Renewable Energy Generation Prediction

Using Weather Data and Machine Learning

Christoph Emeis, Jessica Voß, Hossam Oraby

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Introduction

Problem:

Accurately predict daily solar PV power generation on privately owned solar plants using weather (forecast) data

→ Regression Task using time series

Using own data collections

Time period: Jun 2023- Jan 2026

Locations: Dobersdorf & Elmshorn

Potential use case:
When should I charge the electric car this week?

Literature Review

Paper name	Forecasting renewable energy for microgrids using machine learning (2025)	Towards Accurate Forecasting of Renewable Energy: Building Datasets and Benchmarking Machine Learning Models for Solar and Wind Power in France (2025)
Description	Local generation prediction	Nationwide generation prediction using weighted weather maps
Models	CNN, LSTM	Random forest, Neural Network
Parameters/Variables	7 (without sunlight data)	10 (with solar radiation)
Focus of the analysis	Evalution metrics (RMSE, MSE, MAE)	Cross-validation (Hold-out, K-Fold, Blocking)
Best model	CNN	CNN
Reference	*Discov Appl Sci* **7**, 449 (2025)	arXiv:2504.16100

Dataset Characteristics

- The solar production of two privatly owned roof solar panels
- Obtained weather data from DWD (German Meteorological Service)
- Jun 2023- 15.01.2026
- Chose the closed weather stations
- Various measured parameters

Locations: Elmshorn and Dobersdorf

Dataset Characteristics

Energy Production:

- Daily data (916 days)
- 0- 90 kWh daily generation

Weather data:

Temperature

Humidity

Precipitation

Cloud Coverage

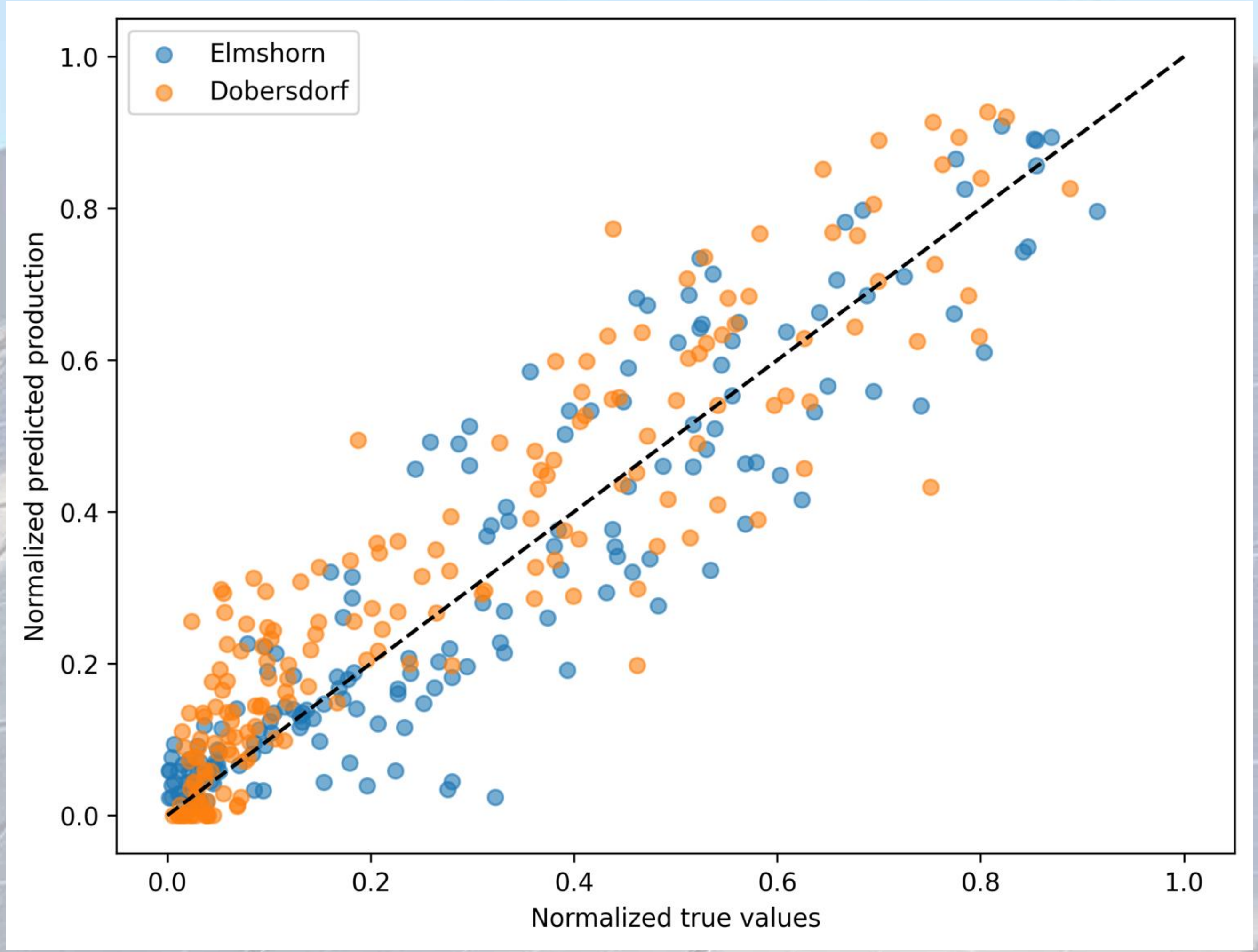
Sunshine duration

Pressure

Missing values were set to 0

Baseline Models

- Simple neural network:
  2 Input variables
  (mean temperature
  & sunlight duration)
- 1 hiden layer with 2 nodes,
  ReLU acctivation,
  MAE, ADAM, lr=0.001
- Training time < 4s
- Accuracy ~ 91%



Advanced Model - LSTM Architecture

Neural Network Architecture

Input Layer
10-day time windows × 8 features
shape: (10, 8)

↓

LSTM Layer 1
LSTM(60, return_sequences=True)
60 units, preserves time dim

↓

LSTM Layer 2
LSTM(60)
60 units, final sequence

↓

Output Layer
Dense(1)
single regression output

Model Configuration

Optimizer
Adam (learning_rate=0.0001)

Loss Function
Mean Squared Error

Metrics
MSE, MAE

Why LSTM?

- ✓ Captures **temporal dependencies** in weather patterns
- ✓ Handles **sequential relationships** in time-series data
- ✓ Maintains **long-term memory** of weather trends

Advanced Model - Hyperparameter tuning

```python
# Implement hyperparameter tuning

from scikeras.wrappers import KerasRegressor
from sklearn.model_selection import GridSearchCV
time_step = 10
def model1(units=40,learning_rate=0.1):
    model1 = Sequential()
    model1.add(Input(shape=(time_step, 8)))
    model1.add(LSTM(units, return_sequences=True))
    model1.add(LSTM(units))
    model1.add(Dense(1))
    model1.compile(optimizer = keras.optimizers.Adam( learning_rate=learning_rate), loss='mean_squared_error')
    return model1

model = KerasRegressor(
        model=model1,
        verbose=0
)

param_grid = {
        "model__units": [50,60],
        "batch_size": [8,16],
        "epochs": [50,60],
        "model__learning_rate": [0.0001, 0.00001]
}

grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=5)
grid_search.fit(X, y)
```

Best Configuration

Units

60

Batch Size

16

Epochs

60

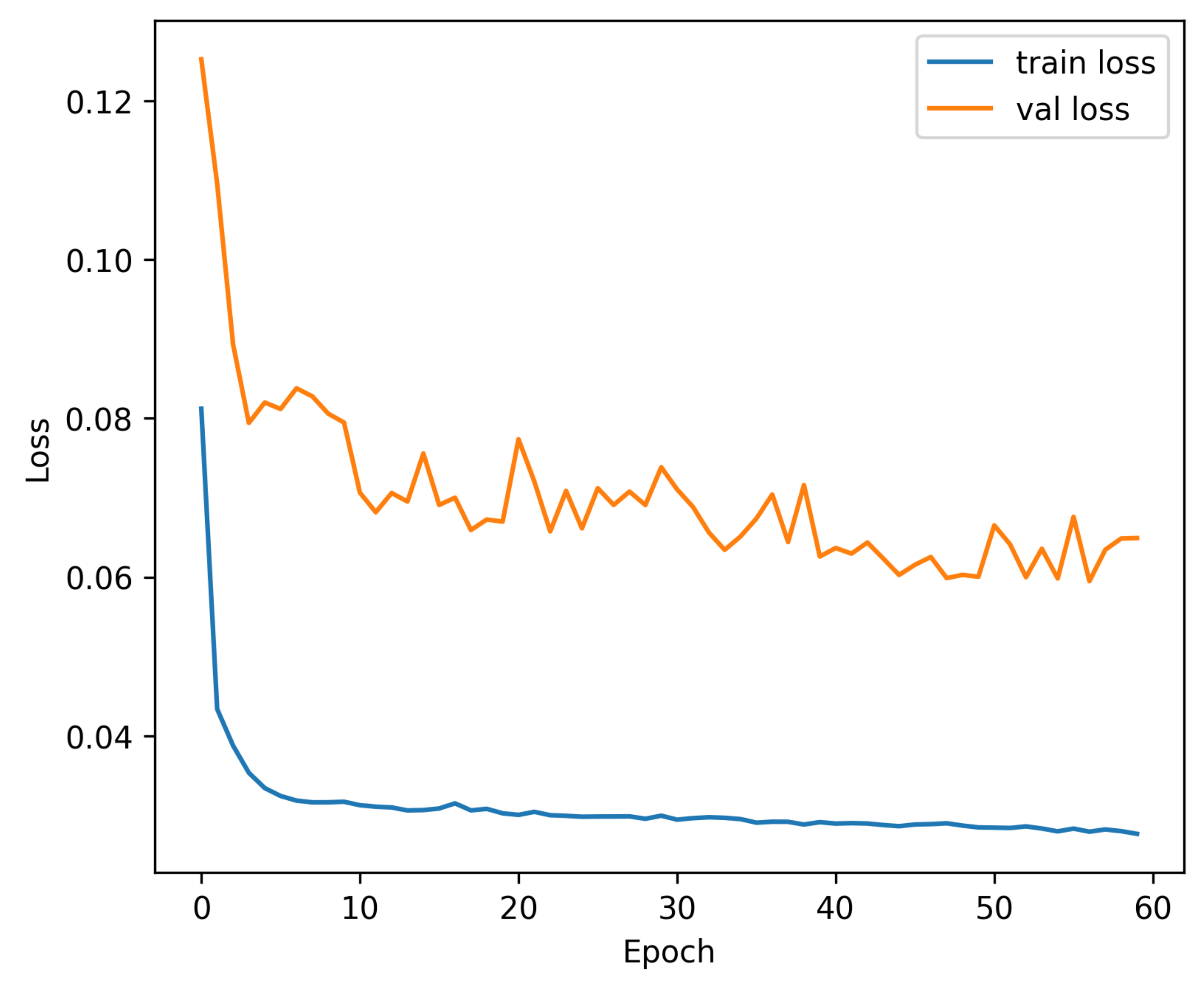
Learning Rate

10-4

Advanced Model – Training process

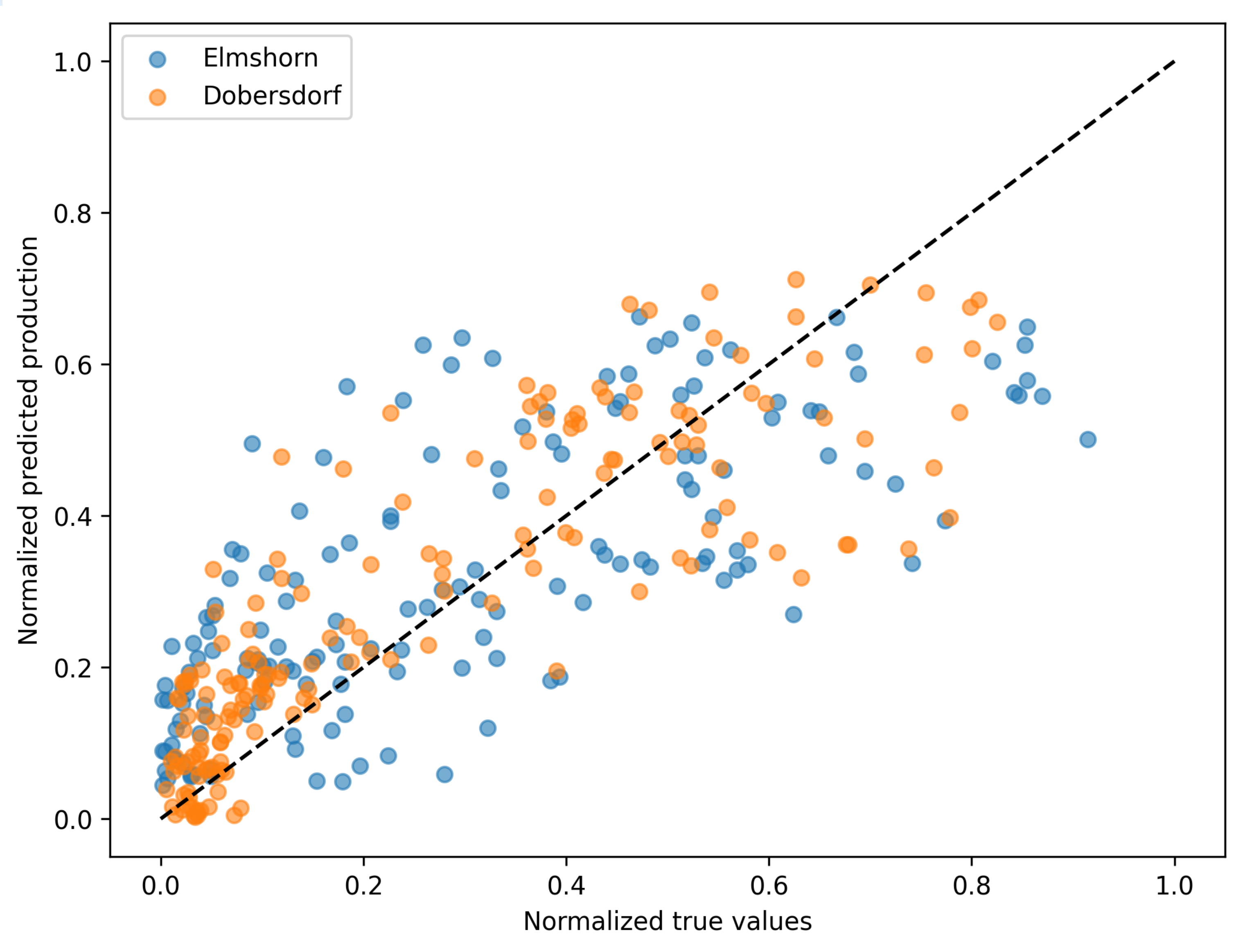
Training Configuration

Epochs 60	Batch Size 16
Validation Split 15%	Optimizer Adam



Advanced Model Performance

- Training time < 20s
- Accuracy ~ 85-88 %
- Non-linear trend/ curved shape
  → bias
- The models avoid predicting large value (>0.8)



Challenges and Errors

Obtaining reliable data:

- Only few weather station in SH that measure sunlight duration

→ We don't know how reliable the weather data is

No comparability between our two locations

- We decided to treat Elmshorn and Dobersdorf independently

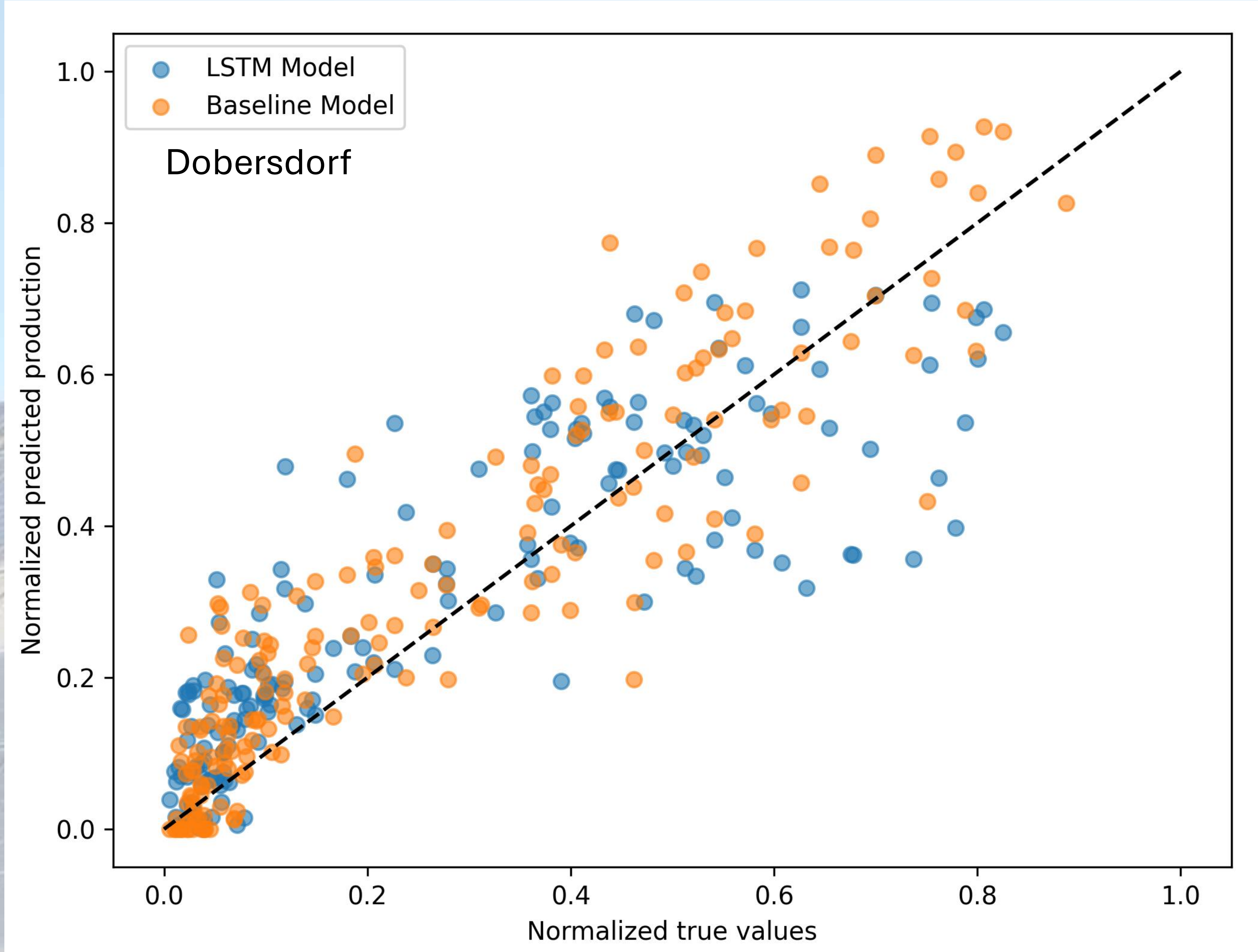
- Hyperparameter tuning:
- Unsuccesfully tried different ways for hyperparametertuning
- Data had wrong shape
- Took a long time

Discussion

- Simple vs. Complex model

- Weak prediction of high and low solar production
  → Not a big enough dataset?

- How will the model be affected when using actual forecast data ?



Conclusion and Future Work

- Both LSTM and Baseline NN performed quite well
  → Accuracy around 90%
- Baseline even outperformed the LSTM
  → strongest features sunlight duration and temperature

- Improve data situation
  → Use real forecast data for the actual locations
- Increase time-resolution
  → Hourly or even shorter 10 min
- View whole regions and contries → SH or Germany

Q&A

Thank you for your attention!

We are happy to answer questions ☺