INCREASING GRID STABILITY THROUGH ACCURATE INFEED FORECASTS OF RENEWABLE ENERGIES

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ABSTRACT

The rapid growth of renewable energies is leading to increasing imbalances between electricity production and consumption. During high-wind periods with local overproduction of energy, the stability of the distribution grid can only be ensured if a fraction of (wind) farms is throttled or shut down. Precise infeed forecasts of wind and solar power production for individual sites assist in reducing these risks because controlling measures for renewables as well as the regulation of conventional power plants (coal, gas etc.) can be planned with longer lead times.

A forecast system is presented which includes the whole chain from weather forecast to infeed forecast. The foundation is made up of weather model forecasts from the UK Met Office and from the high resolution regional model WRF.

The conversion of forecast weather elements (e.g. wind profiles) into infeed energy from the turbines/farms is realized by artificial neural networks (ANNs). ANNs are able to recognize and eliminate the systematic errors produced by weather models.

The quality of the infeed forecasts is validated with results for transmission nodes across the grid of the company E.ON edis, situated in the Northeast of Germany.

INTRODUCTION

The rapidly growing fraction of renewable energy production in Germany brings up new challenges for operators of distribution grids, especially in the northern half of the country. Grid stability is endangered in more and more regions where installed power overtakes actual consumption in high-wind cases. Preparation of stabilizing measures (load control) demands accurate forecasts of energy production down to the producing sites.

The engineering consultancy LEM (Load and Energy Management) has been established in 1997 and worked together with numerous energy suppliers and industrial clients. The company is ever since specialised on load forecasts among other energy-related topics.

FORECAST SYSTEM

The forecast system is required to provide site-specific predictions for wind and solar power generation. In the present case, we make use of two independent weather models which create timeseries of weather elements such as wind speed, temperature etc. Artificial neural networks are applied as post-processing models to link weather and energy production by means of a training period of past data. The system schematic is illustrated in figure 1.

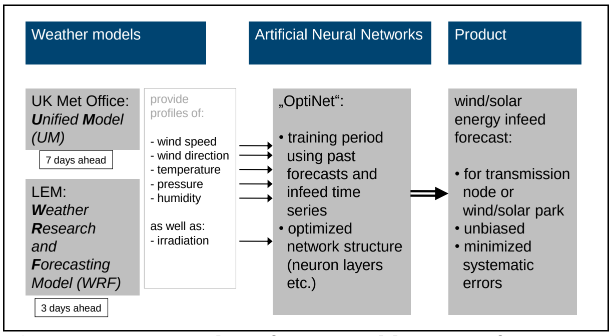

Figure 1. Forecast chain for renewable energy forecasting using two independent weather models and one configured artificial neural network for each of them.

Weather models

Forecasting renewable energy production requires reliable predictions of the steering weather elements such as wind speed or solar radiation. We make use of the weather model chain of the English weather service, the UK Met Office (UKMO). The site-specific model output is updated four times a day with lead times of 60 hours for the regional model and 7 days for the global model. The finer resolved data is used for the short-term predictions.

In addition to the wind forecast of the English model, another 3-day model forecast using the Weather Research and Forecasting Model (WRF, http://www.wrf-model.org; Skamarock et al., 2005, [3]) is provided by LEM. The high resolution runs provide data with a grid spacing of 4 km in a large area surrounding the wind farms. It is thus possible to better describe the influence of small-scale terrain inhomogeneities as well as certain weather elements, such as localized shower activity.

The ability of the WRF model to simulate the temporal evolution of wind fields has been addressed by various researchers. Zelle et al. (2011, [4]) compared the wind speeds of the model for wind farms in the Netherlands with station observations. The employed statistical error measures revealed a good agreement between them, with somewhat better results over land than over water. Hahmann et al. (2011, [1]) studied the model wind fields concerning their vertical structure (shear) und found that the wind profiles varied depending on the chosen boundary layer parameterization. Overestimated winds near the surface together with underestimations above hub height occurred in some configurations. Statistical methods during post-processing are able to minimize those systematic errors in both cases, thus increasing the reliability of the forecast.

Artificial neural networks

The gap between forecast weather conditions (e.g. hub height wind speed and global radiation) and the desired

wind energy production forecast is closed by artificial neural networks (ANN).
ANN are used in the same fashion as other statistical methods like model output statistics (MOS), in the way that they identify correlations between input variables and the infeed energy. A schematic of an ANN is given in figure 2. The input vector (mostly weather elements) is connected with the neurons in the first hidden layer via weightings. During the training period, the ANN tries to learn the pattern connecting the individual influencing variables and adapts the weightings between the neurons with every learning step until a certain search criterion (e.g. error) is reached.

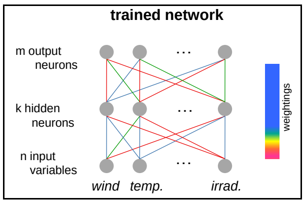

Figure 2. Schematic of an artificial neural network consisting of input and output layers as well as hidden layers. The weightings are coloured according to their impact.

ANN are very effective in reducing systematic errors, such as overestimation of near-surface winds in high-resolution weather models. Furthermore they can learn effects which arise from site-specific properties (terrain bumps, shadowing effects of upstream wind turbines or trees/buildings in the case of solar panels etc.), which are not captured by the weather model.
The application of global and/or regional model forecasts in conjunction with neural networks for wind energy prediction has been described by Salcedo-Sanz et al. (2009, [2]) among many others. They obtained a significant improvement in the wind forecast when compared to traditional methods. In the present paper we make use of the successor (WRF) of the MM5 model which was used by Salcedo-Sanz.

Artificial Neural Networks have been used for load forecasting with LEM for many years. The existing model has been adapted specifically for the purpose of renewable energy infeed forecasts. This implies the incorporation of new influencing variables as well as more complex ANN training methods.
Due to the rapidly growing number and total power of wind farms in Germany, controlling measures by grid operators occur more often compared to previous years. Hence the infeed (load) time series measured at parks or transmission nodes do not always represent the true capacity of production for given weather situations. Therefore, the forecast system has been extended by an algorithm which automatically detects and removes controlled load episodes from the ANN training period in order to provide a clean time series. This procedure minimizes the bias of the forecast and reduces the overall prediction error.

Another challenge arises if existing parks are extended in terms of installed capacity. The current system is able to adapt to an extension of the wind/solar park without loss of information from past time series for ANN training. Otherwise, no reliable data basis (minimum one year) would be available for network training.

IMPLICATIONS FOR GRID STABILITY

The E.ON edis company is a large grid operator situated in the north-eastern part of Germany. The installed power of wind farms in the company's grid currently amounts to 4.5 GW, rapidly growing to a prospected value well above 10 GW within the next two years. Since the maximum production of renewable energy plants is higher than the consumption of customers (max. 2 GW) in the same grid, a collapsing grid would be inevitable many times of the year during high-wind weather situations.
Thus, throttling or shutting down individual parks/farms is one important option to ensure grid stability. There are two main aspects regarding these infeed control measures:

a) Legal obligations: According to German law, the grid operator is obliged to inform the park/farm owner about any controlling measures affecting his/her park. This information has to be published one day in advance.
b) Load of grid lines: The throttling/shutdown needs to be planned for those grid lines which are suspected to be overloaded with renewable energy infeed.

Both aspects are taken into account in the grid operation headquarter by dispatchers on duty. A forecast of infeed renewable energies provides a guideline for planning of control measures. Without it, the current (measured real-time) load of the grid would be the only indication about where and when to throttle or shut down, which would dramatically raise the risk of a grid collapse. High-quality forecasts can therefore be used to plan actions one day in advance or even earlier. Scheduling affects both the parks/transmission nodes to be controlled and the personnel in charge.
Moreover, an early-stage planning of infeed control is mandatory in order to fulfil the legal requirement of an equal treatment of park owners. This implies that one and the same park should not be shut down or throttled more often than others.

FORECAST RESULTS

In this section, we present preliminary results of the achieved forecast quality for wind and solar energy production.
A comparison of measured and predicted infeed energy is exemplarily shown for a transmission node in the E.ON edis grid in north-eastern Germany (fig. 3). The pictured period exhibits both high-wind and calm weather situations with a couple of intermittent peaks. Except for a few underestimated peaks, eyeball verification suggests an accurate forecast in this case.
A more distinct picture is obtained when looking at the frequency distribution of deviations ($P_{forecast}$-$P_{measured}$). Fig. 4 shows the relative deviations over the year 2011 for the same park. It is evident that the raw weather model

forecast does not exhibit significant errors after it was post-processed by the artificial neural networks. The median of the distribution is located within the 0-1% interval. However, underestimation occurs slightly more often than overestimation. This is likely to be originating from the short-lived wind peaks (lasting not longer than 1 hour) which are not satisfyingly captured by the weather models.

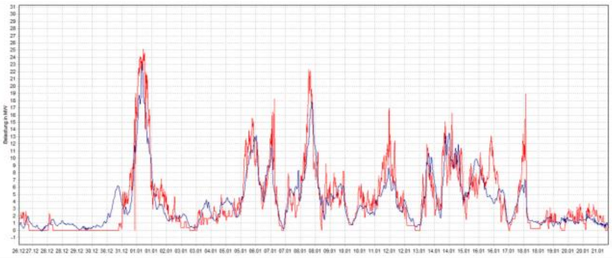

Figure 3. Comparison of 30-hour forecasts (blue) and measurements (red) of infeed wind energy at a transmission node in northeast Germany. The results show only a four weeks period, while one year of past load and weather forecast data has been used for training. During the first days the park has been shut down as indicated by the flat red line.

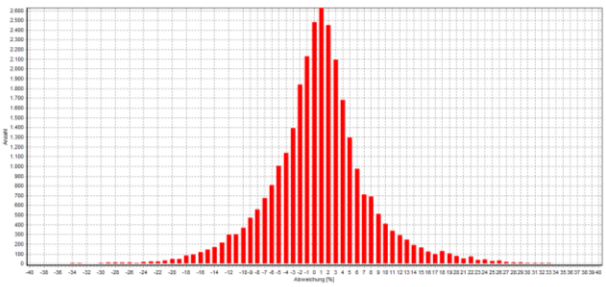

Figure 4. Error frequency distribution of the same wind park as in fig. 3, but including the forecast of the whole year 2011. Values greather than zero represent overestimated infeed energy by the forecast. The deviation is computed in relation to a fixed power value over the whole period.

The accuracy of solar energy production forecasts greatly depends on the weather model's ability to capture low-level clouds. Thus, better results are obtained during the warm season while fog and low stratus clouds in winter and fall tend to lower the overall quality.
Fig. 5 shows an example of aggregated 30-hour forecasts for one solar park. It can be concluded that both the amplitude and the timing of the solar energy are captured quite well on most days. Similar to unresolved short-lived wind peaks, the forecast model chain is not able to resolve the "chaotic" nature of small clouds that cross the park in this summertime case. Those peaks and valleys are averaged out on a reasonable timescale.

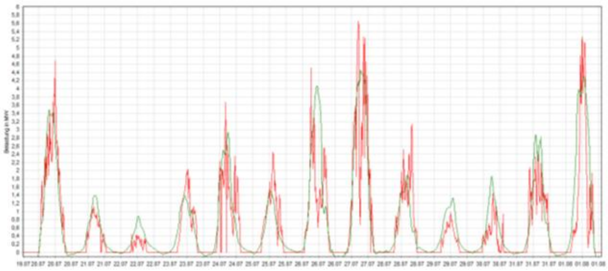

Figure 5. Comparison of 30-hour forecasts (green) and measurements (red) of infeed solar energy at another transmission node in northeast Germany during a 2-week period in summer 2011.

CONCLUSION

A comprehensive forecast chain for wind and solar power prediction is proposed in this paper. It comprises two independent weather models and subsequent trained artificial neural networks.
The results reveal the advantages of neural networks as post-processing models. The forecasts show no significant systematic errors as indicated by the error distribution function for wind. Similar applies to solar power forecasts, which have a seasonal cycle of error though.
The presented results were obtained with a one-year ANN training period only. It is assumed that a longer period will result in higher accuracy. Moreover, the two individual, model results (UKMO and WRF) will be merged to further reduce the uncertainty via time-dependent weightings.
Accurate infeed forecasts are required prior to load control measures which are undertaken by distribution grid operators. Since the current status of the forecast system is currently to be implemented on the operator's side, detailed assessments and implications for grid stability measures have to be addressed in future work.

ACKNOWLEDGEMENT

We would like to thank E.ON edis for providing the measured infeed data as well as for supporting the project. Moreover, we thank the UK Met Office for providing the weather model data.

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