Chapter 50
Meteorological Data Forecast using RNN

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ABSTRACT

Gathering knowledge not only of the current but also the upcoming wind speed is getting more and more important as the experience of operating and maintaining wind turbines is increasing. Not only with regards to operation and maintenance tasks such as gearbox and generator checks but moreover due to the fact that energy providers have to sell the right amount of their converted energy at the European energy markets, the knowledge of the wind and hence electrical power of the next day is of key importance. Selling more energy as has been offered is penalized as well as offering less energy as contractually promised. In addition to that the price per offered kWh decreases in case of a surplus of energy. Achieving a forecast there are various methods in computer science: fuzzy logic, linear prediction or neural networks. This paper presents current results of wind speed forecasts using recurrent neural networks (RNN) and the gradient descent method plus a backpropagation learning algorithm. Data used has been extracted from NASA's Modern Era-Retrospective analysis for Research and Applications (MERRA) which is calculated by a GEOS-5 Earth System Modeling and Data Assimilation system. The presented results show that wind speed data can be forecasted using historical data for training the RNN. Nevertheless, the current set up system lacks robustness and can be improved further with regards to accuracy.

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INTRODUCTION

The 8th May 2016 left an important mark in Germany's change towards a 100% renewable energy supply. On this day, photovoltaic and wind power provided as much energy as has been needed to satisfy the demand and still provided a surplus that led to consumers actually being paid to use energy. The steady development of new photovoltaic modules being mounted and small to large scale wind farms, onshore and offshore, are an indicator for an increase in the number of days similar to the 8th May 2016 in the upcoming years.

The key issue for the stability of the grid is to cope with varying intermittent generation of electrical power. As wind speeds vary with time and location and are different on- and offshore, the level of intermittency for the electricity system depends on the spatial distribution of wind farms (Splett et al., 2008). In general wind speed is mainly influenced by factors that change rapidly over small spatial resolutions such as elevation, roughness and obstacles.

With regards to wind, the large potential of offshore power available in the North Sea supports the urge for predictable power as several German projects are in process. For economic and technical reasons, the determination of wind conditions is an important stage in the frame of the offshore wind farm operation and maintenance. Wind farm capacities have risen drastically in the past and can be compared to conventional power plants with regards to its size. One of Germany's energy suppliers, Innogy, for example has an installed wind energy capacity of about 2.8 GW.

Being able to generate the most profit out of the available power at the energy stock exchange, the knowledge of the next day meteorological data at the energy suppliers wind farm location is of key importance. The energy stock exchange works on the basis of supply and demand. In case of a known meteorological behavior, e.g. wind speed, at the desired location, it is possible to increase the profit by waiting for the highest price available. Load curves for the whole country are available and in combination with the predicted/forecasted wind energy the peak price is predictable as well. This allows energy suppliers not only to increase the price, but also avoid penalties in case of a deficit of sold and supplied power.

Meteorological data of high quality, meaning measured by calibrated and well maintained instruments, without gaps and faulty data, is of high value but in most cases not available. With regards to the offshore wind industry, tall meteorological mast (met masts) with heights of up to 100 m have been erected in the past. These masts were carrying or still carry meteorological equipment as the likes of conventional anemometers and wind vanes, ultrasonic anemometers or, since the last couple of years, LiDAR (Light Detection and Ranging) based measurement devices. The costs, which are liable to non-disclosure agreements, are expected to be in the region of one up to multi million Euros. In addition to that the operation and maintenance of bespoke devices and structures are another cost factor which adds more value to the data measured at these offshore structures. Due to this it is a rare experience being able to work with the data, but mostly limited to internal analysis or company close projects in which the results are for internal use only. An alternative data source is NASA's reanalysis data from the GEOS-5 Earth System Modeling and Data Assimilation system, called MERRA - Modern Era-Retrospective analysis for Research and Applications) (Rienecker et al., 2011) which is available on an hourly basis.

The recurrent neural network which has been implemented for the forecast is based on the deep learning system Theano in Python 2.7. The open source distribution Anaconda, including Python 2.7 plus all essential packages (Numpy, Scipy, Pandas, Matplotlib etc.) has been used for the works presented in this article. In addition to that a graphics card with its 1664 CUDA cores in combination with the CUDA library accelerated the calculations during training.