Improving Grid Integration of Renewable Energies

A success story based on combinational PV power forecasts

Dr. Christian Kurz
Head of Prognoses & Data Analytics
meteocontrol GmbH – Energy & Weather Services
Augsburg, Germany
c.kurz@meteocontrol.com

In this paper we present an integrated combinational solar power forecast based on machine learning algorithms. The forecasting system is used to optimize the grid and market integration of Renewable Energies.

Solar Power Forecasts; Machine Learning; Grid Integration

I. Introduction

Renewable energies represent an increasingly important contribution to our energy supply system. In Germany alone, installed photovoltaic (PV) capacity is around 45 GW (as of July 2019). However, a strong increase in capacity can also lead to challenges in terms of secure grid integration. One way of making it easier to plan the production and feed-in of renewable energies is to draw up and optimize solar power forecasts. This paper presents a combinational approach to improve solar power production forecasts, especially in the short-term area (intraday). The results are discussed as examples for the German market, but can be generalized to other countries.

II. Need for Solar Power Forecasts

A. Energy Trading

Until a few years ago, the market integration of solar power in Germany took place exclusively in the day ahead segment. Due to the uncertainties in the weather models, however, this is associated with forecasting errors that have to be compensated during the actual day. As the share of renewable energies increased, the amount of unbalanced energy due to these forecasting errors for the following day became increasingly large. This was associated with steadily rising costs due to the procurement of balancing energy. For this reason, intraday trading was also opened for renewable energies. This market has developed rapidly since its introduction. Figure 1 shows that the intraday trading volume has increased tenfold within only 10 years to around 50 TWh (for the year 2018). It can be assumed that this process will develop even faster in new, faster growing markets. New, optimized short-term forecasts are therefore essential.

B. Grid Stability and Redispatch

Another important area of application for short-term forecasts is grid stability. The spatial distribution of energy generation and load often differs in grids with a high share of renewable energies. The associated energy flow can lead to a high load on individual power lines. To prevent this, the network operators carry out redispatch measures. This can mean that in case of strong wind or solar power production renewable energy plants have to be reduced in output in certain grid areas. At the same time, conventional plants have to be ramped up. Figure 2 shows the strong increase in redispatch measures (in terms of redispatch energy). Improved short-term forecasts can be an effective means of reducing the further increase in this energy and the associated further increase in costs.

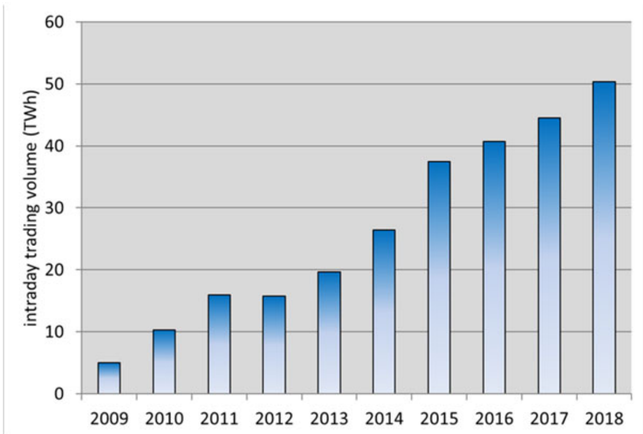

Figure 1. Intraday trading volume in Germany from 2009 to 2018.. Data source: Epex Spot – European Power Exchange.

III. Combinational Forecasts

State of the art forecasting methods combine different information or input forecasts. Especially for short-term applications, numerical weather prediction models, satellite images and current PV production values from monitoring systems are usually used. These 3 products are described in more detail in the following sections. The combination factors are usually learned from machine learning methods based on historic measured values.

A. Cloud Motion Vector Satellite Forecast

For the short-term range of some hours a 'cloud motion vector' prediction based on current satellite images is used [1,2]. The displacement of cloud structures is determined from two consecutive satellite images by pattern recognition. The method is applied to each pixel of the image. This results in a vector field that describes the speed and direction of the atmospheric flow. These vectors are used to extrapolate the current cloud structures into the near future. In the last step irradiance at the ground is calculated from the predicted cloudiness [3]. The latest development is the use of satellite images in the thermal (infrared) spectral range [4]. This makes it possible to calculate forecasts for the early morning hours, even if no satellite information in the visible spectral range is available at the time of calculation. The 'cloud motion vector' forecasts are produced in cooperation with the University of Oldenburg.

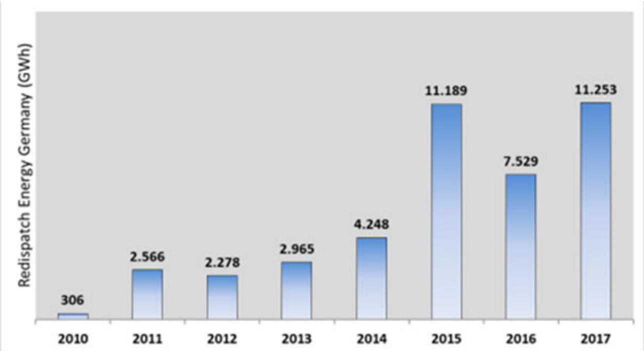

Figure 2. Redispatch energy in Germany from 2010 to 2017. Data source: Bundesnetzagentur.

B. Numerical Weather Prediction

Numerical weather prediction models have been state of the art in calculating renewable energy production forecasts for many years [5]. The models of several international and national weather services are combined in order to generate the best possible combinational forecast depending on the weather situation. The main focus for the use of numerical weather forecasts is the day ahead application. For a long time, these models were also used for intraday short-term forecasting. Due to the complexity and the associated long computing time, however, the accuracy of the numerical models is particularly limited in the short-term range.

C. PV Monitoring Data

Further important information is provided by measured values of solar power production from monitoring systems. In contrast to the two methods described so far, in which the PV output is only calculated, monitoring systems provide real PV power measurements. The data can therefore be used very well for the calibration of satellite and numerical forecasts. At the same time, the actual production value can be used to create an estimate for the next few minutes by means of a persistence forecast. Naturally, the accuracy of a forecast based on a persistence approach, i.e. the assumption of constant cloud structures, may be very limited depending on the weather condition.

D. Combination by Machine Learning

The decisive step in the forecasting process is the optimal combination of the three input forecasts mentioned above. The ideal model combination depends on the geographical location of the PV system, the forecast horizon, the position of the sun, and other parameters. Machine learning methods can be used for the combination. In the present case, a simple linear regression approach was implemented. Production data in 15 minute resolution from 786 solar plants in Germany for one year were used for validation. A new simulation was calculated every 15 minutes. The forecast was adjusted separately for each quarter of an hour of the day to the measured values.

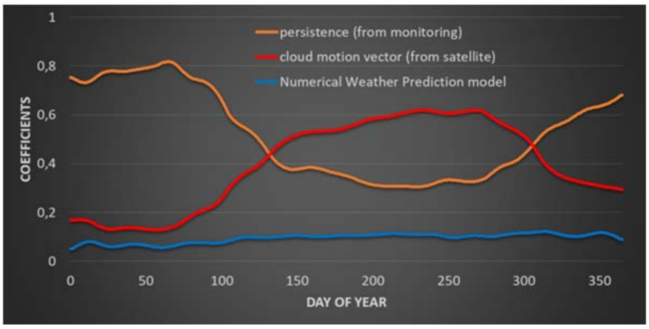

Figure 3. Weighting factors for the 3 input forecasts in dependence of the day in the year. Forecast horizon: 15 minutes.

Figure 3 shows an example of the combination factors determined for locations in Germany for the year 2017 for a forecast horizons of 15 minutes depending on the day in the year. The variation of the weighting factors depending on the season is clearly visible. For this short forecast horizon of 15 minutes the persistence forecast dominates in winter. Summer, on the other hand, was characterized by unstable weather conditions with frequently changing clouds. Accordingly, the cloud motion vector satellite forecast was increased in weighting by the regression models. The numerical weather models receive only a low weight throughout the year.

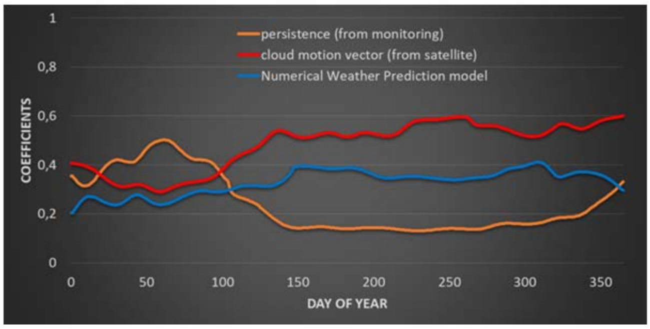

Figure 4. As figure 3, but for a forecast horizon of 2 hours.

A changed picture emerges in the short-term range of 2 hours, see figure 4. Even in winter, the dominance of the persistence forecast is no longer very pronounced. In summer it even receives the lowest weight of all 3 input forecasts. Here, as already for the 15 minute horizon, the satellite forecast dominates. The consistently high weight of the numerical forecast is conspicuous, especially in combination with the satellite forecast. This can be explained by the cloud motion vector prediction method. This is based on a shift of existing cloud patterns into the future. Meteorological effects such as cloud formation or dissipation are not represented in this method. This information was taken from the numerical weather models, whose weighting was chosen accordingly high by the regression algorithm.

IV. RESULTS

In summary, figure 5 shows the accuracy achieved with the combined forecast system as a function of the forecast horizon. Results are normalized to the root mean square error of the numerical weather forecast, which was used as standard for forecasts also in the short-term range for a long time. The graph also summarizes the respective advantages and disadvantages of the individual forecast approaches. The persistence forecast derived from the measured values has advantages especially for the current time step and the short term range, since it concerns real power measurements. However, the accuracy decreases rapidly as the forecast horizon increases. The cloud motion vector forecast derived from the satellite data is, as described above, subject to certain uncertainties due to the conversion of a cloud image to irradiance. Nevertheless, it is the most precise source for the forecast period between about 2 and 4 hours. Decisive for the approach chosen here is the result that the calculated combination forecast always has a higher accuracy than each of the 3 individual input forecasts. This applies to all forecast horizons.

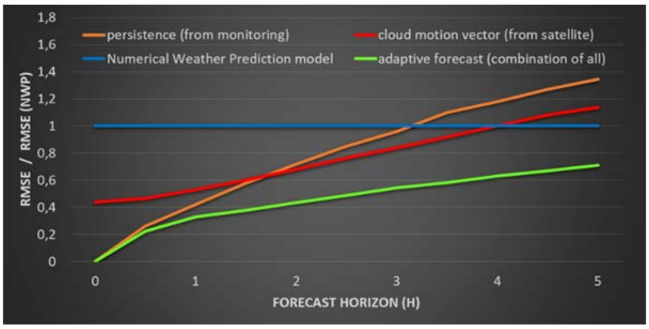

Figure 5. Normalized root mean square error of the 3 input forecasts, and the combinational forecast in dependence of the forecast horizon.

V. CONCLUSION

Current forecast solutions for the short-term sector generally consist of a combination of different forecast approaches. This paper presented a combination of numerical weather prediction, a cloud motion vector forecast derived from satellite data, and measured production data from a monitoring system. The weighting factors were learned by linear regression models depending on the season, the weather situation, and the forecast horizon. It was shown that by this combination the forecast quality in the short-term range could be clearly increased. These improved forecasts are an important prerequisite for secure grid integration and successful market integration of renewable energies.

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BIOGRAPHICAL INFORMATION

Dr. Christian Kurz is a senior expert in energy meteorology for almost 20 years. After his studies of Atmospheric Physics at Munich University he worked at the German Aerospace Center (DLR) for many years. He mainly worked on the parameterization of clouds and cloud-irradiation interactions in a Global Atmospheric Circulation model. His Ph.D. thesis was about the development of a coupled model for atmospheric chemistry and circulation.

Since 2007 he is Head of Prognoses & Data Analytics at the international energy service provider meteocontrol in Augsburg, Germany. He is responsible for the development of Renewable Energies power forecasts for grid operators and trading companies. Together with his team he set up the first operational system for online feed-in estimations and forecasts of PV power for the German Transmission System Operators. A further focus of his work is Data Analytics of monitoring data by using machine learning methods.