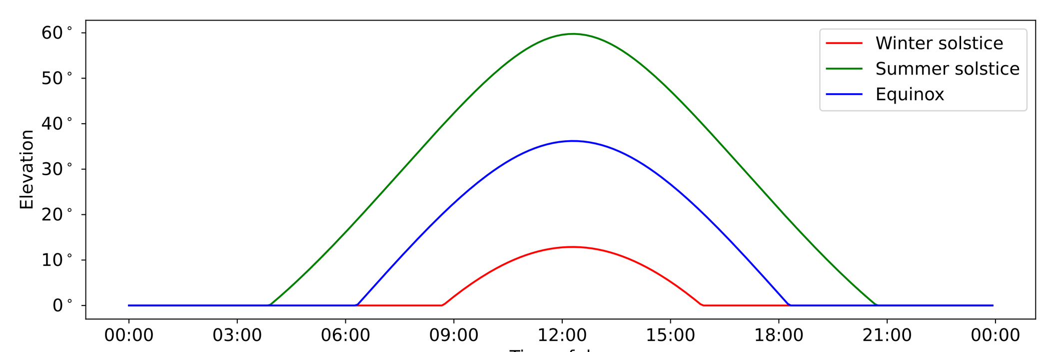

Figure 2: Comparison of Sun's elevation during most characteristic days: summer solstice, equinoxes, and winter solstice for a location with a latitude of 53.671^o.

From the simulation of the sun's altitude, we can conclude that the power that is delivered to the earth and so to the panels varies day by day. Due to this, we cannot analyze the production time series in a time domain omitting this significant factor.

Time approach

Figures 3 and 4 portray 2.5 years of observation presented by semitransparent lines. Each line stands for one day. Observing the charts, a conclusion may be made that only the maximum (the most optimistic) shape of the production is clearly visible. The distribution of values inside the blue region is similar to uniform distribution. That concludes that the appearance of any value inside is equally possible.

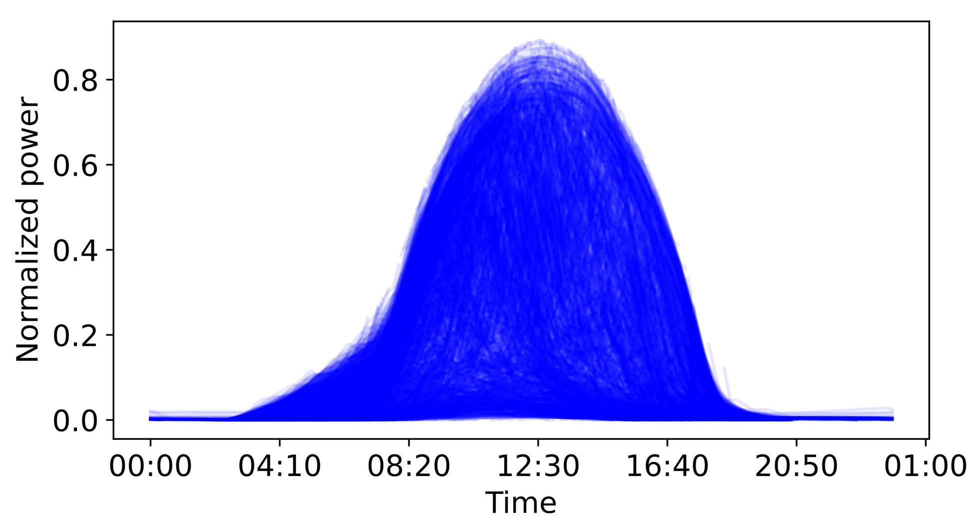

Figure 3: Overlapped 2.5 years observation in time domain

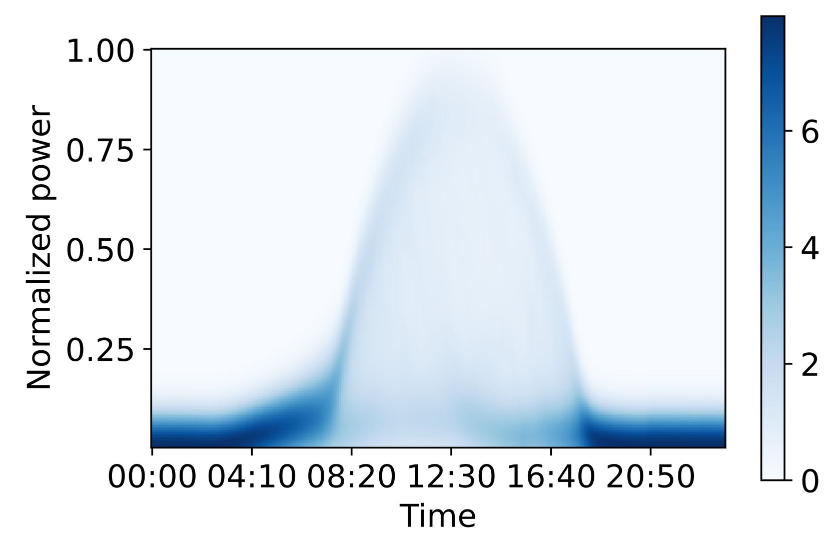

Figure 4: 2.5 years observation in time domain - heatmap

Elevation approach

Considering the weaknesses of the time approach, we propose an elevation angle approach to predict photovoltaic power. The figures 5 and 6 portray the same dataset as was mentioned in the "Time approach" section. However, in the elevation domain. The differences between those charts are clearly visible. Moreover, looking at the heatmap (figure 6), we can observe more intense regions. That means we can use that information to estimate the most probable shape of the production.

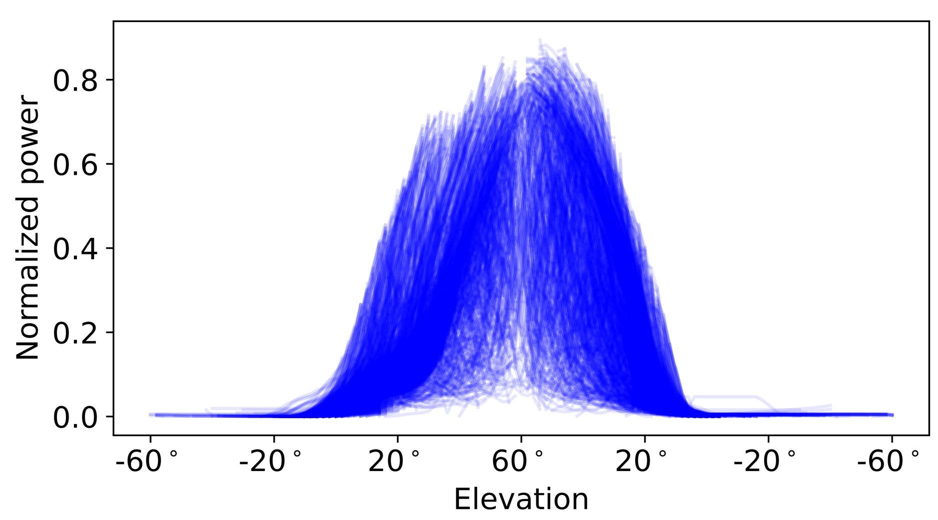

Figure 5: Overlapped 2.5 years observation in elevation domain

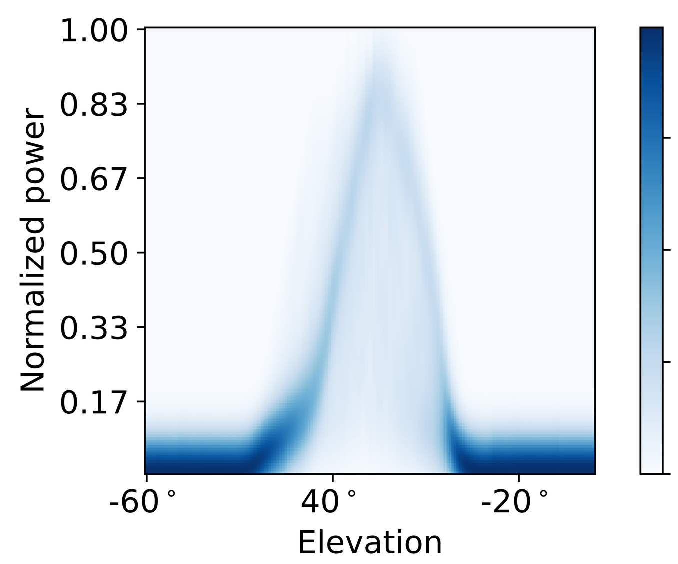

Figure 6: 2.5 years observation in elevation domain - heatmap

Model

The fitting process starts with the selection of the fitting window. Then fitting data are transposed into the elevation angle domain. Later, similar elevation angles are grouped into bins. The number of bins depends on parametrisation. The next process is to calculate histograms and estimate the kernel densities for each bin. Then, kernel densities are simplified into one variable by their mass centers.

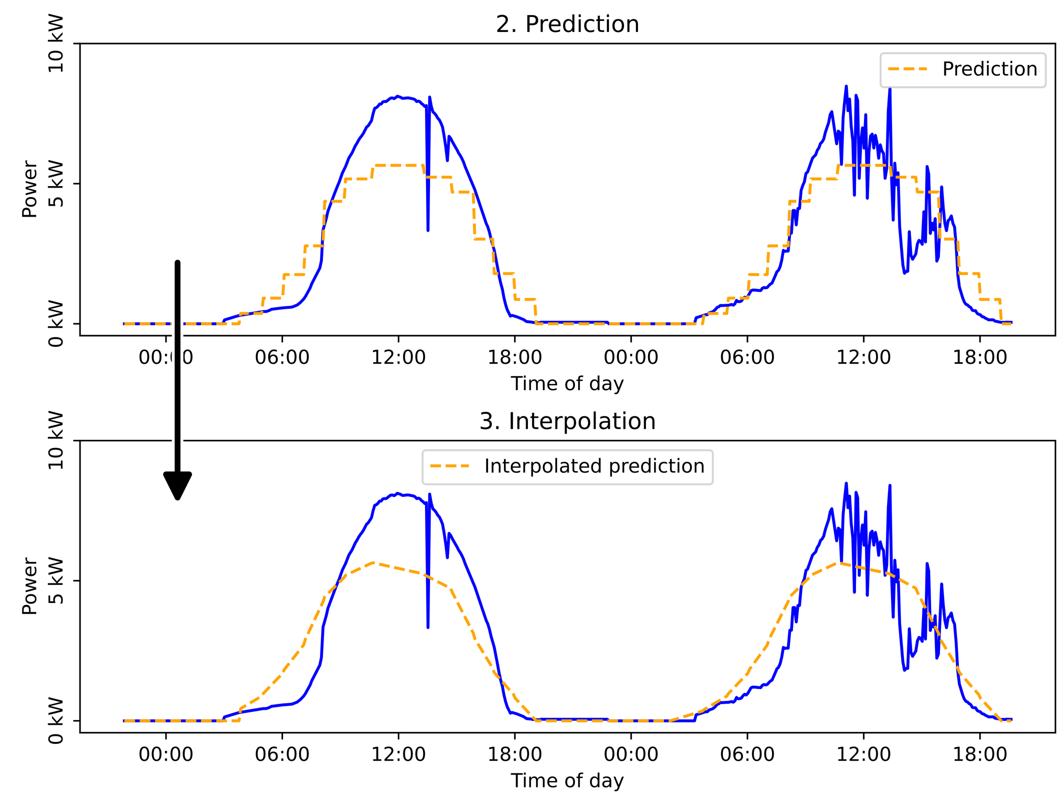

Figure 7: Sample 6 hours ahead forecast (the upper graph: generated from calculated weighted averages for each group of elevation angles) and forecast after applying linear interpolation (the lower graph: forecast after interpolation) for an exemplary period of two consecutive days containing a sunny day (from the left) and a day with transient cloudiness (from right).

Prediction is a reverse process of the fitting process. It is to assign model parameters to the timestamps that were transposed into the solar elevation domain.

Results

This section presents the evaluation results that were carried out on two datasets spanning 2.5 years of observations obtained from two different installations.

Model	Averaged annual prediction results			
D1				
	6h			
	MAE	$RMSE$	$NMAE$	$R2$
LSTM	0.81 ± 0.032	1.47 ± 0.076	0.81 ± 0.100	**0.43 ± 0.034**
Proposed	**0.59 ± 0.139**	**1.30 ± 0.220**	**0.66 ± 0.054**	0.47 ± 0.078
	12h			
LSTM	0.80 ± 0.065	1.46 ± 0.124	0.79 ± 0.058	**0.44 ± 0.037**
Proposed	**0.60 ± 0.141**	**1.31 ± 0.220**	**0.66 ± 0.057**	0.46 ± 0.084
	24h			
LSTM	0.64 ± 0.038	1.33 ± 0.082	**0.65 ± 0.012**	0.48 ± 0.011
Proposed	**0.59 ± 0.141**	**1.31 ± 0.218**	0.66 ± 0.057	**0.46 ± 0.086**
D2				
	6h			
	MAE	$RMSE$	$NMAE$	$R2$
LSTM	0.44 ± 0.041	0.77 ± 0.066	0.82 ± 0.159	**0.42 ± 0.102**
Proposed	**0.33 ± 0.057**	**0.69 ± 0.080**	**0.64 ± 0.041**	0.53 ± 0.050
	12h			
LSTM	0.45 ± 0.035	0.79 ± 0.051	0.76 ± 0.061	**0.47 ± 0.042**
Proposed	**0.34 ± 0.059**	**0.70 ± 0.086**	**0.64 ± 0.036**	0.52 ± 0.046
	24h			
LSTM	0.35 ± 0.032	0.72 ± 0.064	**0.62 ± 0.030**	0.54 ± 0.030
Proposed	**0.34 ± 0.059**	**0.70 ± 0.087**	0.64 ± 0.036	**0.52 ± 0.047**

Conclusions

The proposed model is a simple solution based on the relationships that were observed in the dataset. Despite its simplicity, the model achieved competitive results when compared with the reference LSTM model. Therefore, we can conclude that this research is a good starting point for further research, which will first focus on enlarging the model with weather data.

References

[1] Steve Matthewman and R H B. Blackouts: a sociology of electrical power failure. *Socialspace*, pages 1–25, 01 2014.

[2] Joseph Akpan and Oludolapo Olanrewaju. Sustainable energy development: History and recent advances. *Energies*, 16(20), 2023. ISSN 1996-1073. doi: 10.3390/en16207049. URL `https://www.mdpi.com/1996-1073/16/20/7049`.

[3] Gang Li, Shunda Guo, Xiufeng Li, and Chuntian Cheng. Short-term forecasting approach based on bidirectional long short-term memory and convolutional neural network for regional photovoltaic power plants. *Sustainable Energy, Grids and Networks*, 34:101019, 2023. ISSN 2352-4677. doi: https://doi.org/10.1016/j.segan.2023.101019. URL `https://www.sciencedirect.com/science/article/pii/S2352467723000279`.

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