



# Generalized Model for Solar Irradiance Forecasting

Jesus Lago

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- 2 Modeling Framework
- 3 Case Study
- 4 Forecast Competition

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  - ▶ Forecasting Importance
  - ▶ Solar Irradiance Forecasting
  - ▶ Motivation
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## Problems

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2. Intermittent generation.

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## Importance of RES forecasting

Forecasting generation of RES needed to improve grid management tasks:

1. Ancillary services and reserves activation.
2. Operational planning and scheduling.
3. Congestion management.
4. Peak load matching.

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## Observation

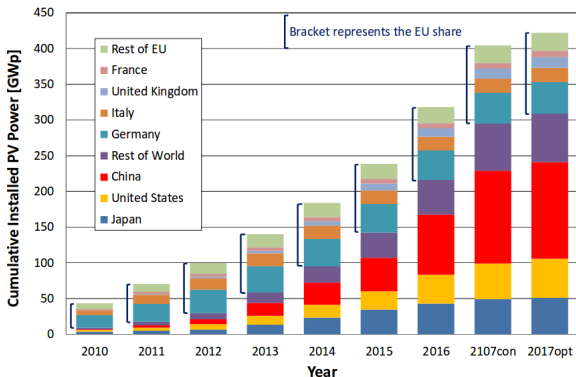
- ▶ Solar energy is one of the most unpredictable RES.
  - ▶ More and more solar energy generation is being deployed worldwide.
- ⇒ Forecasting of solar energy generation is key in grid management.



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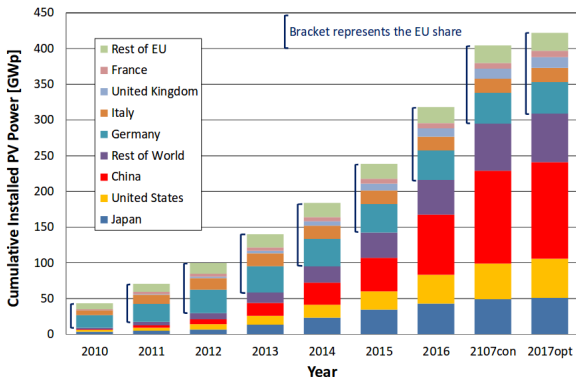
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## Standard Models for Irradiance Forecasting

Techniques categorized according to prediction horizon:

1. **Time series models:** short-term forecasts up to 6 hours ahead.
  - 1.1 Statistical and artificial intelligence models: **ground data**.
  - 1.2 Cloud moving vector models: **satellite images**.
2. **Numerical weather prediction models:** suitable for 6 hours onward. Simulate weather conditions, i.e. long computation time  $\approx$  several hours.

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## Contributions

- ▶ General forecasting model for solar irradiance with ground measurements not required:
  1. Uses satellite images but easier to deploy than cloud moving vectors.
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## Note

- ▶ The aim of the model is not to be the most accurate.
- ▶ The aim is to be as good as local models to save operating cost.



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## Model requirements

1. Model structure flexible enough to generalize across multiple geographical locations.
2. Model inputs that, while correlating with irradiance, are general enough to be easily obtained for any given location.

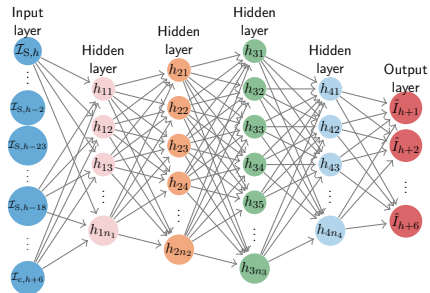
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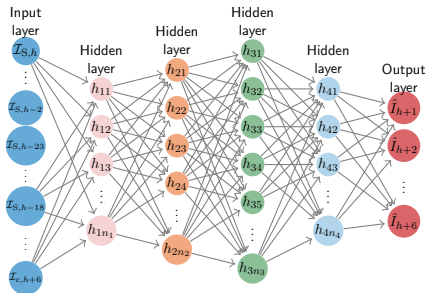


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- ▶ 6 hours ahead  $\implies$  6 output neurons.
- ▶ 4 hidden layers.
- ▶ Optimized number of neurons.



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3. Weather-based forecast (NWP) at prediction times.



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## Generalization across sites

To forecast without ground data, model needs to generalize across geographical sites:

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## Generalization across prediction horizons

To further strengthen the generalization capabilities, the model is trained to forecast at different hours of the day.

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Four different local models per location:

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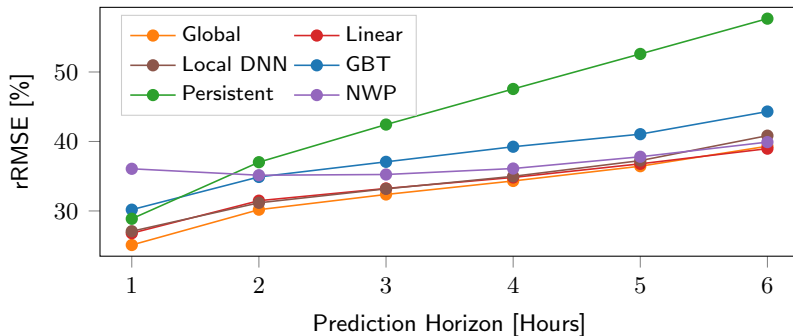
## Result

- ▶ Global model equal or better than local models.

<b>Model</b>	<b>rRMSE [%]</b>
Global DNN	31.32
ARX	32.20
Local DNN	32.32
Weather-based (NWP)	35.18
GBT	36.09
Persistent	42.27

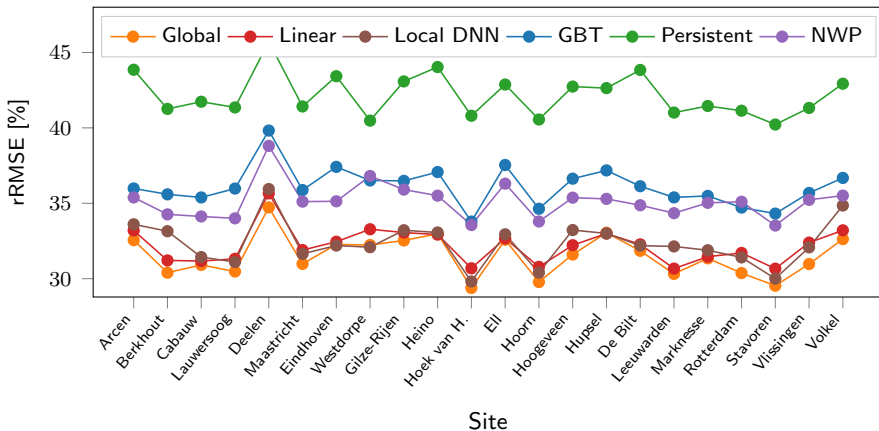
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- ▶ Organized by French grid operator RTE.
- ▶ Real-time contest: before 21:00 of day  $d$  each participant submitted the demand forecasts for day  $d + 1$ :
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## Result

- ▶ 3<sup>rd</sup> in probability forecasting.
- ▶ 4<sup>th</sup> in point forecasting.
- ▶ Developed models better than many commercial solutions.

# Thank you. Any Questions?



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