PREDICTING RENEWABLE ENERGY PRODUCTION USING MACHINE LEARNING METHODS

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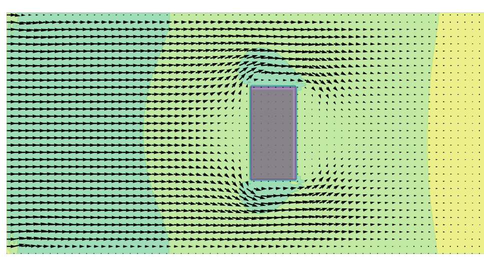

Machine Learning Methods in Mechanics
Report
-
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Contents

1 Introduction

The increase in the share of renewable energy sources in total energy production leads to a increasingly fluctuating power generation. Therefore, measures for a stable energy supply will gain importance. Information about future energy production could enable power plant operators to control their power production up and down in order to match the incoming renewable energy. A future prediction could also help to store energy in a targeted manner. With this background, the goal of this work is to develop a machine learning model that predicts the renewable energy production 12 hours into the future.
There is a variety of model architectures for this problem, including CNNs (Convolutional Neural Networks), RNNs (Recurrent Neural Networks), Autoencoders, GRUs (Gated Recurrent Units) or LSTMs (Long Short Term Memory). This paper will first explore and evaluate existing models regarding their accuracy, then iteratively develop an advanced and optimized model architecture.

Description of the project. Images are always a plus. You should reference each figure in the text and explain what can be seen. The flow field shows particle velocities. It is taken from [**?**]. What is the problem? What is the goal? What is your idea?

You can include wrapped figures and tables, like Table **??**. To make it work, there should be no newlines between the wrapped table or figure and the surrounding text. Normal tables work just as usual, like in Table **??**.

2 Data and Feature Engineering

In order to predict future energy production from renewable sources, data showing energy production in recent years is needed. Old data sets are not representative because the number of solar and wind power plants in operation has increased significantly in recent years.(**Zitat**) Therefore, years 2017-2021 were selected for neural network training in this paper.
Future solar and wind energy generation depends not only on past energy generation, but also on weather conditions. To account for this, a second dataset of past-year weather information (2017-2021) was chosen as an optional additional input to the models. The following data sets were used in this paper:

- Electricity data (2017-2021) obtained from Energy-Charts (from Fraunhofer ISE), hourly resolution
- Weather data (2017-2021) from DWD (Deutscher Wetterdienst) including 468 meteorological station in Germany, hourly resolution

2.1 Feature Engineering

Raw data cannot necessarily be included directly as a feature in the model. Different pre-processing steps and a thoughtful selection of features can significantly improve the final result.

Figure **??** shows the wind and solar energy production of 2017-2021. Seasonal and daily fluctuations can be observed. To further investigate this phenomenon, a fourier analysis, shown in figure **??** was performed.

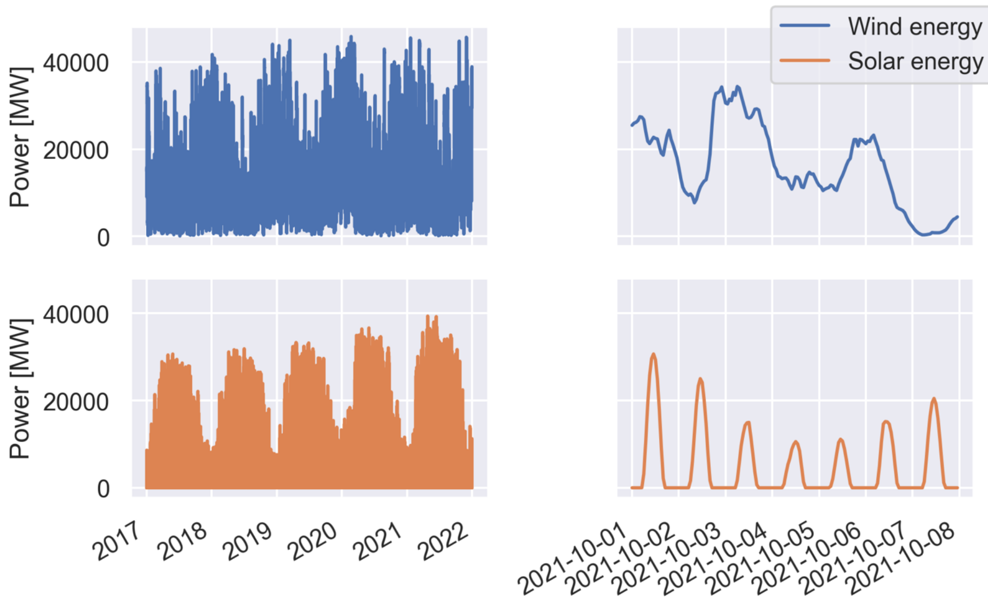
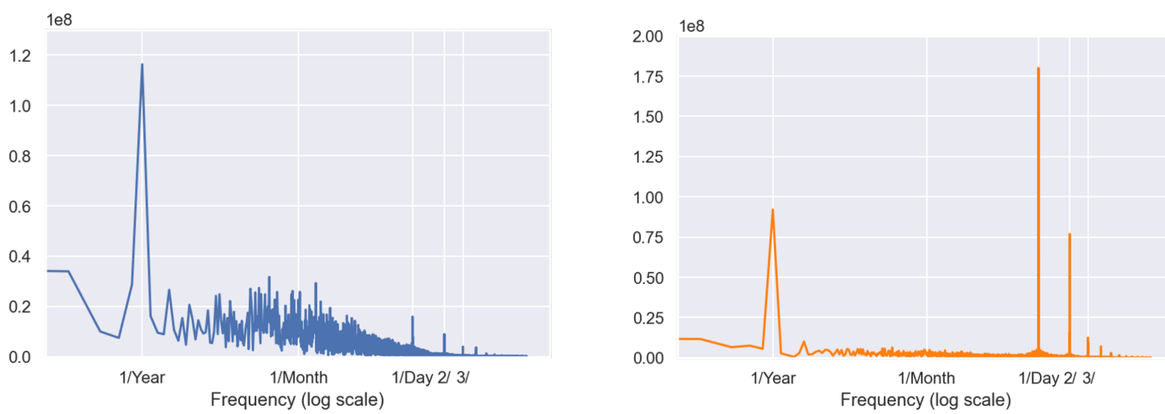


Figure 1: Wind and solar energy production 2017-2021



(a) Fourier analysis of wind energy production **(b)** Fourier analysis of solar energy production

Figure 2: Fourier analysis of electricity data

The fourier analysis reveals the frequencys that appear in the wind/solar energy production data. The solar energy production shows the highest peak at a frequency of 1/day, matching the daily elevation of the sun. For both, wind and solar energy the yearly and daily fluctuations are dominant.

To account for these two frequencies, time is mapped to sine and cosine functions representing the periodicity of year and day (Figure **??**). In addition, the solar elevation is determined, which, as expected, correlates strongly with solar energy production. The bottom plot in Figure **??** shows the actual solar elevation by truncating the previous solar elevation curve to zero. In this way, the lack of sunlight during night is represented.

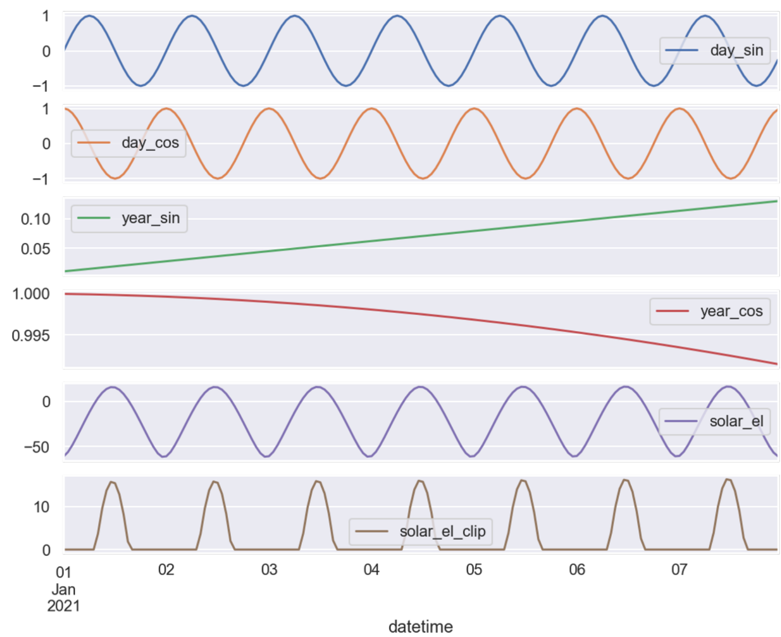


Figure 3: Periodic features

The modified time features as well as air pressure, sunshine duration, temperature and wind speed were subjected to a correlation analysis.

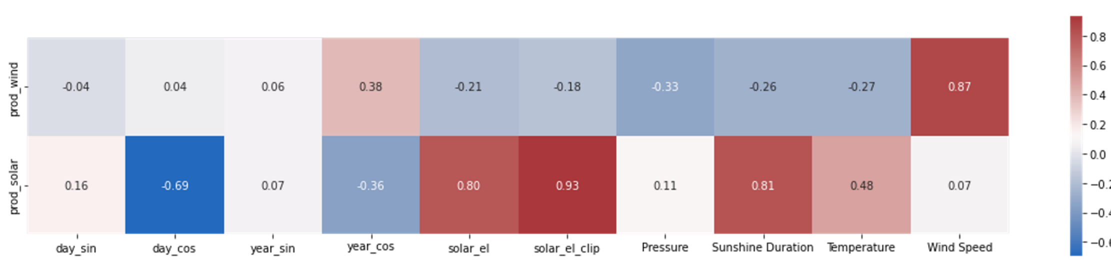


Figure 4: Correlation analysis

Figure **??** shows the correlation matrix. Darker colors indicate a higher (anti-)correlation. The solar energy production is strongly correlated to the cosine of the day, sunshine duration, temperature and clipped solar elevation. In contrast, wind energy production is only strongly correlated with wind speed and slightly correlated with pressure and temperature, which can be explained by the ideal gas equation. Although the sine of day and year do not hold a high correlation, they were included in the feature vector for completeness.

The final feature vector is a combination of two energy production features, six analytically determined time and solar elevation features, and 4 weather features (per weather station) as displayed in Table **??**.

Of 468 meteorological stations in Germany, only 117 provide reliable data (2017-2021). Of these remaining stations, 12 were selected for further representation of German weather. Decisive for the selection was the spatial proximity to offshore and solar installations as well as a broad distribution across Germany. The final weather stations are displayed on **??**

Energy Production	Time and Solar Elevation	Weather
solar energy prod.	day sine	temperature
wind energy prod.	day cosine	windspeed
	year sine	pressure
	year cosine	sunshine duration
	solar elevation	
	clipped solar elevation	

Table 1: Features

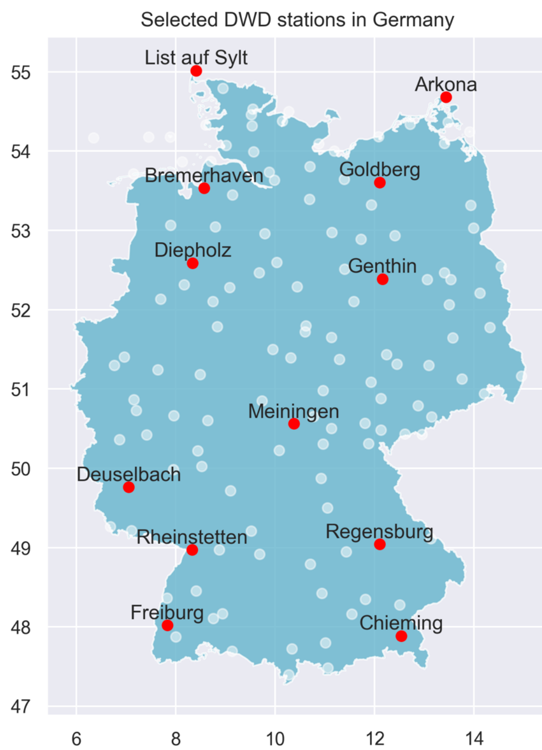


Figure 5: Selected weathe3 stations in Germany

3 Methods and Model Architectures

The goal of this work is to predict solar and wind energy production 12 hours into the future. Current research offers a variety of machine learning models for this problem. Therefore, as a first step, different models were applied to the problem and evaluated regarding their prediction accuracy. Unpromising approaches were then discarded while succesful models were further explored and improved.

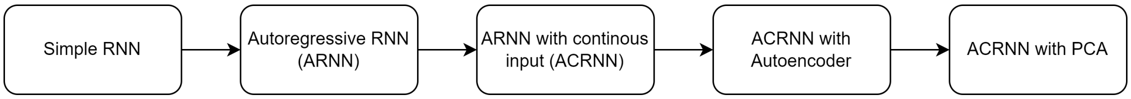


Figure 6: Iterative model development

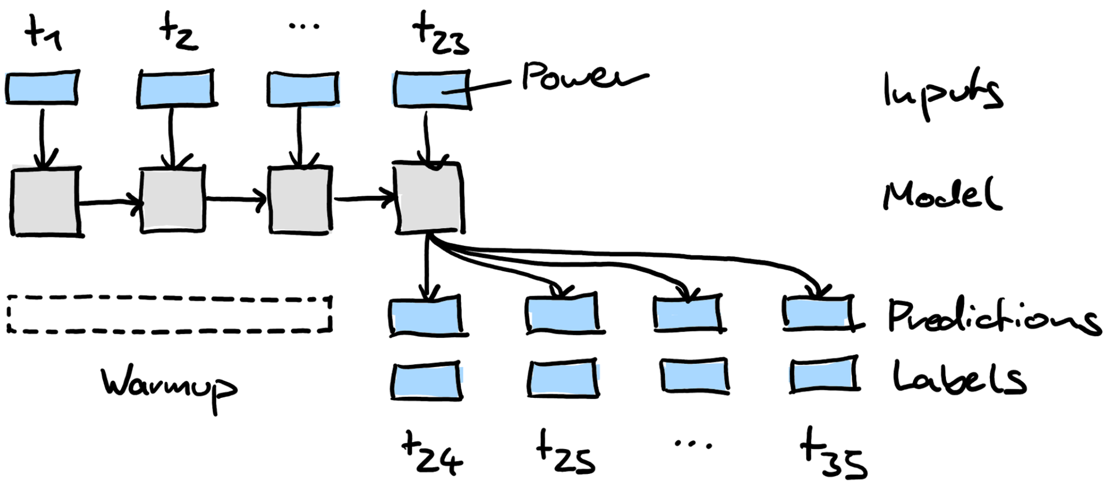


Figure 7: Simple recurrent neural network (SRNN)

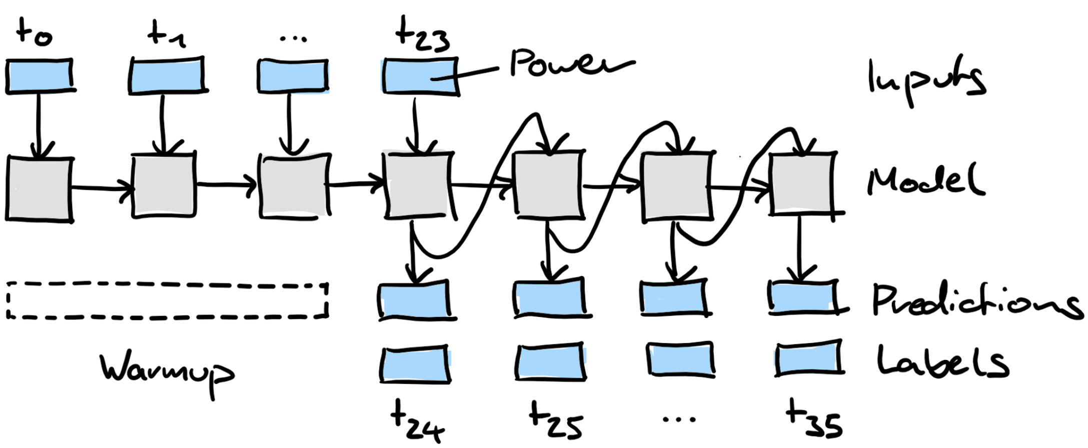


Figure 8: Autoregressive recurrent neural network (ARNN)

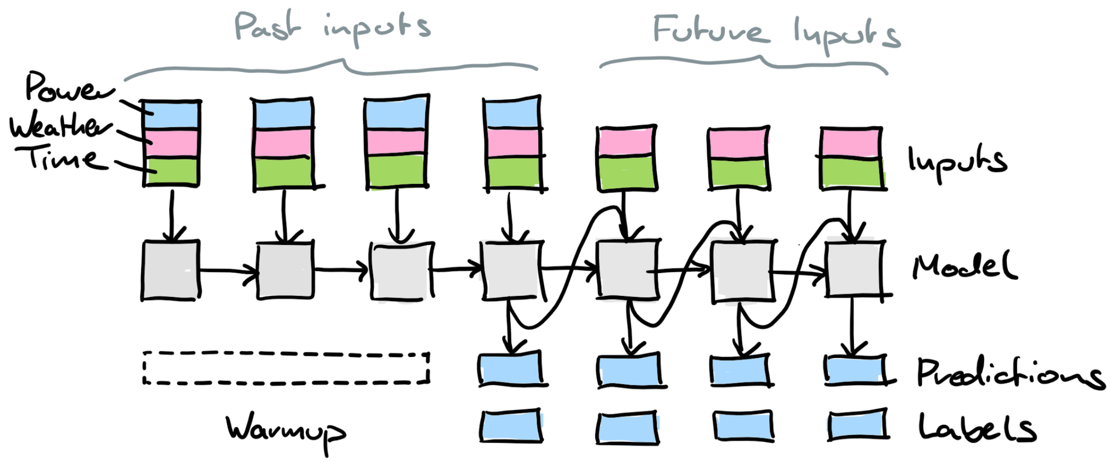


Figure 9: Continous autoregressive recurrent neural network

4 Results and Optimization

5 Conclusion

6 Outlook

6.1 The Navier-Stokes-Equations

Equations as usual, like in Equation **??**. Recall that equations like

$$\phi_{\max} = \max_{\theta} \left[\log(\sin(\theta - \exp(\theta))) - \theta^2\right] \tag{1}$$

are part of the text and should be treated like a word.
Or without numbering, like the realtivistic kinetic energy

$$E = \frac{mc^2}{\sqrt{1 - \frac{v^2}{c^2}}},$$

which yields the Newtonian kinetic energy $E = \frac{1}{2}mv^2$ when linearized for small velocities v.

6.2 Solution Method

Figure **??** shows how to include wrapped figures that text can float around. Depending on what is depicted and how large it is, it may look better than a full figure.

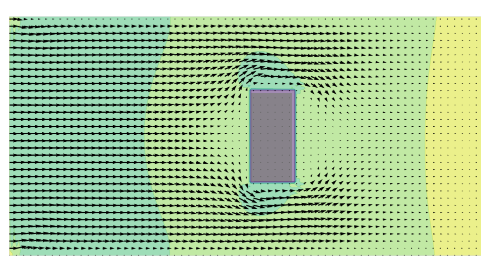


Figure 10: You can also use wrapped figures like this.

7 Convolutional Neural Networks

8 Idea and Data Generation

9 Results