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Prediction of feed-in power from photovoltaics in local distribution networks

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Abstract: Due to the shift of power production from highly centralised power plants to decentralised power production with renewable energy, the role of local distribution networks has changed. Originally, these networks were designed to distribute electric power from a centralised source to consumers. However, nowadays, the increasing number of climate-dependent decentralised energy production systems connected to local distribution networks, such as photovoltaics, affect the network stability. Thus, network operators need decision support methodology in order to cope with the network uncertainty. As a central part of the decision support system, climate-dependent forecast for feed-in power is required with high spatial resolution. In this paper, a method for the prediction of feed-in power production from photovoltaics, based on georeferenced power production and meteorological data is introduced.

1 Introduction

For decades, centralised power plants have been the operating model for electricity generation across Europe. This means, that huge quantities of electricity are being generated by power plants, that are physically clustered in a specific area or region located far away from the consumer (GREEN & SONNREICH 2014). The electricity being generated by the centralised power plants is being distributed through the electric power grid to multiple users (ACKERMANN et al. 2001).
Based on the Department of Economic and Scientific Policy within the EU parliament in June 2010, there has been a paradigm shift from centralised power plants to a more decentralised energy system. This shifts the narrative from passive to active consumers, in the sense that they can act as power producers as well (ALTMANN et al. 2010; COSSENT et al. 2009). End consumers, in turn, are often installing solar panels to cover their power needs and the excessive power are to be fed-in to the grid (CARLEY 2009). However, these climate-dependent decentralised energy production systems affect network stability. Hence, network operators need decision support tools for coping with network instabilities.
In this contribution, a method for feed-in power prediction from photovoltaics, based on georeferenced power production and climate data is described. The method takes into account that photovoltaic power production is influenced by various parameters: a) geographical location on earth and orientation of the panels, b) time of the year (changing sun elevation over the year), c) time of the day (HOSTE et al. 2009) (changing sun position over each day), d) climate (e.g. weather, wind, cloud, atmospheric conditions, etc.), e) shadowing effects caused by local topography (SALVATORE & FRANCISCO 2015), and f) panel-specific parameters (e.g. efficiency of the solar

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panel, condition like dust, dirt or snow cover). Whereas, the aforementioned parameters (a-e) do play a pivotal role in the global horizontal irradiance (GHI), diffuse horizontal irradiance (DHI), and shortwave radiation received on the Earth surface, the panel-specific parameters are highly individual.

Within the course of this research, diverse meteorological aspects that play a role in the feed-in power have been investigated. As part of a state-of-the-art analysis, two approaches to compute or predict the feed-in power from photovoltaics have been identified: An analytical approach and an observation-based one.

2 Related Work

The amount of solar irradiation that reaches the surface of the solar panels determines how much power can be produced by a specific solar panel. Additionally, the panel-specific parameters (see section 1) contribute to the amount of power being produced and fed into the network. In this contribution, we have identified two approaches for tackling the issue of predicting the feed-in power from photovoltaics: an analytical approach and an observation-based approach.

2.1 Analytical Modelling

In the analytical approach, each and every aspect that plays a role in the computation of the amount of power being generated by the solar panel is to be thoroughly studied and a computational formula is to be obtained. As earlier mentioned, there are a variety of factors that do influence the feed-in power from photovoltaics.

One of the areas that have been studied in depth was the cloud coverage and its impact on the solar irradiation. In a research study by LUMB (1963) founded on a former study by KIMBALL (1928), an empirical correlation function between the average daily short-wave radiation and the fraction of sky covered by cloud has been introduced. However, that empirical formula that has been introduced did not take into account the different types of clouds. LUMB (1963) complements KIMBALL'S (1928) work by classifying and identifying different types of clouds. In his study, clouds were divided into nine categories, mainly based on their intensity (amount of cloud) and altitude. In addition to that, scattering of solar irradiation also varies based on, the cloud optical depth, cloud geometry, and the direction of the incident solar radiation (MCKEE & COX 1974; AIDA 1977).

However, the data required for these computations are typically not available, which makes it not practical in deducing a computational formula for estimating the short-wave radiation that is received at the solar panel. Also, due to the diversity of the domains that ought to be covered to precisely compute the amount of feed-in power from photovoltaics, an analytical model considering all the aforementioned factors would be very complex. Furthermore, from a practical point of view, the panel-specific parameters (see section 1) cannot be obtained for individual households. Hence, the second approach, which seems to be more applicable and more examined recently, is the observation-based approach.

2.2 Observation-based Modelling

In contrast to analytical modelling, observation-based approaches rely on correlating the observations of different phenomena with each other using statistical methods. In a study by YUAN et al. (2015), a correlation between the normalised solar radiation difference and the cloud optical thickness was built. An exponential correlation between the amount of solar radiation increase and the cloud optical thickness decrease was observed. In another research work by YANG et al. (2012), a forecast analysis between the Global Horizontal Irradiance (GHI) and Direct Normal Irradiance (DNI) based on a cloud cover index was developed. These studies rely on an observation-based approach to detect the correlation between cloud coverage and solar irradiation using NASA MODIS data (PLATNICK et al. 2015).

By taking into account these research studies, we concluded that an observation-based approach does overcome individual missing or prone to error parameters, as of the case in the analytical one. Additionally, various meteorological parameters can be correlated to the solar irradiation. This, in turn, allows for studying certain meteorological phenomena and their direct or indirect impact on the photovoltaic power generation (JEREZ et al. 2015).

As a result, it has been decided that we further investigate the observation-based approach in order to predict the power output from photovoltaic cells under certain weather conditions.

However, the studies mentioned above do not take into account local topography and panel-specific parameters (see section 1), which are important for predicting the feed-in power in local distribution networks, but which are not obtainable in most cases. In our research we propose an observation-based approach, which tries to overcome these problems.

3 Proposed Observation-based Approach

Our approach relies on statistical analysis of georeferenced historic power production measurements from photovoltaic systems installed in local distribution networks and georeferenced historic meteorological data. Figure 1 gives an overview of our approach. The numbers shown in the Figure correspond to the numbering of the sections in this paper.

3.1 Acquisition of power production data from photovoltaics stations

The first step in this research project was to obtain a reliable and continuous stream of photovoltaic power production data. Online services for providing crowd sourced photovoltaic power data, such as PVOutput[2] were inspected and analysed. More than 50 photovoltaic stations in the area of Utrecht (Netherlands) were picked from PVOutput and selected for further investigation (see Figure 2). Power production data acquisition was limited to a period of 12 months back, because of PVOutput limitations. However, although PVOutput provides free online service for photovoltaic output data, it does not guarantee their consistency or sustainability.

In order to take the observation-based approach a step further and correlate power production to meteo-rological factors, a con-tinuous stream of power readings was essential.

[2]http://www.pvoutput.org

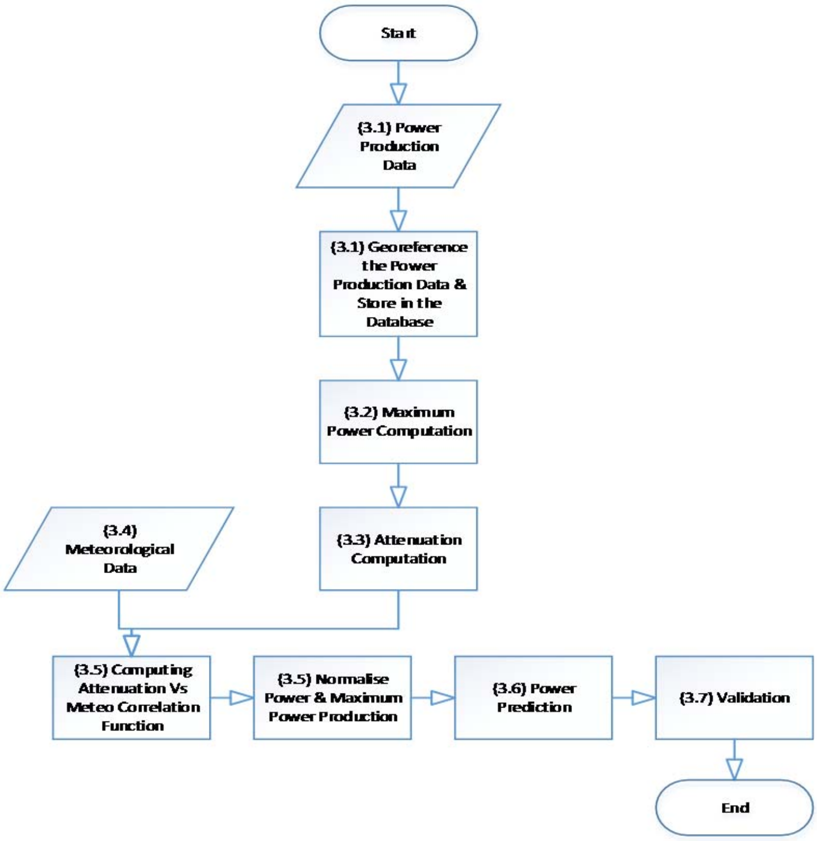

Fig. 1. Overview of the proposed approach

Therefore, the German energy company EnBW ODR provided us with photovoltaic power production data for 22 stations (spatial distribution see Figure 3) over the course of 13 months with 15 minutes temporal resolution. The same workflow has been applied on the EnBW ODR and the PVOutput data and the readings have been geo-referenced and stored in a geo-database in order to allow for spatial analysis, such as spatial autocorrelation of the power production data, spatial interpolation, and spatial correlation with meteorological data (see 3.5). In the following sections, the further steps of our approach are described. The outcomes are illustrated using either the crowd sourced PVOutput data or the data provided by the energy company EnBW ODR.

3.2 Maximum Power Estimation for each Station

In order to overcome the individual panel specific characteristics, we needed to derive a parameter, which accounts for all the influences and makes different photovoltaic systems comparable. Hence, we needed to identify the maximum expectable power that can be generated by a specific station at a particular point in time on a particular day. The maximum generated power varies on daily basis, because of the factors, such as change of inclination of the sun during the year (shadowing situation), and season specific atmospheric conditions. Therefore, we had to create the maximum power curve for each individual day of the year. In order to measure the maximum power at each point in time produced by a certain solar panel, we resorted to historic measurements. The maximum power produced for a specific station was computed for each day of the year applying a moving window approach as follows: for each day of the year, for every 15 minutes time step, the generated power is compared to its relevant time values for +/-15 days, then the maximum reading is being selected (see Figure 4). The period of +/-15 days was chosen, because we assumed, that within this period the probability is high to find clear sky conditions. The maximum generated power was then assumed to be the maximum expected power that can be obtained from a particular solar panel under clear sky conditions at this point in time.

Fig. 2: PVOutput stations

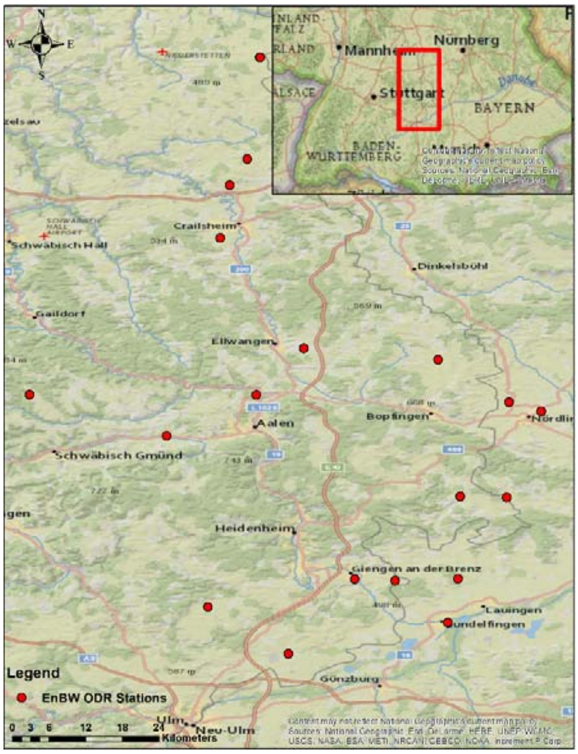

Fig. 3: EnBW ODR stations

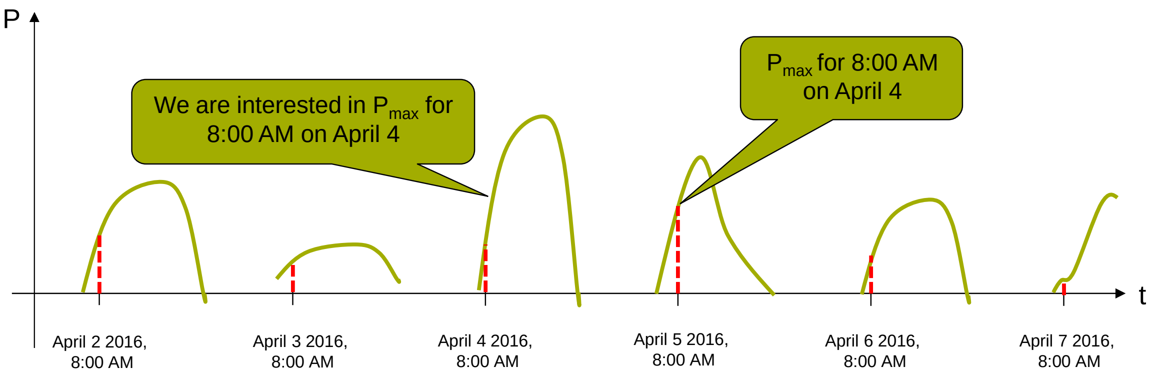

Fig. 4: Moving window approach for maximum power computation

3.3 Attenuation Computation and Spatial Interpolation

Considering the fact that various meteorological conditions may reduce the amount of power being generated by a certain percentage and by learning the maximum expected power production for each station at a specific point in time (see section above), we derived a specific attenuation function for each station along the year. Attenuation is defined as the percentage of power being lost, due to meteorological conditions. An attenuation value of 0% means that a specific station generates the maximum expectable energy for this point of day and time, taking into account the station-specific non-meteorological factors, such as date and time, efficiency, panel-condition and local topography. An attenuation value of 100% means that this station produces no power at all. In order to determine the current attenuation percentage, a ratio between the measured and maximum expectable power at a specific point in time has to be built. The attenuation accounts for all the influences and the afore-mentioned parameters – apart from meteorological factors - and therefore makes different stations comparable:

$$\text{Attenuation } A\ [\%] = \left(1 - \frac{P}{P_{max}}\right) * 100$$

where P is the measured power at a specific point in time and P_{max} is the maximum expectable power at this point in time under clear sky conditions (see 3.2).

Then, we generated daily-based, seasonal-based, and station-based, diagrams for plotting the actual power that is being produced by a specific station, maximum power at each point in time, and the attenuation percentage (see Figure 5).

Then, three scenarios have been considered, in order to observe various correlation aspects. The first one is to indicate the meteorological influence, such as cloud coverage and its impact on the power production. Thus, we decided on two consecutive dates where one is cloudy and the other one has clear sky conditions (see Figure 5). It can be noted, that there is severe power drop on the cloudy day, compared to the clear sky day. However, there might have been other meteorological factors that have played a role also. In the second scenario, we checked for spatial auto-correlation between nearby stations, in order to observe for certain meteorological phenomena, such as cloud movement, that occur over a certain region (see Figure 6). It can be noticed that the power curve is

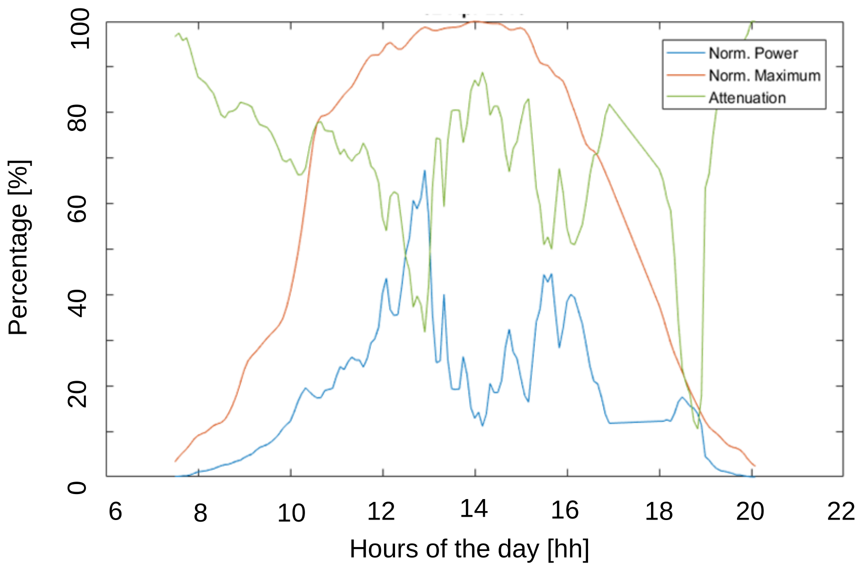

Fig. 5: An example for actual power production, maximum power, and attenuation percentage for Pasij station on April 2nd 2016. Example using PVOutput

almost the same for both nearby stations, because they do get exposed to similar conditions at this point in time. The last scenario was studying the seasonal effect and its correlation to the amount of power that can be produced by a certain station (see Figure 7). In that last scenario (see Figure 8), we can study seasonal effects of photovoltaic power production.

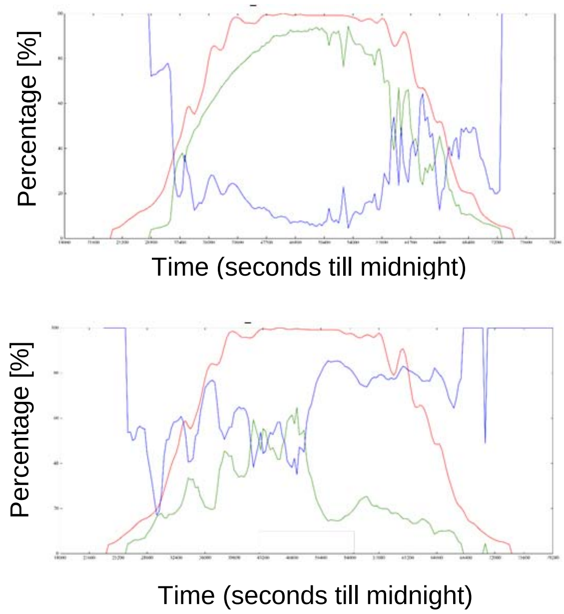

Fig. 6: Clear Sky vs Cloud for Moorstenweg station on 9th and 10th of May consecutively – examples using PVOutput data. The green curves differ substantially.

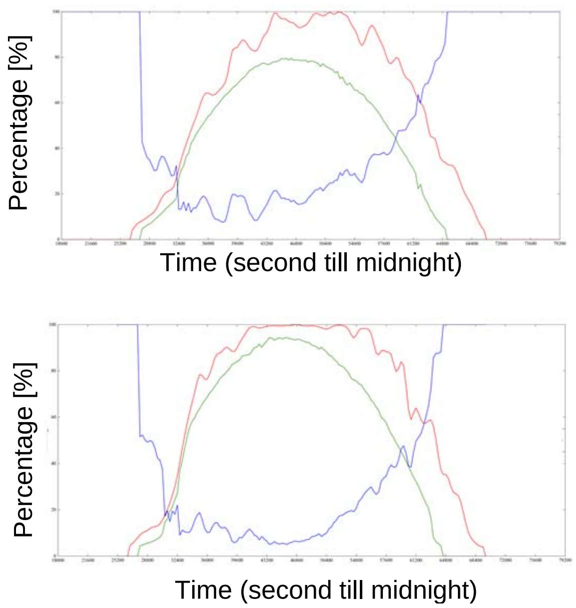

Fig. 7: Spatial auto-correlation on Fregatstraat & Moorsterweg on March 17th 2016 consecutively using PVOutput data. The green curves have nearly the same shape.

Legend

Normalised actual power

Smoothed normalised maximum power

Smoothed attenuation percentage

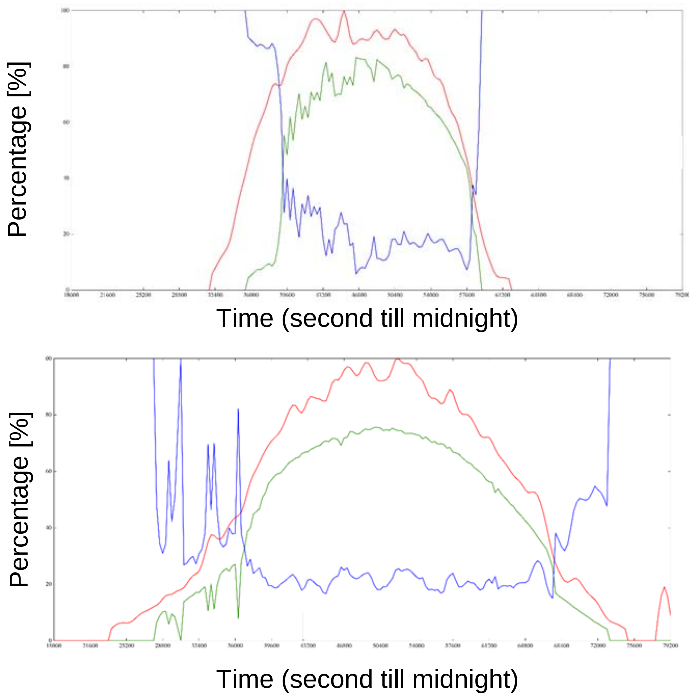

Fig. 8: Seasonal effect for Fregatstraat station on January 25th and July 18th 2016 consecutively using PVOutput data

Afterwards, a spatial interpolation between the stations has been performed, in order to deduce attenuation fields, which show spatial distribution and the change of attenuation throughout the day, month, and year for the whole area of study (see Figure 9). The spatial interpolation was carried out using the natural neighbours interpolation algorithm (SIBSON 1981), because of it creates a smooth field, whereas the observations at the known data points are preserved.

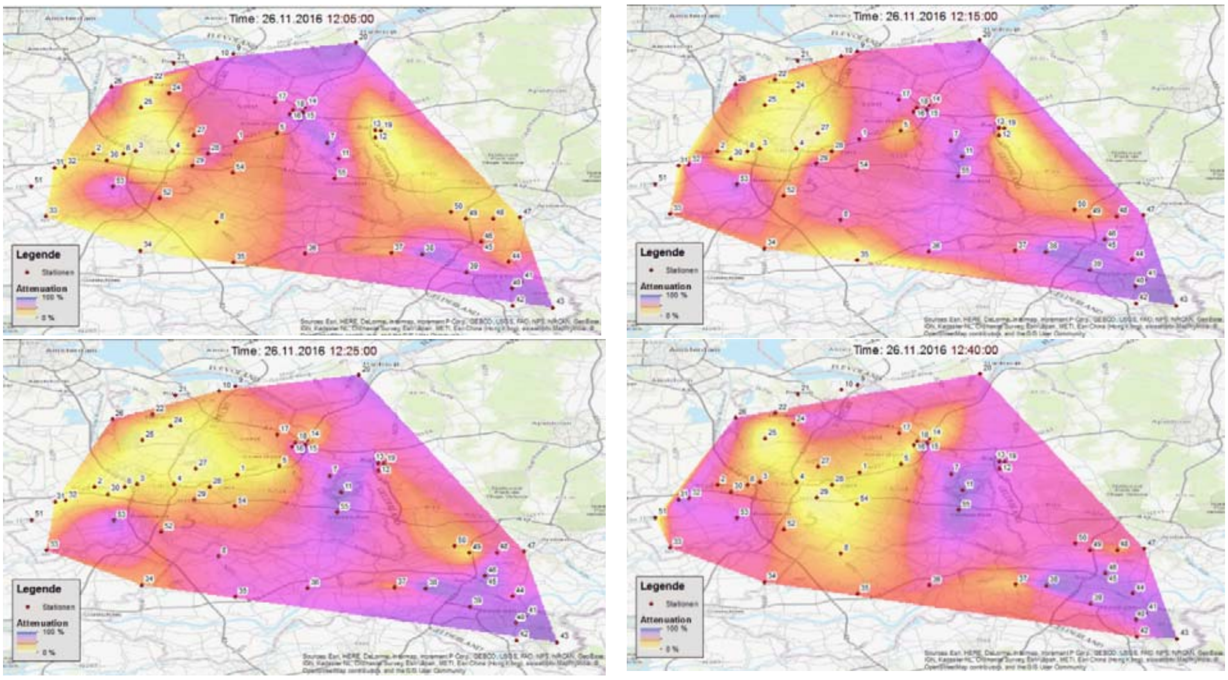

Fig. 9: Attenuation field of four consecutive points in time in the Utrecht area: Top left 12:05 pm, top right: 12:15 pm, bottom left: 12:25 pm, bottom right: 12:40 pm. Data source: PVOutput

The attenuation field now allows to predict the feed-in power for a station installed at an arbitrary location within the extent of the field and for a specific point in time. This use case is related to a real-world problem, that energy companies face. Whereas, only few stations have smart meters installed, the energy companies need to predict feed-in power for all stations connected to their network. Thus, the attenuation field can be used to predict the potentiality of power production for stations with no smart meters installed, by extracting the attenuation values for the geographic locations of the power stations from the field. The amount of power to be produced is then to be computed from the extracted attenuation values. In order to do so, the maximum power that is ought to be generated from this particular panel still has to be known.

3.4 Meteorological Data Acquisition

Acquiring meteorological data for the same spatial region as of the photovoltaics stations is crucial. Also, the time span and temporal reference system for the various meteorological attributes has to match with that of the power production readings. Hence, within the scope of this project, we obtained satellite-based meteorological data for our test region with a spatial resolution of

3x3km and a temporal resolution of 15 minutes from the company METEOBLUE[3]. The obtained data varied from cloud coverage and temperature to Global Horizontal Irradiance (GHI) and Diffuse Horizontal Irradiance (DIF). In order to prepare for correlation with power production data, the meteorological data had to be geo-referenced. Then, as a last step before correlating the meteorological readings with the power production readings, both of those readings had to be transformed to the same time base (UTC offset of one hour was chosen).

3.5 Finding a correlation function

By analysing the historic observations and meteorological data, a correlation function between the attenuation and the various meteorological factors derived from satellite observations, such as cloud cover and solar irradiance could be determined. The derived correlation function, allows to predict the attenuation field for a specific future point in time from weather forecast.
As a first step of the correlation process, geo-location and date-time of the power production, attenuation and meteorological data were used for joining the readings in a common database table. Then, scatter plots were produced to examine for potential correlation. It is to mention, that night time was excluded from our study, since it gives us a false indicator of strong correlation where readings from power production as well as solar irradiation are zero.

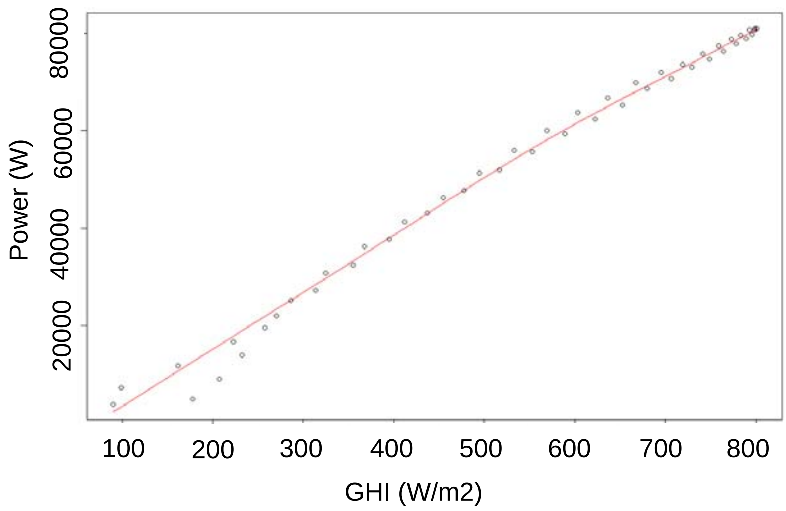

Fig. 10: Scatter plot between GHI & power for Spraitbach station in August 24th 2016. Data source: Power production: EnBW ODR; Meteorological data: Meteoblue

By analysing Figure 10, a mostly linear correlation between the GHI (W/m2) and the produced power (W) for a specific station can be observed. A linear regression function was then generated and checked thoroughly. In addition to that, we inspected the correlation between the attenuation and GHI. However, a linear regression in that case was not the best fit (see Figure 11). Thus, we generated a polynomial regression function of the 5th degree to correlate GHI with the attenuation percentage.

[3] https://content.meteoblue.com/

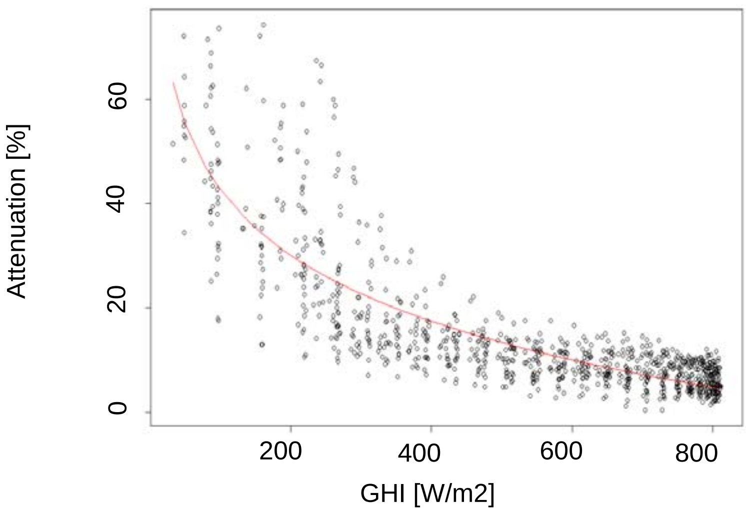

Fig. 11: Scatter plot between GHI & attenuation for all the stations on September 24th 2016. Data source: Power production data: EnBW ODR; Meteorological data: Meteoblue

By examining the correlation for longer periods of time, we concluded that there is a higher correlation between the GHI and the attenuation, than between the GHI and the power production, specifically under non-clear-sky-conditions. Hence, as a last step before forecasting, we extended our correlation over a 12-months timespan to assess the goodness of fit of the model. Furthermore, we studied the correlation separately for each season, in order to evaluate the fitting model and determine if the correlation varies from season to season.

As a result, of that, the goodness of the fitting model across the whole year is estimated to be 0.74 R squared. The fitting model operates during autumn with 0.85 R squared and the least during summer with 0.63 R squared. Additionally, it was found out that by taking into account 12 months of historical data, a linear regression equation could be deduced, which is in contrast to the results when we take only small sample data as seen in Figure 11.

We plotted the diverse meteo-rological aspects that we have obtained, such as cloud coverage and temperature against the attenuation to examine if there is a noticeable correlation between them (see Figure 11). However, temperature did not play a significant role in the amount of power being generated. As for cloud coverage, while it plays a role in the amount of solar radiation received on the earth surface, as we explained in the introduction, there was no direct correlation between the power production and the cloud coverage. This is because, in the meteorological data available, cloud coverage is expressed as a percentage representing the fraction of a 3×3 kilometres tile covered by clouds with 15 minutes temporal resolution. This means, that clouds can be formed within this time period without being detected. Also, different formations of clouds react to solar radiation differently as earlier discussed in section 2.2, and cannot be discriminated in the meteorological data available. Based on the regression model that has been generated in section 3.5 and by feeding GHI as input to the model, we could predict the attenuation percentage on that particular day. As demonstrated in Figure 13, the blue line in the middle is the estimated fitting line, while the red and the green ones are the lower and upper boundaries consecutively of the 95% confidence interval. Thus, the correlation function enables us to predict the attenuation field for a specific future point in time from weather predictions. Moreover, it allows us to predict the feed-in power for a specific station and for a specific future point in time from the predicted attenuation field, by reversing the attenuation formula:

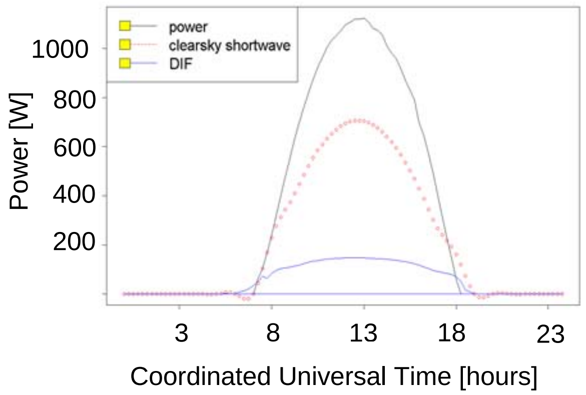

Fig. 12: Meteorological factors vs photovoltaics power production for a clear sky day for Altheim (Alb) on September 14th 2016. Data source: Power production data: EnBW ODR; Meteorological data: Meteoblue

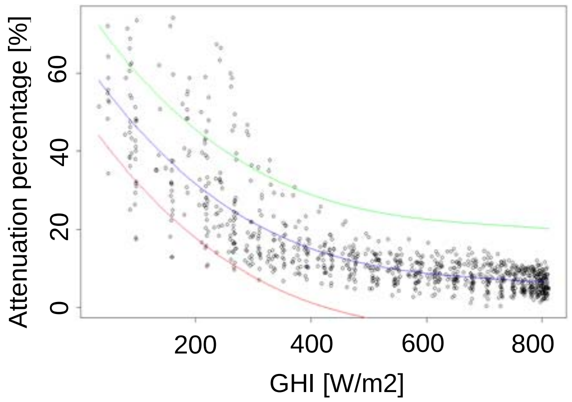

Fig. 13: Estimated attenuation percentage for Schrozberg on July 11th 2016. Data source: Power production: EnBW ODR; Meteorological data: Meteoblue

$$\text{Power } [W] = \left(1 - \frac{A[\%]}{100_{max}}\right) * Pmax[W]$$

Validation

In order to evaluate the estimation, we divided our data into training data and test data. By taking into account the seasonal influences, we used training data from different seasons, in order to be able to have a proper estimation. Validation in our approach went through different steps. In a first step the acquired data was validated. In order to determine if the power production and meteorological data are in the same time zone, we generated diagrams for various meteorological factors against power (see Figure 12). It can be clearly observed that the power production (W) and the clear sky shortwave (W/m2) do overlap and there is no time lag. Also, it can be clearly observed that the given day has clear sky conditions.

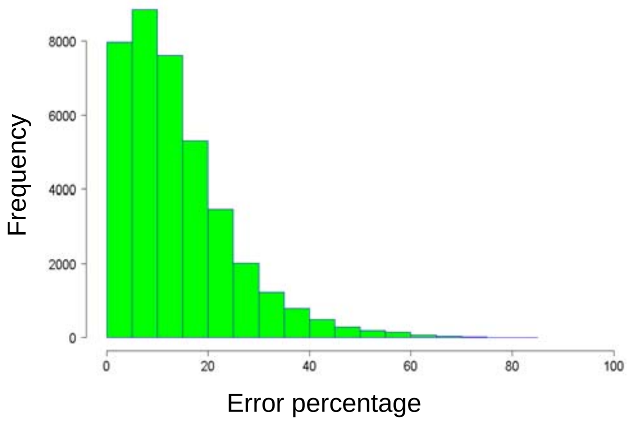

Fig. 14: Histogram showing the frequencies of the absolute differences between measured and predicted attenuation in Winter. Data source: Power production: EnBW ODR; Meteorological data: Meteoblue

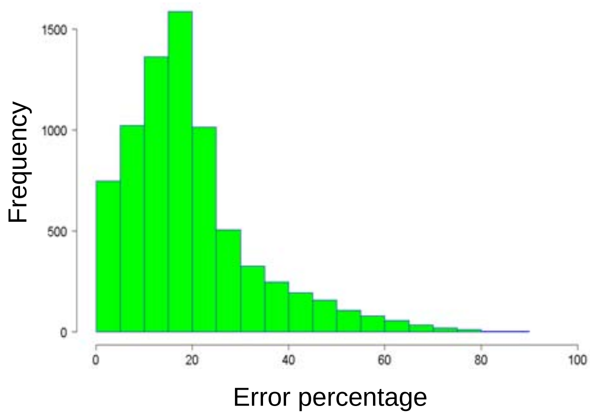

Fig. 15: Histogram showing the frequencies of absolute error percentages for power estimation in Spring. Data source: Power production: EnBW ODR; Meteorological data: Meteoblue

In order to validate the prediction model that has been created in section 3.5, we extracted a table containing the predicted attenuation, the actual measured attenuation, and the attenuation difference of each of the 812842 data items. In addition to that, we computed the estimated power and compared it to the actual power reading, in order to measure the power difference and generate the error percentage. We then generated histograms for the attenuation difference across different seasons to evaluate which seasons have higher correlation than others (see Figure 14). By observation, we can conclude that in winter, most of the attenuation differences lie between 0% and 20%. As a last step, the table below was created to provide statistical description of the validation.

Tab. 1: Statistical description of the validation results: differences between measured and predicted power (absolute percentage)

Season	Mean	Median	Standard deviation	Min	Max
Winter	31.3	27.9	21.3	0.0	93.3
Summer	19.9	14.5	16.9	0.0	91.7
Spring	23.0	18.6	17.8	8.0	91.0
Autumn	19.4	17	13.5	0.0	86.0
All seasons	25.2	20.1	19.6	8.0	93.3

4 Conclusions & Outlook

In this paper, the correlation between photovoltaic power production and heterogeneous meteorological and topographical aspects have been studied. Two approaches have been investigated, an analytical-based approach and an observation-based approach. In the first approach even though it gives a clear depiction of the amount of solar irradiation received on the Earth surface, the data sources required for these computations are generally not available. Additionally, it does not take into account the local topography and panel-specific parameters, such as efficiency and condition and its impact on the amount of power being produced by the solar panels. Furthermore, there is a plethora of domains that do play a role in the amount of power that is being produced, and predicting power values requires deep knowledge in all these various domains.

In the observation-based approach, we studied the actual power that is being produced by solar panels and its correlation to meteorological factors. This allowed us to take into account all the influences on the solar panel by analysing the actual power that is being produced. Hence, by computing the attenuation factor, as well as normalising the power, we could compare different PV systems and overcome station-specific characteristics that might be hard to obtain in an analytical approach. By using historical data for training our system, we could then deduce a correlation function between GHI and attenuation that counts for all these factors and their influence on the power production. We could apply this function for predicting power production from GHI forecast. In addition to that, the attenuation field that has been created enables us to do the prediction also for stations that do not have smart meters installed and also to locate solar panels, in order to generate the most power.

The accuracy of the prediction was determined by a cross-validation approach showing acceptable results. However, taking into account the use case of decision support for operators of local distribution networks, the spatio-temporal resolution of the weather data available today is still insufficient. This leads to a potential future research area, trying to perform now-casting of energy production from smart meter readings of georeferenced stations by applying methods like Gaussian Markov random fields. In this future approach, the attenuation fields could be extrapolated, which would have the strength to overcome the necessity of weather information in the prediction process.

The research presented in this paper was carried out in the project VerNet-LEM funded by the Bavarian Ministry of Economic Affairs in cooperation with the company AED-SICAD, based on a geospatial database system with data from EnBW ODR.

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