High-Resolution Solar Power Nowcasting by Deep Learning:

On extracting features from historic time-series + remote sensing + NWP

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Solar power

- growing **renewable energy** source, can yield very different output for each location of interest
- effective integration to **power grid**: need **forecasts** of the **expected power curve** (e.g.: serves for grid stability, energy trading, scheduling of maintenance / energy transfer, ...)
- various **data sources available**: power generated, met. site observation, satellite, numeric prediction (NWP)
- strong **seasonal** and **diurnal variation** in the data → want these variations in the nowcasts

https://commons.wikimedia.org/wiki/File:Solar_PV_Austrian_Alps.jpg

→ investigate machine learning/ML such as **Artificial Neural Nets**, **Random Forest** as efficient forecast tool

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Data for CASE STUDY 2021

We optimize **site specific models** and select data for each site from:

I N P U T :

- **AROME:**
  forecasts in various p/z levels of solar radiation related parameters (e.g.: short-wave radiation, cloud cover, …)
- **CAMS – site interpolated radiation timeseries**:
  radiation related parameters
- **Observation site**:
  observed solarpower
- **TAWES/INCA** – closest observation/analysis at surface level:
  global radiation, temperature, wind, humidity

+ computed **climatology**

Check missing, normalize, etc.

O U T P U T : solar power forecasts
in 15 min. resolution
+6 hours, hourly runs

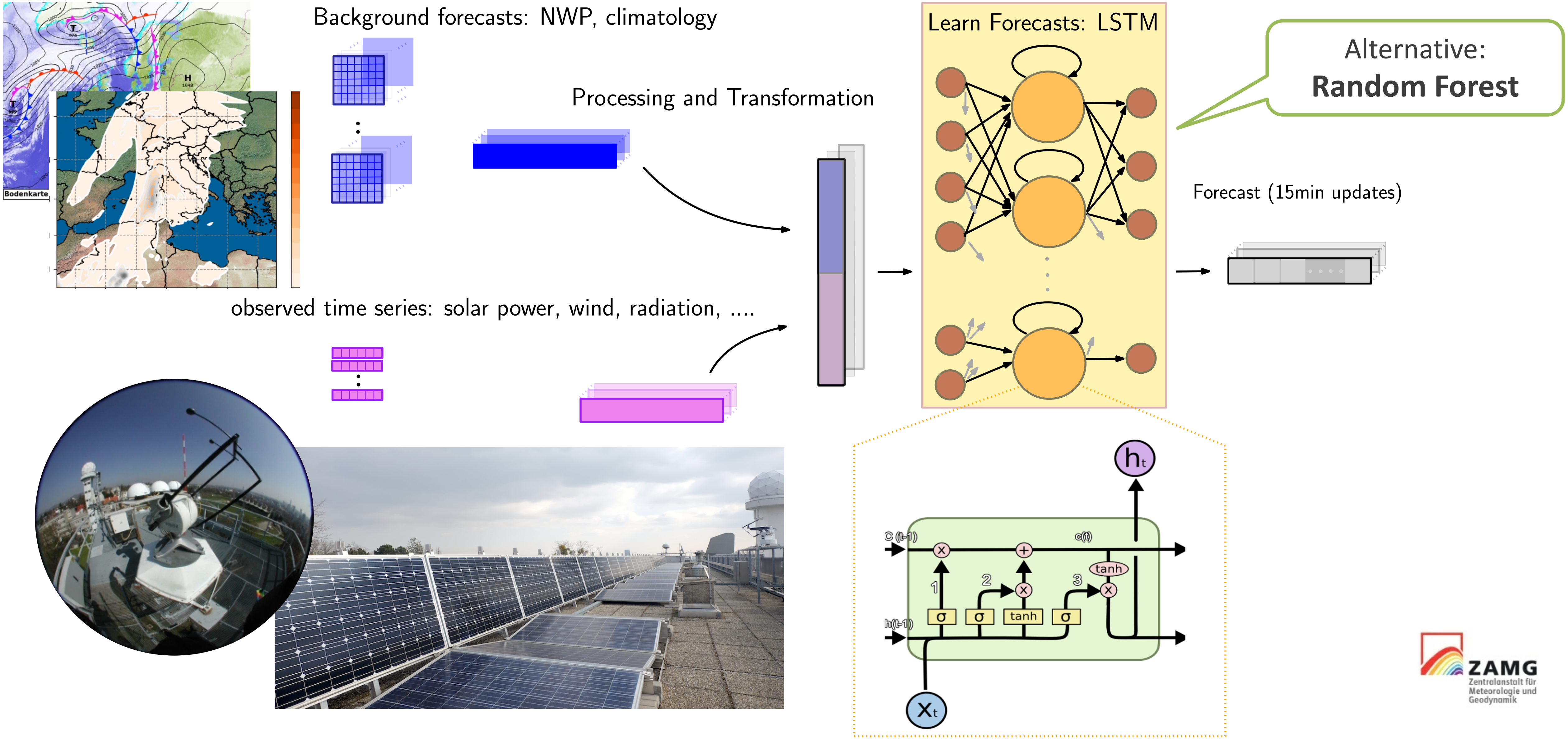
CASESTUDY

Training:
- ✓ **2015-2020** (incl. artificial)
- ✓ **2020** (real only)

Testing:
- ✓ **2021**

3 **Austrian sites** selected

Post-processing Methodology: update a Background Model(s) by ML

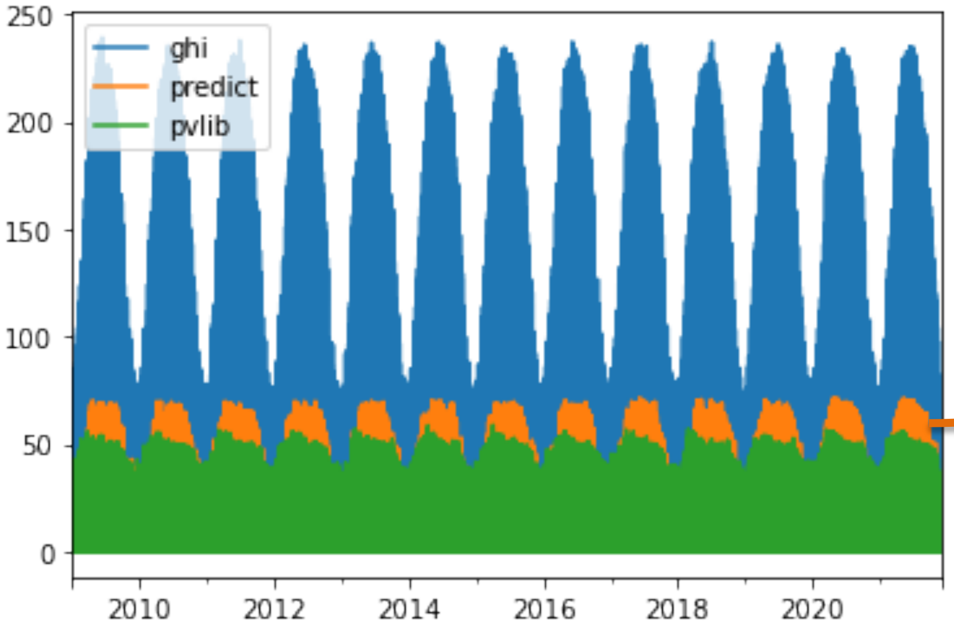


Issue: Short Observation Time-series of Power Plants

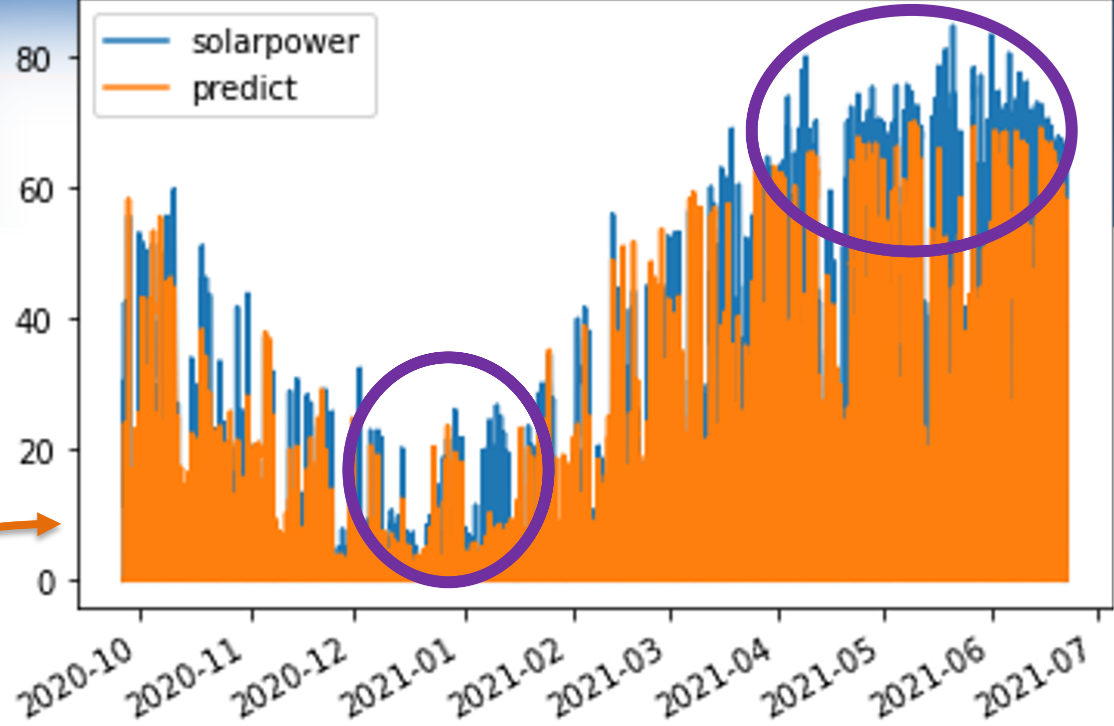
29.03.22
Folie 5

→ generation of **artificial training data**, as more is needed for complex models (LSTM etc.)

Data: Obtaining Artificial Time-series

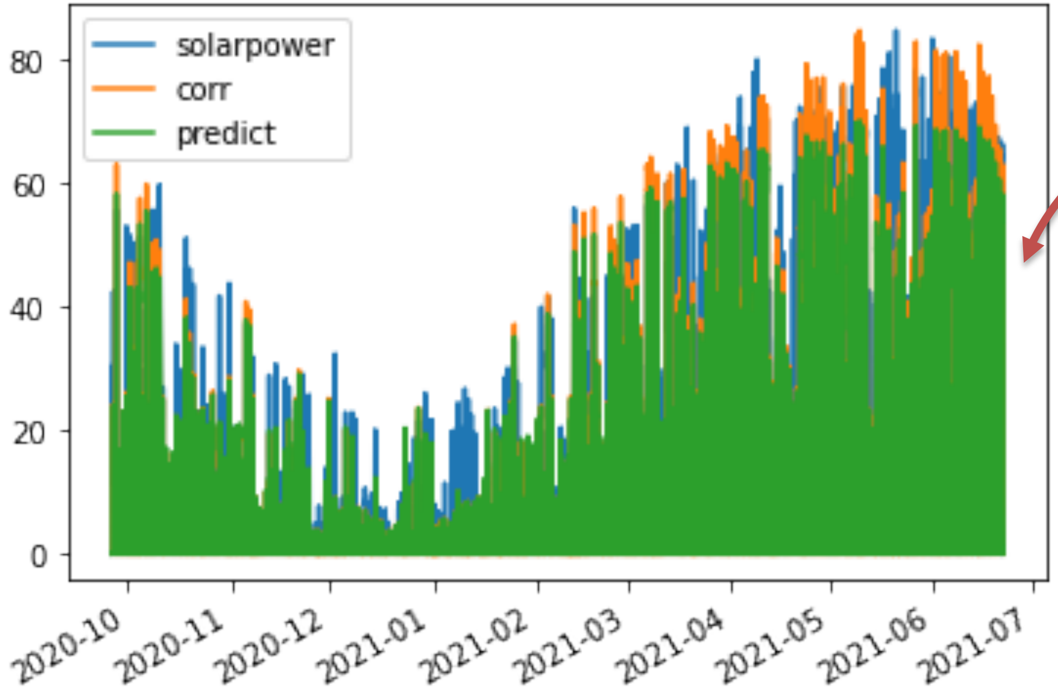


RF+pvlib good but often seems to **underestimate** real PV



Long time series obtained: ghi, pvlib

... deviate in scale for our specific site



1st opti. approach: transform by percentiles of PV-OBS

predict :=RF output based on CAMS-radiation + TAWES observation + pvlib

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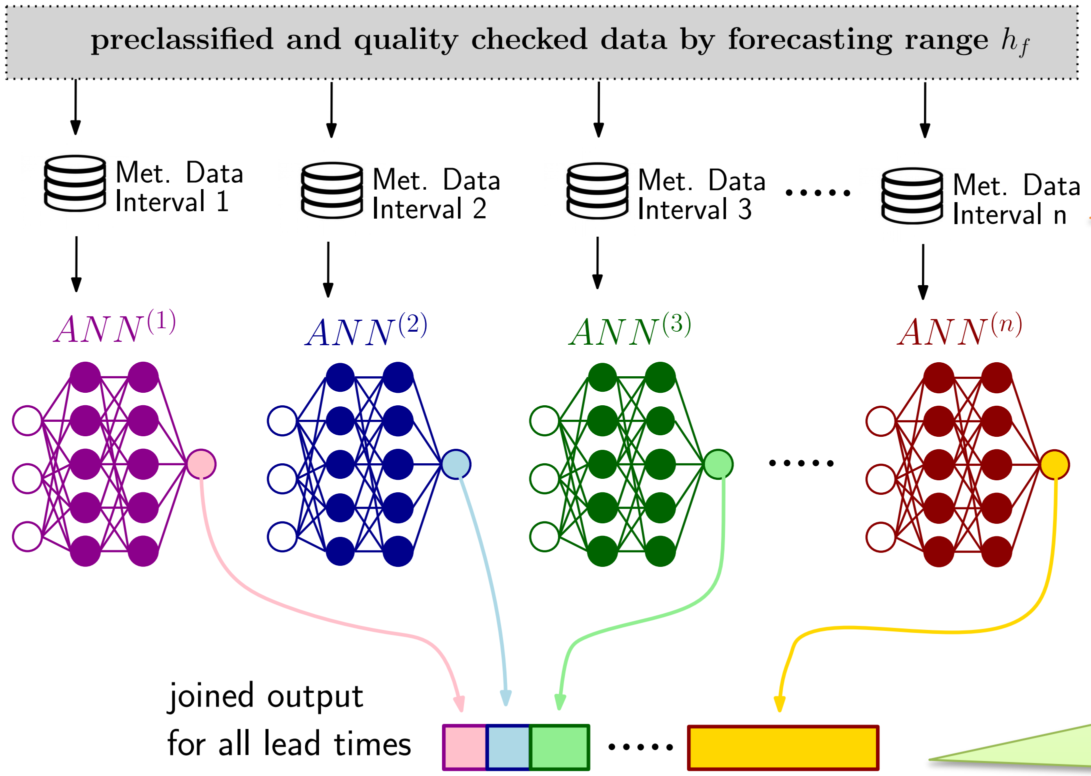
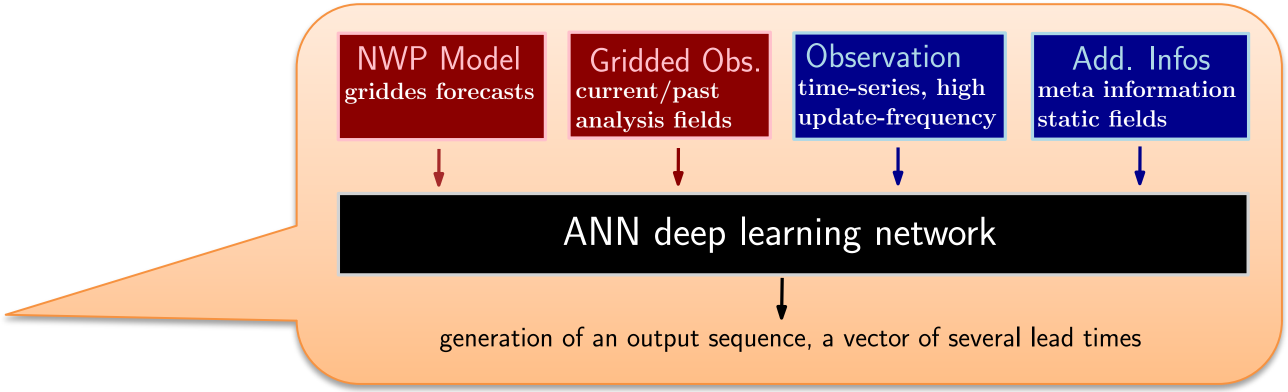
Selection and Transformation of Inputs

1. **input feature X** selection: simple methods such as RF weights, Target Y: solar power
2. replace / remove **missing** values, check quality
3. 0-1 **normalization**, using (here hourly) climatological standards
4. for longer vectors / sequences: **intervalization** by lead time steps





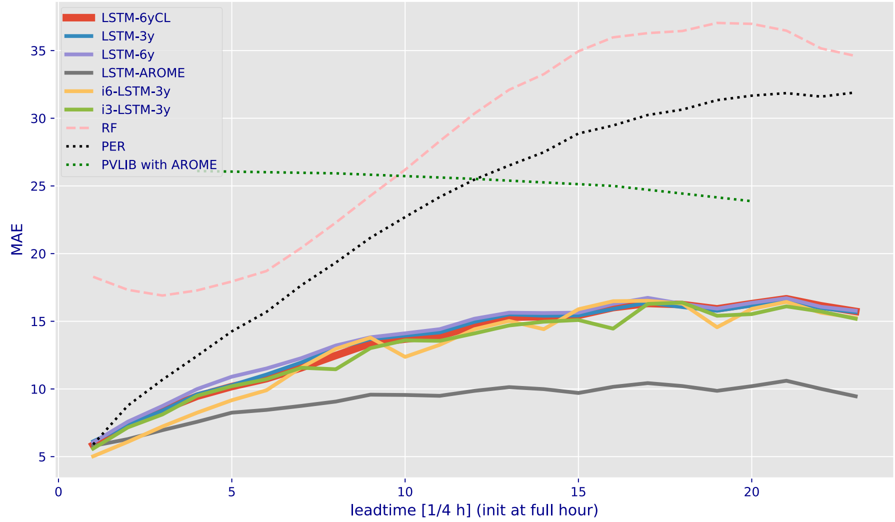
Basic climatological transformation from normalized X

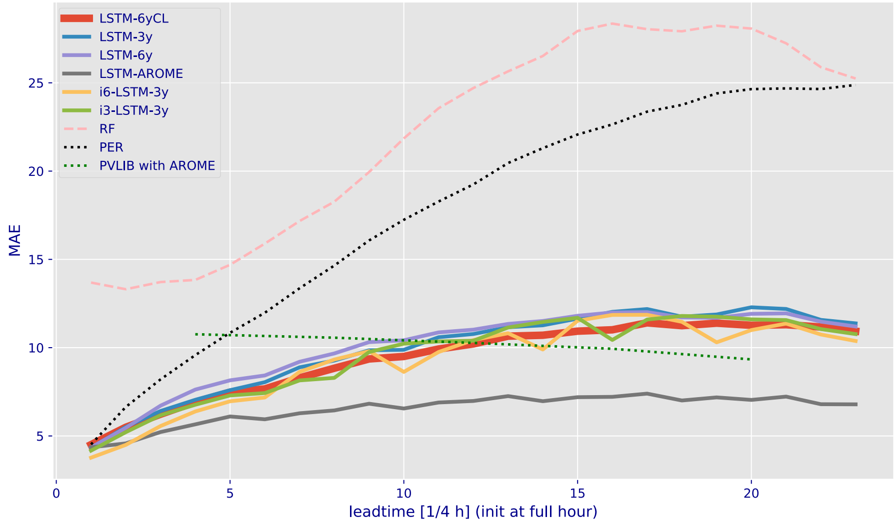
$$\Delta x_i(t) := \frac{1 + norm\left(xi_{\{OBS\}}(t)\right) - norm\left(xi_{\{CLIM\}}(hour(t))\right)}{2}$$

$$pv = \mathrm{denorm}(2\Delta pv - 1 + norm(pv_{clim}))$$

$$i = pv, rad, ff, u, v, T, CC, TOA, \ldots \quad t = 1,2,\ldots,24$$

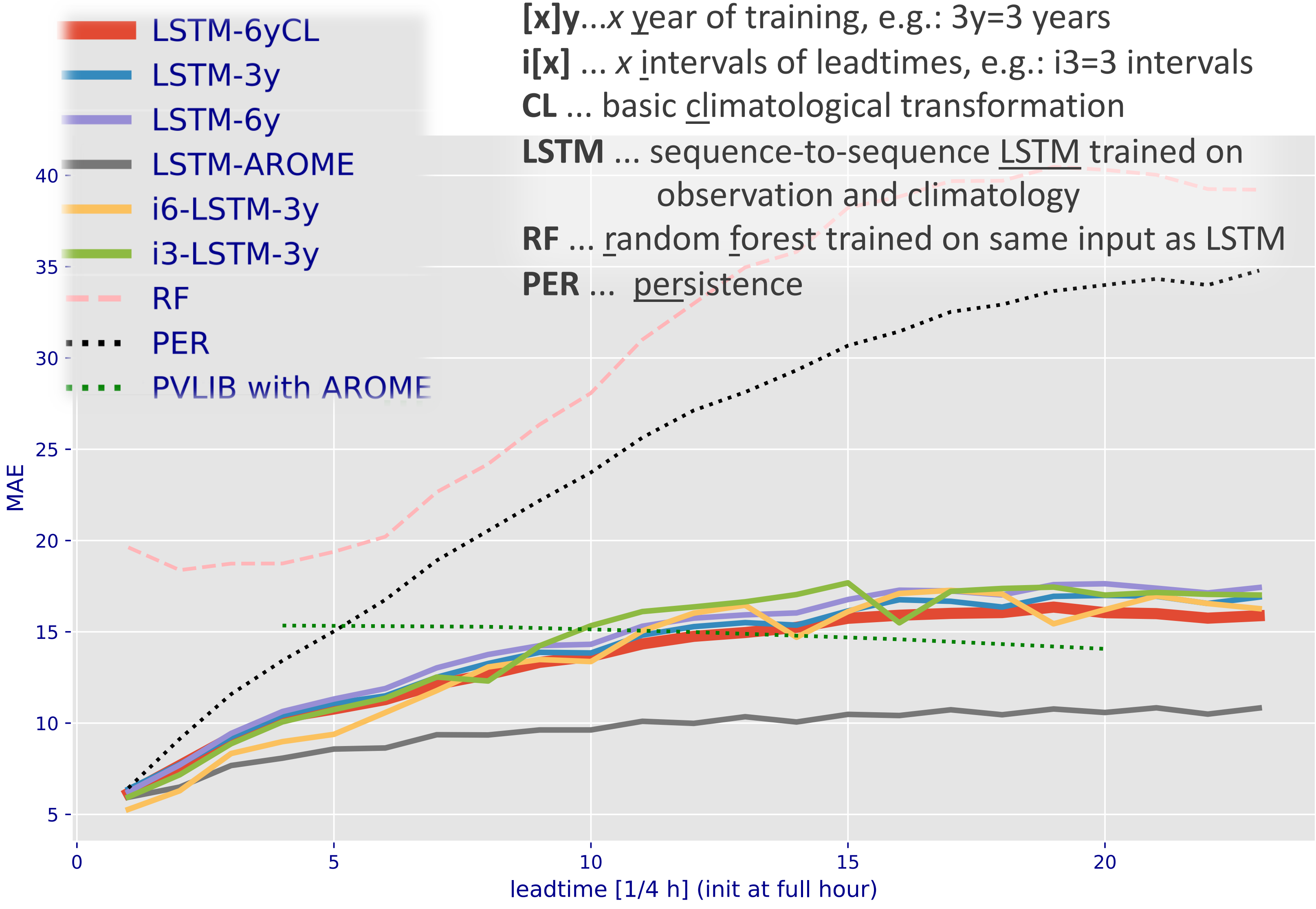
Case Study Results – Scores



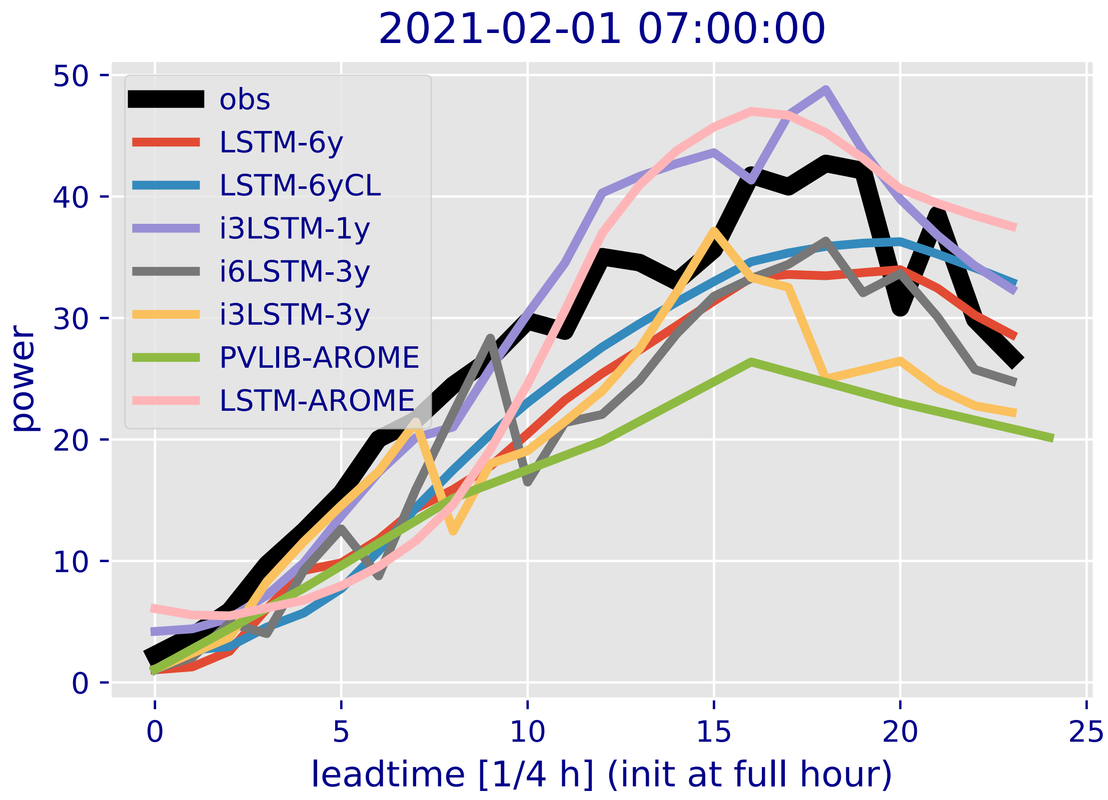


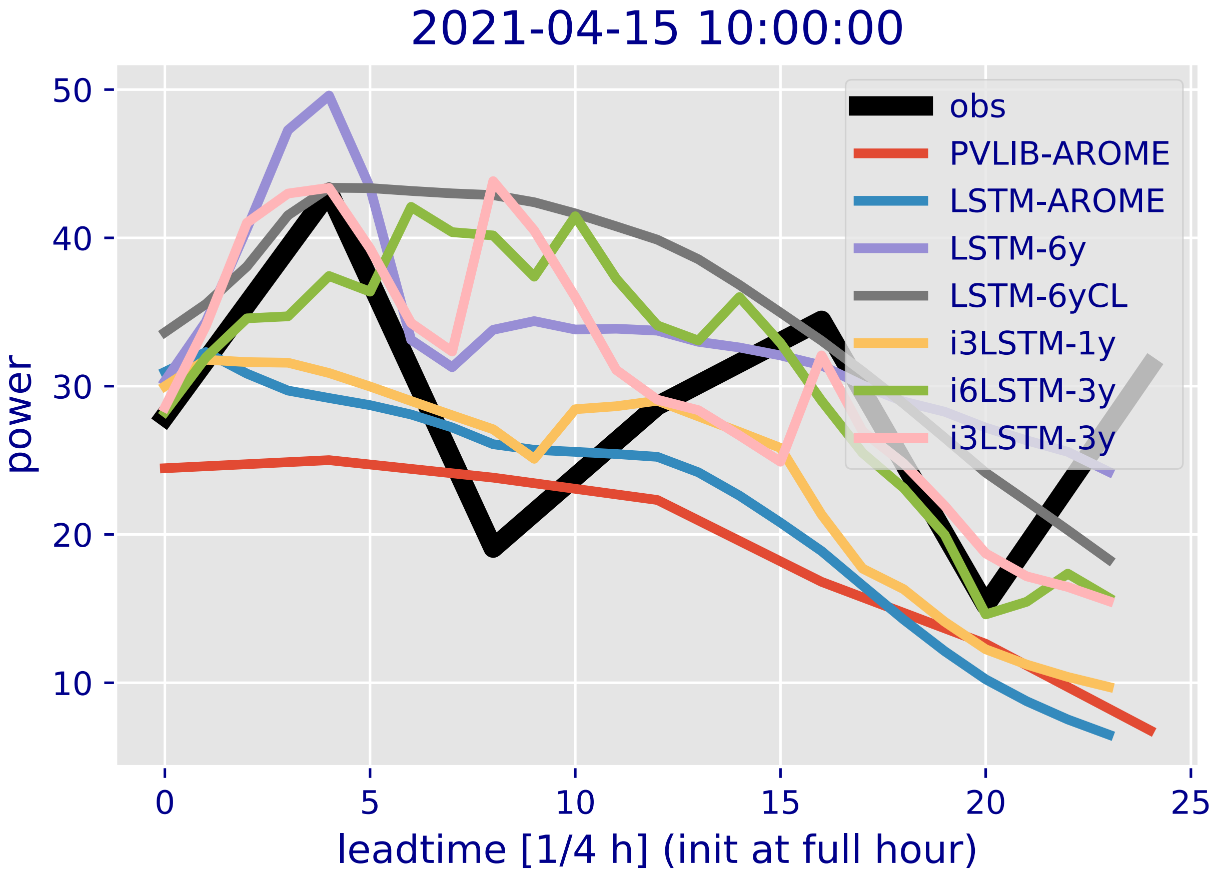
MAE of stations

[x]y...*x* year of training, e.g.: 3y=3 years
i[x] ... *x* intervals of leadtimes, e.g.: i3=3 intervals
CL ... basic climatological transformation
LSTM ... sequence-to-sequence LSTM trained on observation and climatology
RF ... random forest trained on same input as LSTM
PER ... persistence



Case Study Results – Sample Forecasts

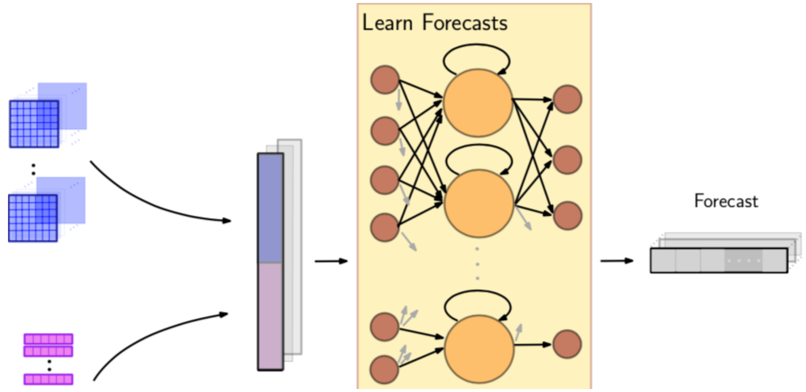




Conclusion

Machine learning method for solar power nowcasting evaluated on first case study in 2021:

- machine learning useful for post processing in nowcasting
- sufficient data needed – artificial data investigated
- diverse data sources available – various temporal and spatial resolution
- promising first results in little data coverage sites
- efficient computation once trained



Topics of future and ongoing work:

- extension of spatial related time-series + satellite deriven fields
- further improvement of artificial data and their transformation
- feature, hyperparameter and model optimization
- climatologic transformation in addition to simple back ground model
- more locations in different topographic situtation to investigate

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Thank you for your attention!

Any questions?

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