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A deep learning LSTM forecasting approach for renewable energy systems

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In this study, we address point-forecasting using a deep learning LSTM-approach for renewable energy systems with focus on the short- to medium-range. Hourly resolution (medium-range) as well as 10-minute resolution (nowcasting) are the anticipated forecasting frequency. The forecasting approach is applied to: (i) wind speed at 10 meters height (observation sites), (ii) wind speed at hub-height of wind turbines, and (iii) solar power forecasts for selected solar power plants.

As input to the proposed method numerical weather prediction (NWP) data, gridded observations (analysis and/or reanalysis), and point data are used. The data of studied test-cases is extracted from the Austrian TAWES system (Teilautomatische Wetterstationen, meteorological observations in 10-minute intervals), SCADA data of wind farms, solar power output of a solar power plant, INCA's (Integrated Nowcasting through Comprehensive Analysis) gridded observation fields, reanalysis fields from Merra2 and Era5-land, as well as, NWP data from the ECMWF IFS (European Center for Medium-Range Weather Forecast's Integrated Forecasting System). These data-sources embrace very different temporal and spatial semantics, thus, careful pre-processing was carried out. Four daily runs over the course of one year for 12 synoptic sites + 38 wind turbines + 1 solar power plant test locations are conducted.

The advantage of an LSTM architecture is that it includes recurrent steps in the ANN and, thus, is useful especially for time-series, such as meteorological observations or NWP forecasts. So far, comparatively few attempts have been made to integrate time-series with different semantics of a sensor network and physical models in one LSTM. We tackle this issue by conserving the time-steps of the delayed NWP along with their difference to recently observed time-series and, additionally, separate them into forecasting-intervals (e.g., of 3 to 12 subsequent forecasting hours being shortest in nowcasting). This enables us to employ a sequence-to-sequence LSTM based artificial neural network (ANN). The benefit of a sequence-to-sequence setup is to match an input- and output time-series in each sample, thereby, learning complex temporal relationships. To fully use the advantage of the diverse data a tailored pre- and post-processing of these heterogenous data sources in the renewable energy applications is needed.

The ANN's results yield, in general, high forecast-skills, indicating a successful learning based on the used training data. Different combinations of inputs and processing-steps were investigated. It is shown that combining various data sources and implement an adequate pre- and post-

processing yields the most promising results in the case studies (e.g.: a heuristic to estimate produced power based on the meteorological parameters and prediction of the offset to NWPs tailored to the studied location). Results are compared to traditional forecast methods and statistical methods such as a random forest and multiple-linear-regression.