Article

Solar irradiance nowcasting using deep networks

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Received: date; Accepted: date; Published: date

Abstract: Accurate solar irradiance nowcasting using deep neural networks. Robust to missing values in sensors. Study of influence of the wind in the prediction. Interpolation of missing values using Gaussian process regression. A strategy to place new sensors in order to improve accuracy on target sensors.

Keywords: Solar Irradiance; Nowcasting; Deep Neural Networks; Gaussian Processes.

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1. TODO

- Introduction of problem.
- Literature review.
- Data preprocessing in Section 4.
- Description of models in Section 5.
- Write results of different models in Section 6.
- Compare results with other papers?
- Repeat models using wind data. Are we improving?
- Write nice story about wind influence in Section 6.1.
- Include robustness study in Section 6.2.
- Think and write framework for sensor positioning in Section 7.
- Write conclusions in Section 8.

2. To Decide

- Remove Robustness.
- Join related work and introduction in a compact section.

3. Introduction

Solar irradiance estimation has critical applications in the forecasting of energy generation from solar power plants, the heating and cooling loads of buildings, and in weather forecasting and climate modeling. Thus, it is of vital importance to develop systems that make accurate predictions to increase the performance of posterior decision making systems. On the other hand, the volume of generated data from sensor measurements has quickly exploded in the past years, making the development of efficient and scalable algorithms that require little human tuning a requirement.

3.1. Related work

Previous approaches to the solar irradiance nowcasting problem has been based on...

In this work, we propose the design and application of deep neural networks for solar irradiance nowcasting. We test empirically the accuracy of the proposed approach using the OAHU dataset. We observe that there is a strong spatial pattern in the accuracy of the predictions which is clearly related with the wind direction. In light of these results, we perform a thorough analysisis of the influence of

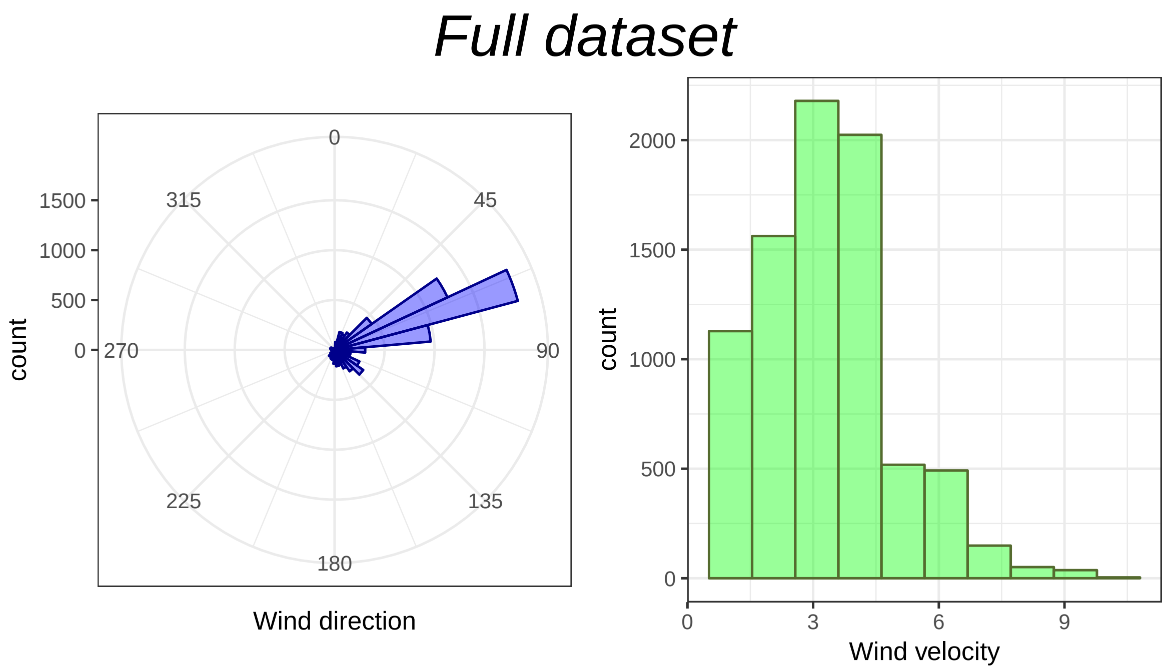

Figure 1. Caption here

the wind in solar irradiance nowcasting. This analysis suggest a strategy to place new sensors in order to improve accuracy on different targets that we present in Section 7.

What problems will be addressed in the paper?

- Propose a framework to do short term forecasting of solar irradiance which is robust to missing values in sensors.
- Discuss why is this problem important.
- Study robustness.
- Study influence of wind direction.
- Propose a strategy to place new sensors in order to improve accuracy on target sensors.

4. Data preprocessing

5. Deep Networks in solar irradiance nowcasting

In this Section we describe several architectures developed and tested for the solar irradiance nowcasting task. All models from this Section are based on deep artificial neural networks [1], since they offer greater flexibility compared to shallower models for data in which complex, non-linear interactions may arise.

The models were implemented in Python, using the `tensorflow` [2] and `keras` [3] frameworks for deep learning. With the aim of enabling reproducible research, the code for running the experiments is located at https://github.com/albertotb/solar.

5.1. Convolutional architectures

Convolutional neural networks [4] have recently gained vast interest as they have become the *state of the art* model for image and signal processing tasks [5–7]. By replacing a dense linear projection with a convolution operation, these networks exploit the data invariances to location and scaling and greatly reduce the number of parameters.

In the following subsections we describe several alternatives developed to arrange the sensor data in a more profitable way for the convolutional models.

5.1.1. 1D convolutional

Stemming from the hypothesis that the forecast of any given sensor might be improved using the information of nearby sensors, a first sensor arrangement can be obtained by sorting the sensors by their geographical longitude, that is, $x_{\sigma_{long}(i),t} \in \mathbb{R}$ will denote the solar irradiance measured at time-step t and sensor $i \in \{1, \ldots, 17\}$, where σ_{long} is a permutation that sorts the indices in non-decreasing longitude coordinate (CHECK).

Then, we applied a series of one-dimensional convolutional layers, which have shown superb performance in diverse tasks such as sentence classification [8].

Distinguish between locally-connected and 1d convolutional...

Residual connection to upper-bound the persistence model...

5.1.2. 2D convolutional

Since we only have a discrete set of measurements over a spatial region, we propose to use Gaussian process regression [9] (a.k.a. *kriging*) to spatially interpolate between sensor measurements and obtain a bidimensional irradiation map.

Then, we use a standard 2D convolutional layer...

5.2. Recurrent architectures

In order to avoid a fixed window size, we explore the applicability of recurrent layers, in particular the *long-short term memory* (LSTM) network [10].

Mention the convolutional-recurrent architectures which have found great success in tasks such as scene labelling [11] and text classification [12].

5.3. Optimization

In this Section we describe the training procedure. All models were optimized using the backpropagation algorithm [13] through the automatic differentiation library `tensorflow`. The chosen optimizer was Adam, which is a popular modification of the standard stochastic gradient descent algorithm [14].

Regularization, hyperparameters and cross-validations...

6. Experimental results

Table 1 reports the results over the test dataset.

Table 1. Prediction metrics over the held-out period.

	MAE	**Metric 2**
Model 1	0.270	0.239
Model 2	2.537	2.401
Etc	15.247	13.461

6.1. Wind influence

6.2. Robustness

7. An efficient sensor positioning approach

Given the influence of wind direction in solar irradiance nowcasting, we propose a efficient approach to place sensors in order to improve accuracy on target sensors...

(in what sense it is efficient!?)

8. Conclusions

In this work we have found the following take-away points:

- Leveraging the expressive power of deep, non-linear models helps in solar irradiance forecasting.
- Data arrangements specially tailored to convolutional models (1D and Gaussian process interpolation).
- Helps auxiliary tasks such as robustness and sensor placement.

Several lines of further work are possible:

- Design of energy-efficient network architectures, such as the MobileNet model [15], so they can be deployed *in situ* over low-cost hardware.
- Application of Bayesian models for forecasting a full predictive distribution, not only a point estimate.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "conceptualization, X.X. and Y.Y.; methodology, X.X.; software, X.X.; validation, X.X., Y.Y. and Z.Z.; formal analysis, X.X.; investigation, X.X.; resources, X.X.; data curation, X.X.; writing–original draft preparation, X.X.; writing–review and editing, X.X.; visualization, X.X.; supervision, X.X.; project administration, X.X.; funding acquisition, Y.Y.", please turn to the CRediT taxonomy for the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

Funding: This research received no external funding.

Acknowledgments: The authors acknowledge support from ...

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

MDPI	Multidisciplinary Digital Publishing Institute
LSTM	long short term memory
MAE	mean absolute error

Appendix A

Appendix A.1

Something

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