University of Stuttgart
Institute for Statics and Dynamics

Machine Learning Methods in Mechanics

Predicting Renewable Energy Production using Machine Learning Methods

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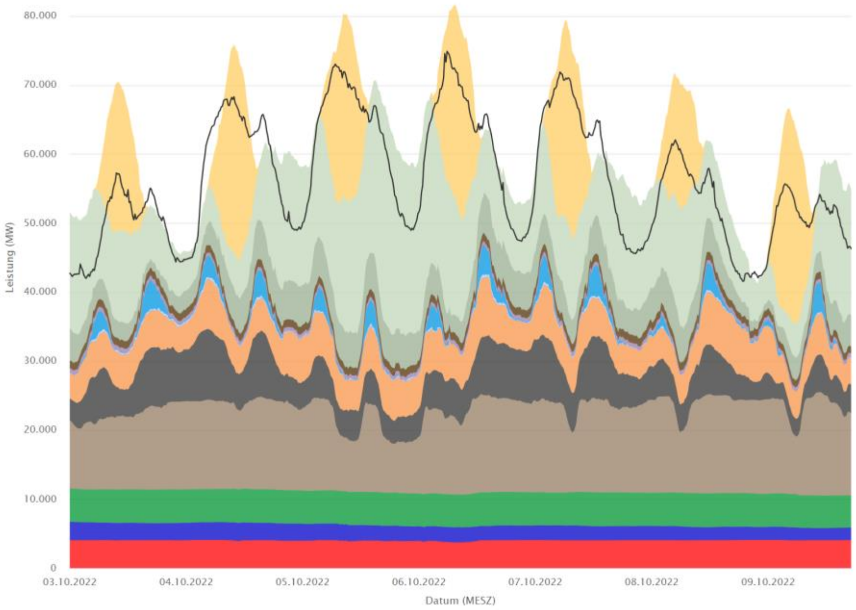
Outline

1. Motivation
2. Electricity Data
3. Feature Engineering
4. Benchmark Model Exploration
5. Iterative Model Development
6. Hyperparameter Optimization
7. Results
8. Outlook

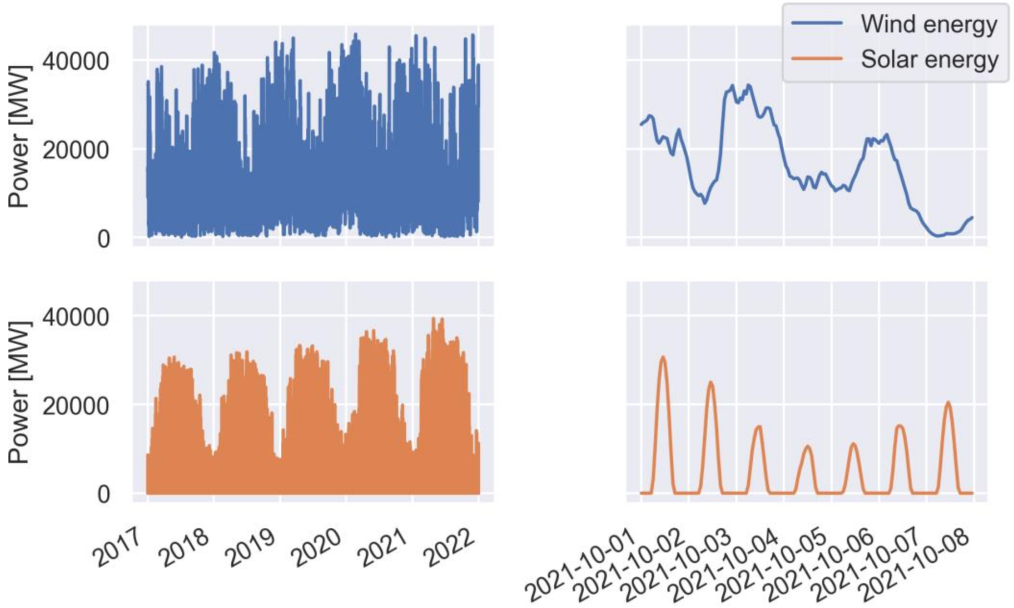
1. Motivation

- Renewable energies are fluctuating
- Useful for power plant operators
- **Goal:**
  - Predict renewable energy production 12 hours into the future



2. Electricity Data
Past inputs and labels

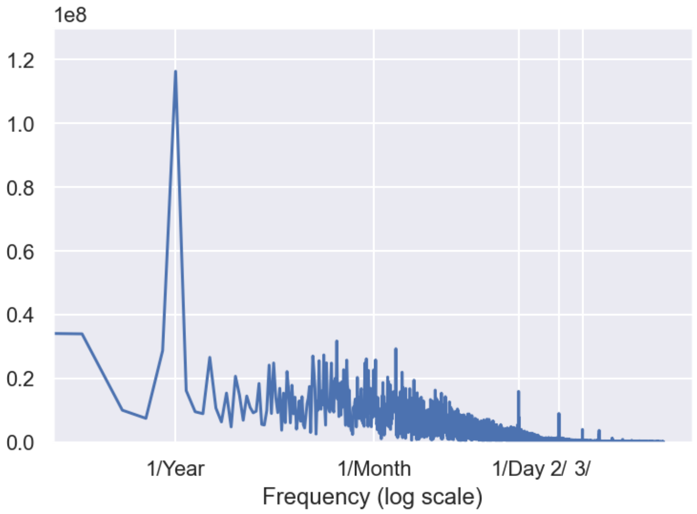
- Hourly production of wind and solar energy in Germany
- Timeframe: 2017 - 2021
- Source: Energy-Charts (from Fraunhofer ISE)



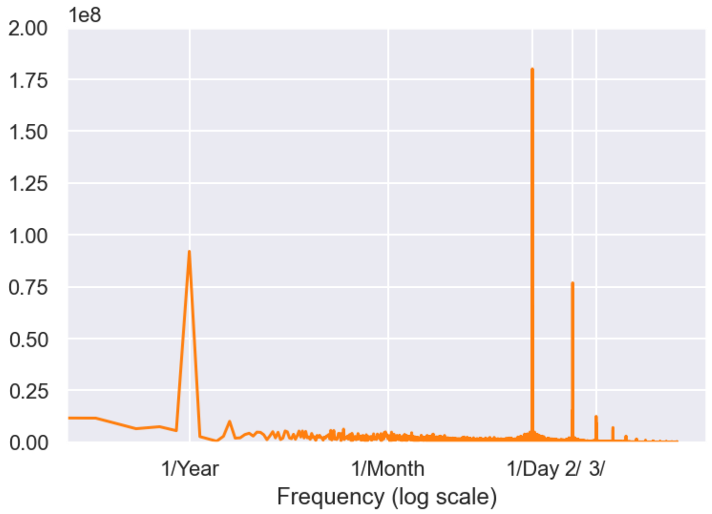
3. Feature Engineering
Frequency Analysis

- Solar and wind energy production show high yearly and daily periodicity

Wind energy production:



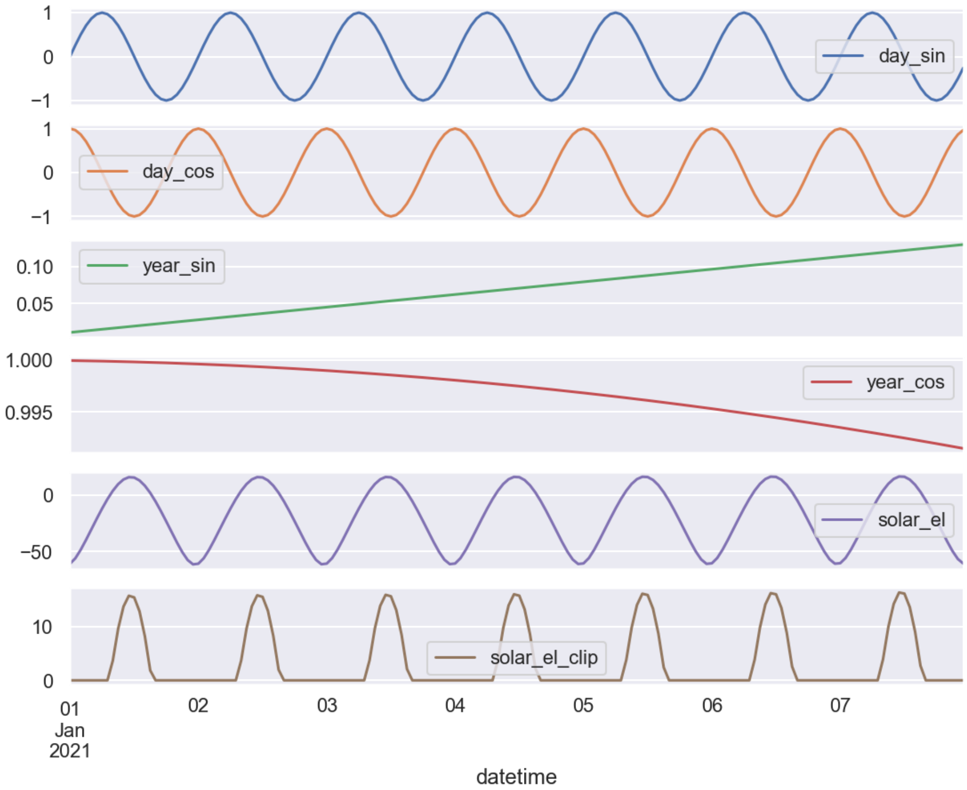
Solar energy production:



- → Create yearly and daily time signals

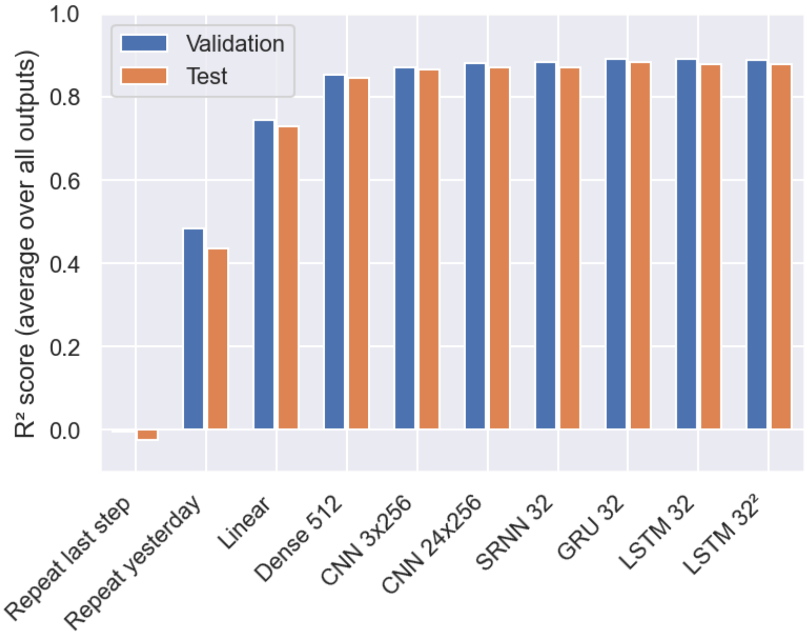
3. Feature Engineering
Time Signals and Solar Elevation

- Time of day and time of year:
  - Periodic representations
  - Sine and cosine signals
- Solar elevation:
  - Clipped and unclipped signals
- Precisely known for the past and future



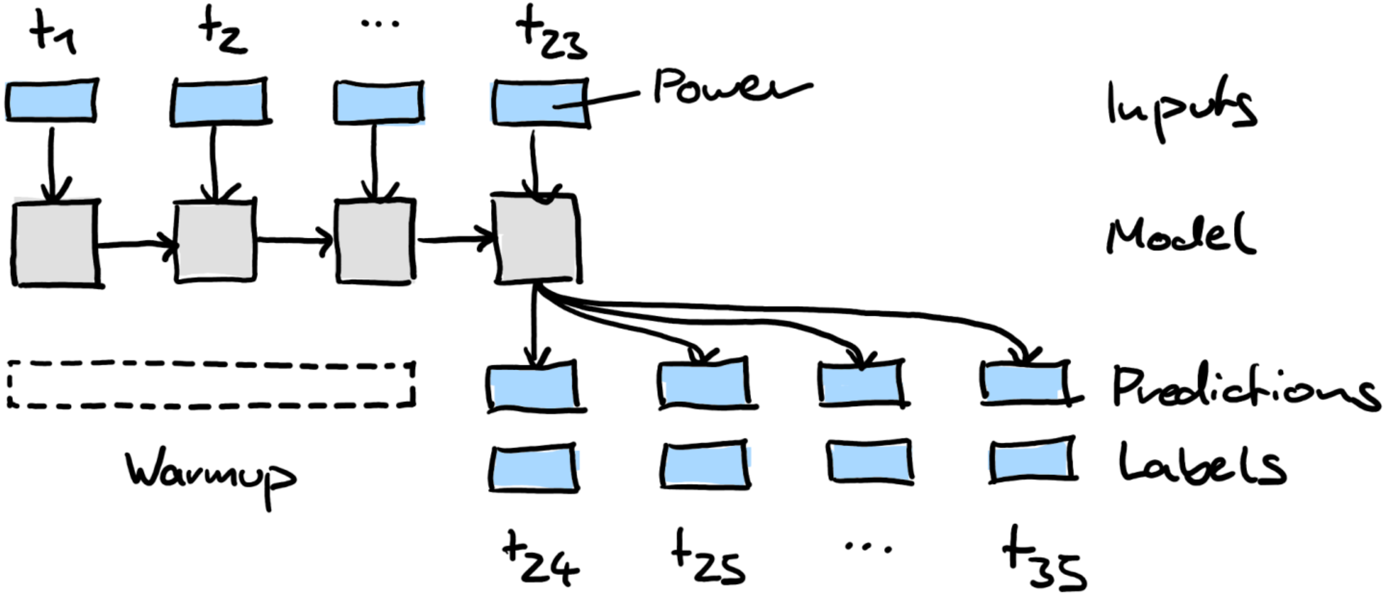
4. Model Architecture Exploration

- Creation of non-trainable benchmark models:
  - Repeat last step
  - Repeat yesterday
- Searching for feasible model architectures
- Results:
  - CNNs and RNNs show best performance: GRU 32 with best R^2 score: 0.882
  - Continuing with RNNs due to their better performance for increased input and prediction lengths



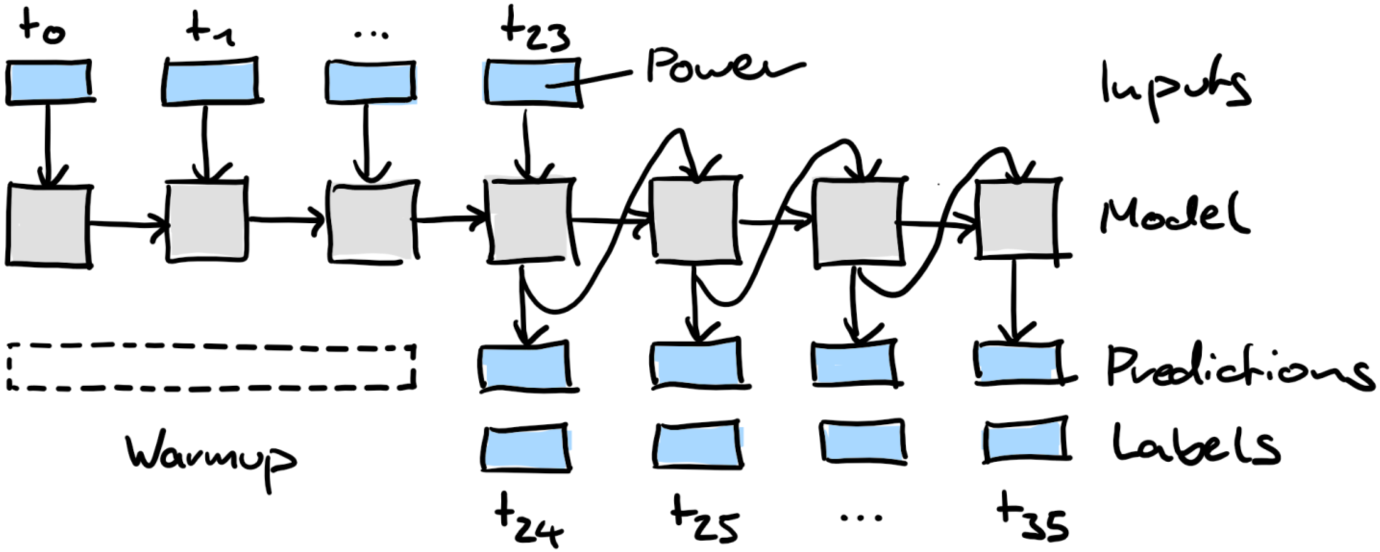
5. Iterative Model Development
Single-shot RNNs

- Prediction of multiple time steps at once (usually with an added Dense layer)



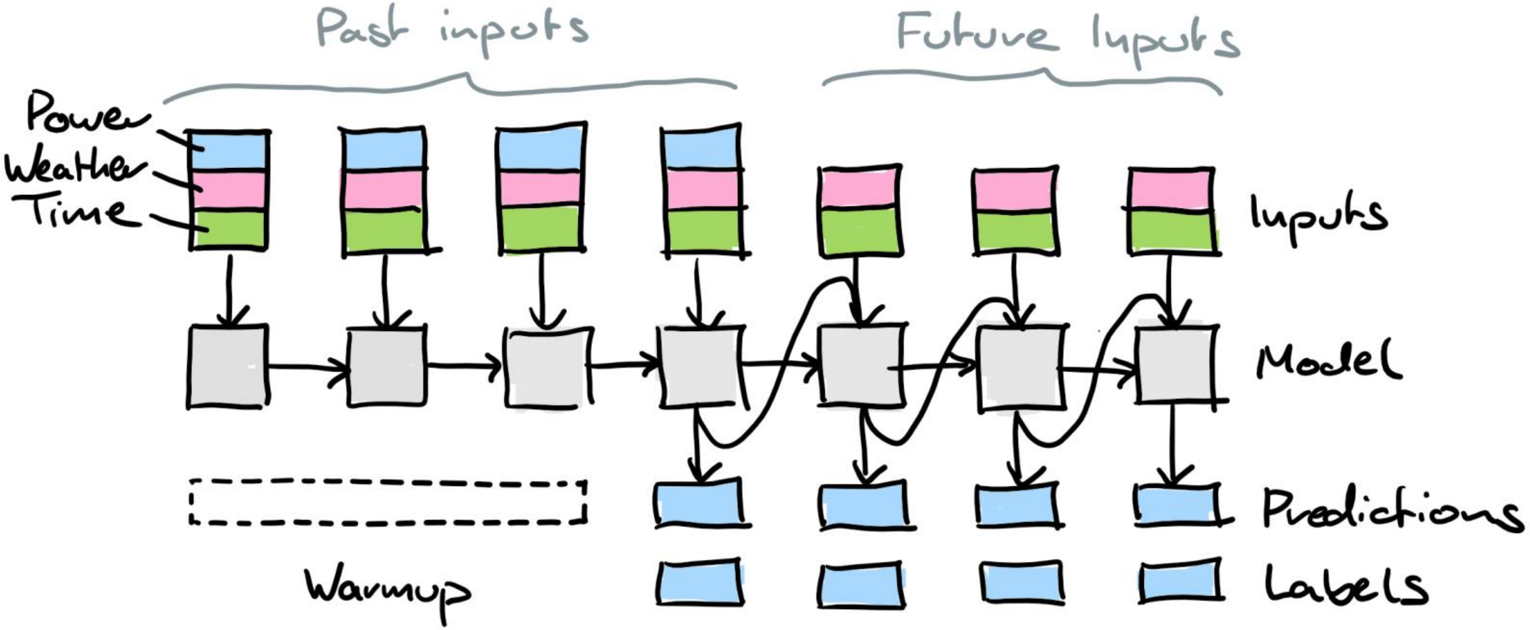
5. Iterative Model Development
Autoregressive RNNs

- The prediction of the last time step is used as input for the next time step
- Prediction of varying output length without retraining



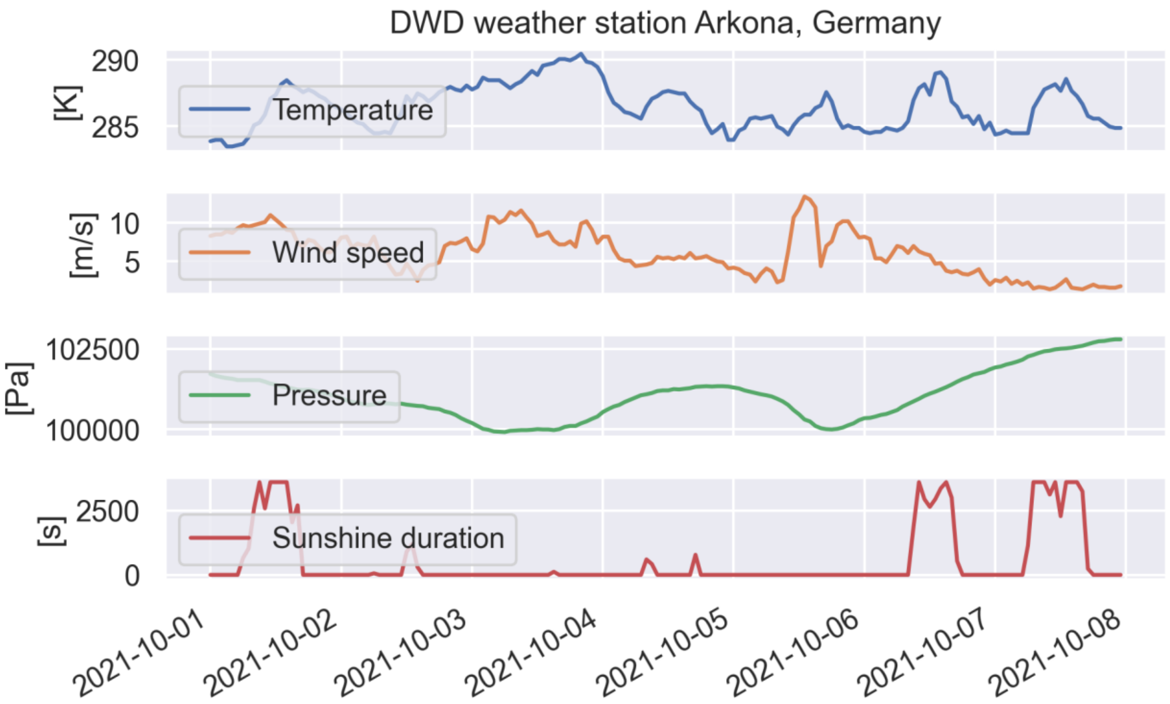
5. Iterative Model Development
Autoregressive RNNs with continous input

- Our approach: Combine the autoregressive predictions with forecasted inputs



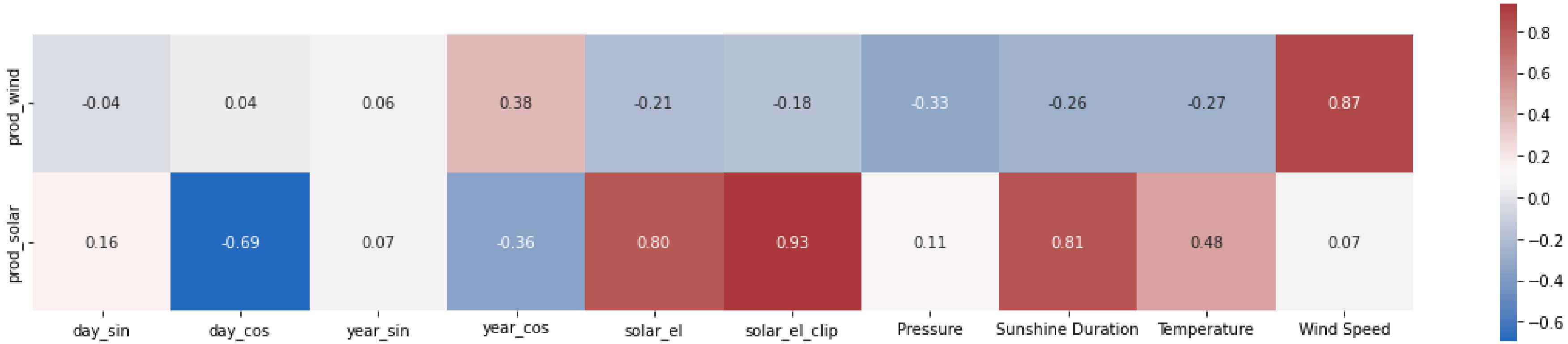
5. Iterative model development
Additional inputs

- Hourly resolution
- Timeframe: 2017 - 2021
- Source: DWD
- Available for up to 117 DWD stations across Germany



5. Iterative Model Development
Correlation analysis

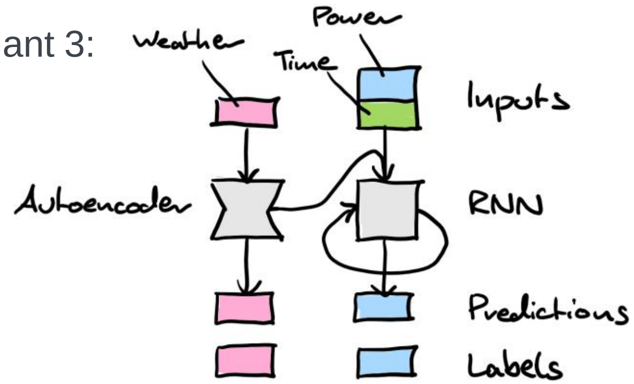
- Decision on which features are interesting/important
- Determine which features to include in model



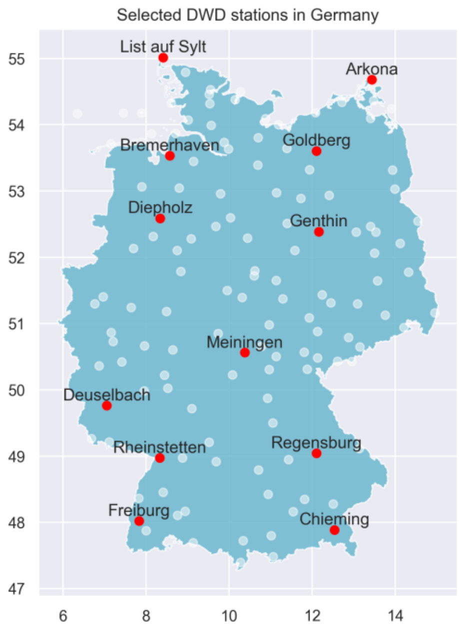
5. Iterative Model Development
Weather feature reduction

- Input variants:
  1. No weather input
  2. 4 Parameters of 12 DWD stations: 48 features
  3. Autoencoded input of 117 stations: 468 → 48 features
  4. PCA reduced input of 117 stations: 468 → 8 features

Variant 3:

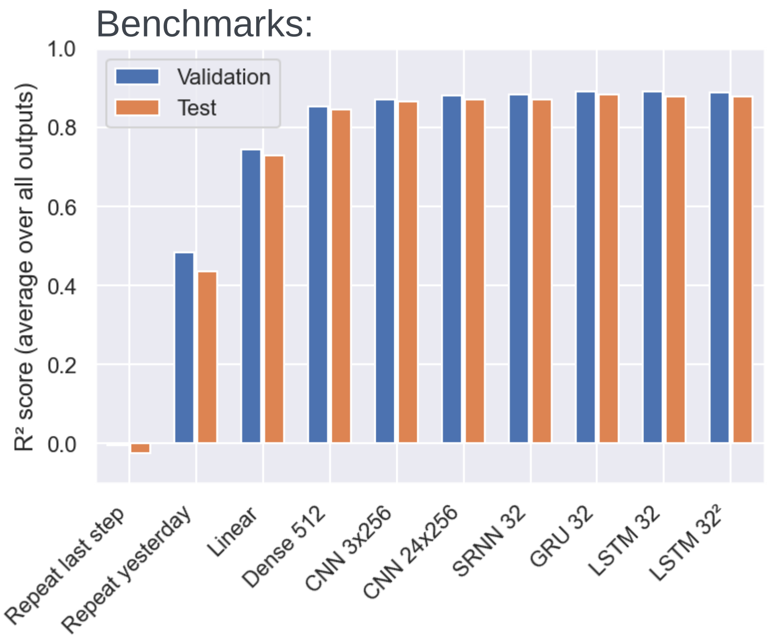


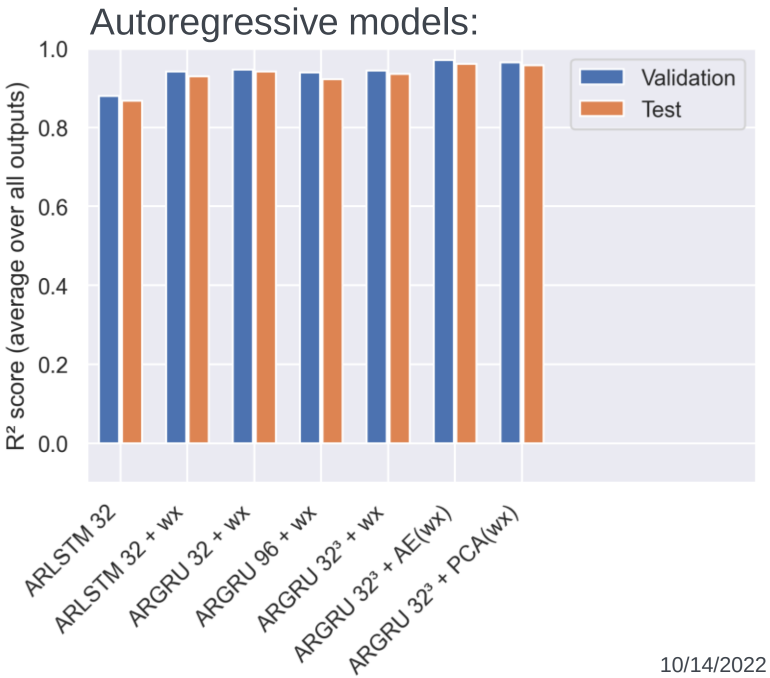
Selected stations:



5. Iterative Model Development
Performance Comparison

- Best performance: ARGRU 32^3 + AE(wx): R^2 0.962
  ARGRU 32^2 + PCA(wx): R^2 0.957

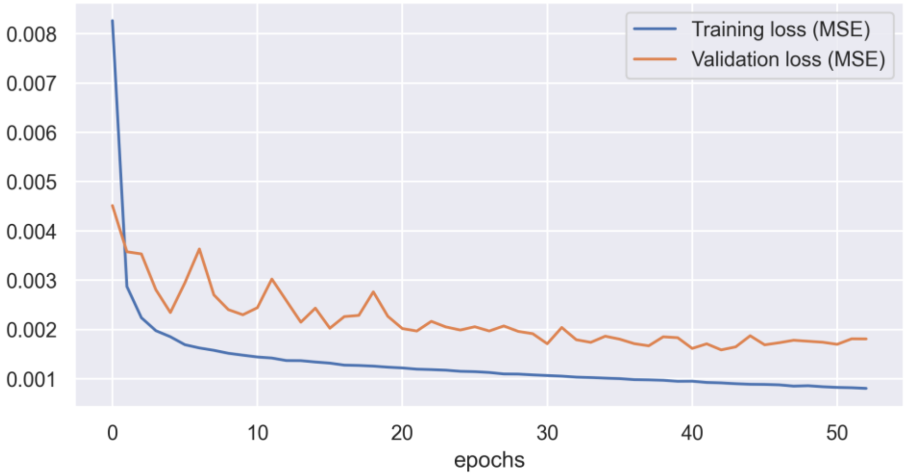




5. Iterative Model Development
Final Model Architecture

- Deep autoregressive GRU with continous input
- 3 layers [32, 32, 32]
- Inputs (24 time steps):
  - Solar and wind energy production (during past/warmup phase)
  - 8 time and sun elevation features
  - 8 PCA reduced weather features
- Prediction of 12 time steps

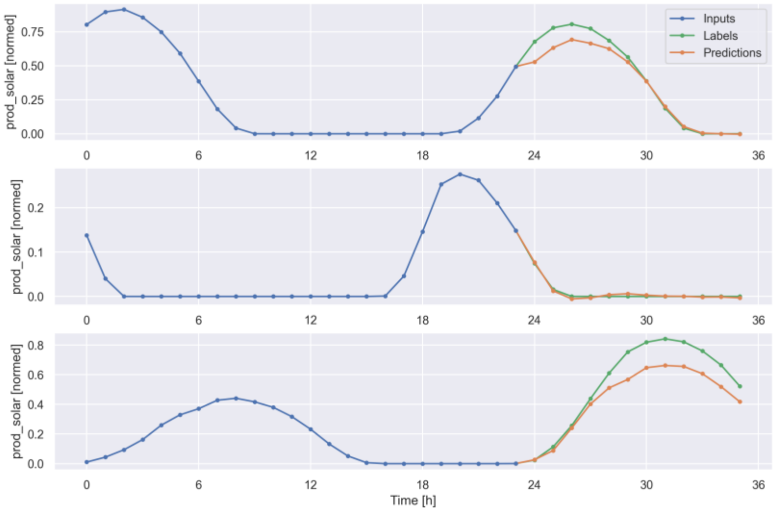
Loss plot:



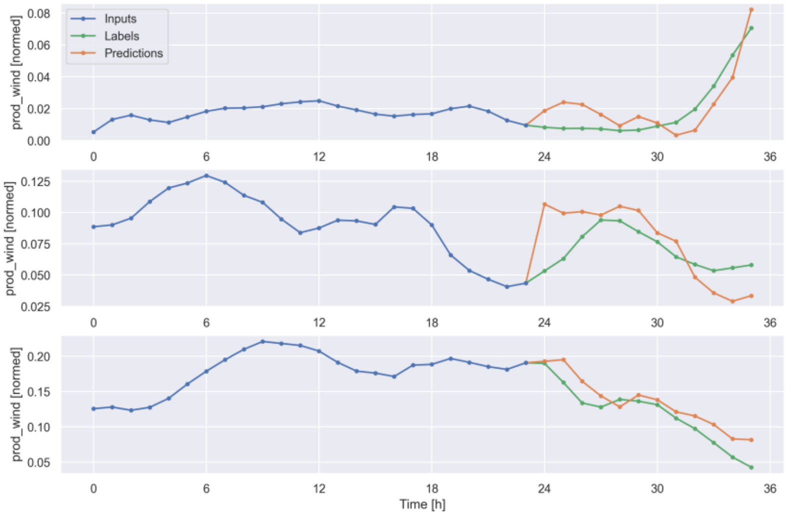
5. Iterative Model Development
Final Model Prediction Examples

- Better performance for solar energy predictions

Solar energy production:

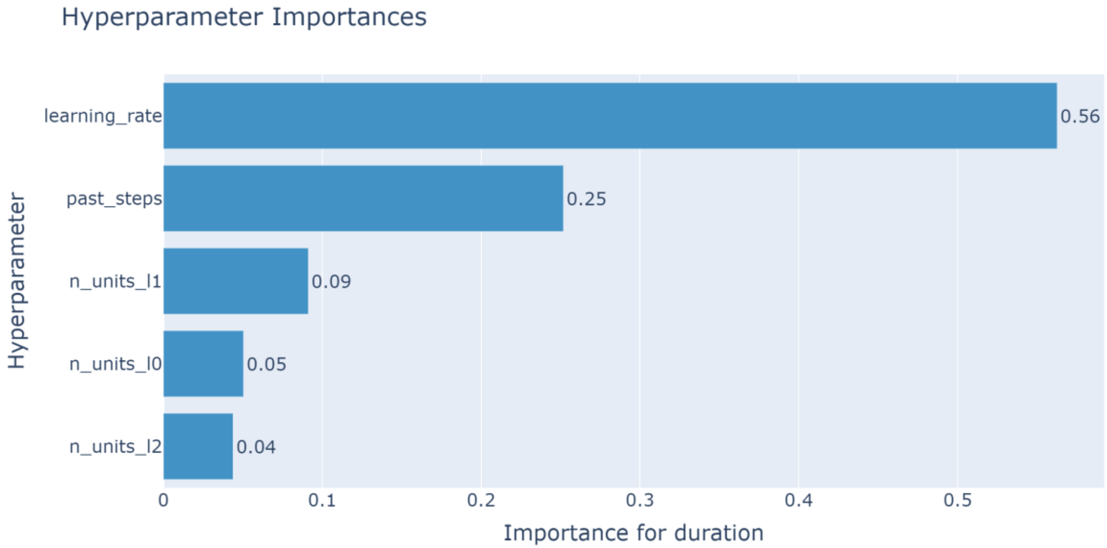


Wind energy production:



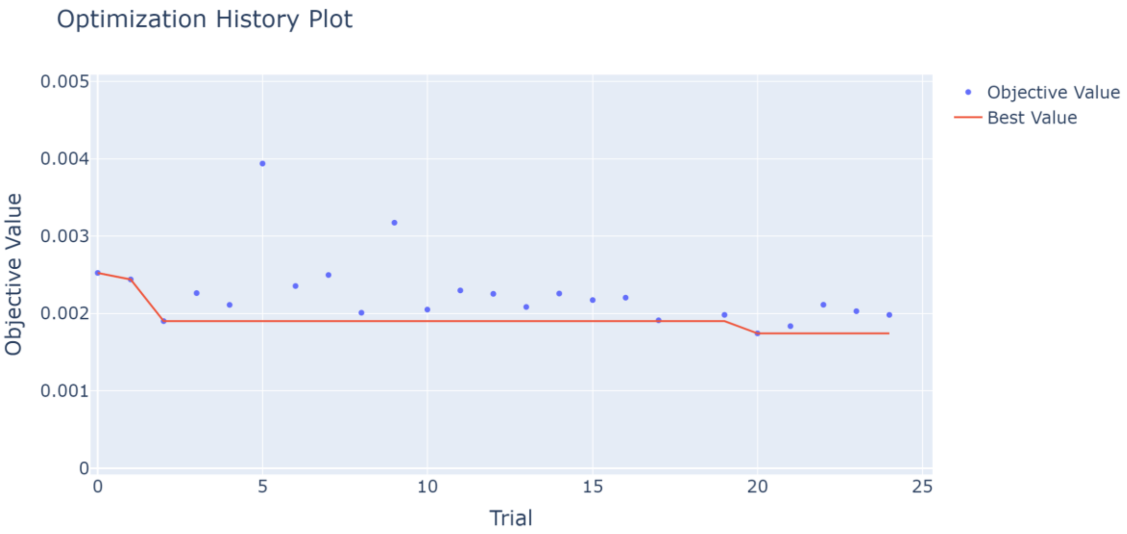
6. Hyperparameter Optimization

- Optuna: open source hyperparameter optimization framework
- Optimized parameters:
  - Learning rate
  - Units per layer
  - Past input time steps
- Optimization trials: 25



6. Hyperparameter Optimization
Optimization history and final parameters

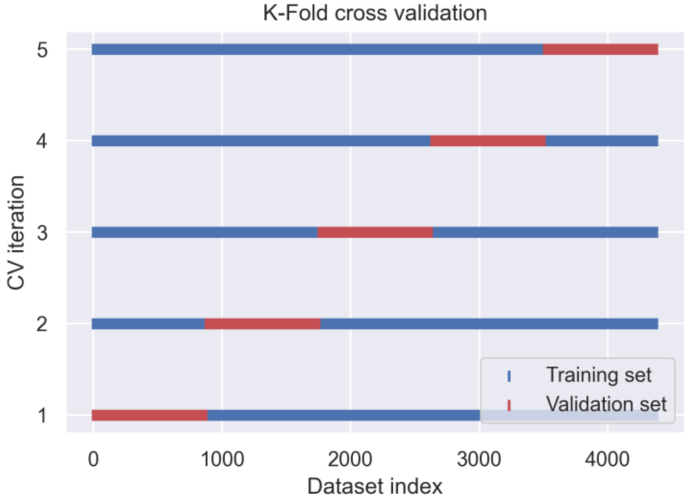
Parameter	Optimized Model	Previous Model
Past steps	92	24
Learning rate	1.7 e-3	5 e-4
Units 1st layer	15	32
Units 2nd layer	10	32
Units 3rd layer	11	32
Test R^2 score	0.9616	0.9567



7. Results
K-Fold cross validation

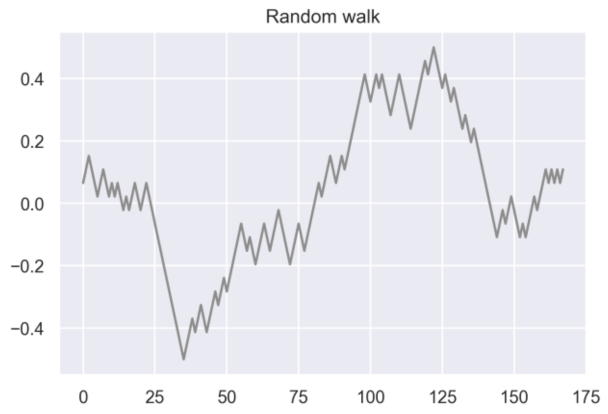
- The dataset was split into 5 subsets and the model was trained 5 times
- Each time a different subset was the validation set
- Results:

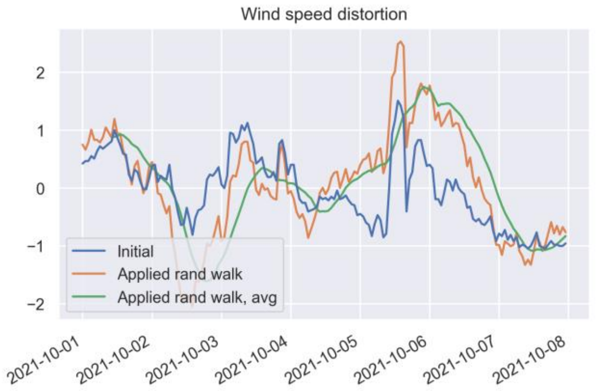
Fold	Val R^2	Test R^2
1	0.9617	0.9315
2	0.9690	0.9574
3	0.9686	0.9607
4	0.9659	0.9558
5	0.9516	0.9444
Average	**0.9633**	**0.9500**



8. Outlook

- Account for weather forecast inaccuracy:
  - Train with real forecast data
  - Distort weather data: Random walk?
- CNN Auto-encoder → Detect spatial relationships
- Employ statistic methods
  - e.g structural time series





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Thank you!

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https://github.tik.uni-stuttgart.de/Leon-Senguen/Electricity-Prediction