Short-term photovoltaic power forecasting using cloud tracking methods

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Abstract—Concerns about greenhouse gas emissions lead to government incentives and lower prices of photovoltaic (PV) solar panels which in turn causes larger integration of renewable energy sources into the electric power system. Considerable integration of PV power generators into the power grid threatens power system secure operation due to unpredictable power fluctuations following cloud cover variations. Ramp rates of PV power plants can be in the order of seconds to minutes therefore appropriate spinning or non-rotating reserves must be provided to cover production variations (in both direction positive and negative) and to achieve power system balance and economic operation. Having at disposal accurate PV production short-term forecasts, a reduced volume of operating reserves would be necessary with the added possibility to engage slower-ramping units and smaller amount of energy storage facilities. Solar forecasting, in short spatial and time scales, such as 0-1000 m and 0-30 min, is a challenging task for numerical weather predictions using satellite images due to technical restrictions (long intervals and low-resolution satellite images). Hence, in recent time, images from ground-based sky cameras are more and more used. Therefore, methods utilizing ground-based sky images successfully deal with considerable cloud spatial and temporal variability. In this paper an overview of existing methods for short-term solar forecast will be presented following with research on how to improve them in terms of forecast system equipment cost and accuracy.

In the proposed research low-cost security cameras will be used to capture pictures of the sky providing input data for very short-term solar forecast at several different temporal scales.

Keywords—short-term forecast, cloud tracking, renewable energy, PV integration, power system control

I. INTRODUCTION

The global demand for renewable energy integration to the power grids shows the importance of economic and technological issues associated with growing levels of flat-panel Photo-Voltaic (PV), Concentrated Solar Power (CSP), and Concentrated PV (CPV) penetration into the power grid. There are many concerns which arise from the variable nature of the solar resource, seasonal deviations in production and load profiles, the high cost of energy storage, and the balance between grid flexibility and reliability. As a result, solar plants are often backed by ancillary generators for periods of high variability, which increases the capital and operational costs of solar generation. For Independent System Operators (ISOs) or equivalent grid balancing authorities to be able to successfully integrate increased levels of solar power generation while maintaining reliability, accurate solar forecasts over several time periods are required. As solar penetration grows for the purposes of grid regulation, load-following production, power scheduling and unit commitment solar forecasts on multiple time horizons become increasingly important. Short-term, intra-hour solar forecasts are particularly useful for power plant operations, grid balancing, real-time unit dispatching, automatic generation control (AGC) and trading. Forecasts for longer time horizons are of interest to utilities and ISOs for unit commitment, scheduling and for improving balance area control performance. For planning operational and balancing needs of both the distribution and the transmission grids, a spectrum of solar forecasts is required. Solar forecasting is therefore crucial for the integration of ever increasing level of solar penetration into the grid because it improves the quality of the energy delivered to the grid and reduces the ancillary costs associated with weather dependency. Driving motivation for the development of a complex field of research that aims at producing better solar forecasting capabilities for the solar resource at the ground level and for the power output from different solar technologies that depend on the variable irradiance at the ground level has been the combination of these two factors (better energy quality through information that is capable of lowering integration and operational costs). Solar, wind and load forecasting have become integral parts of the so-called ‘smart grid concept’. To date, high-fidelity, robust solar forecast systems that work for widely different microclimates remain evasive. The problem is of great complexity due to the non-linear and chaotic effect of cloud motion on solar irradiance at the ground level. By aggregating diverse areas of knowledge such as atmospheric physics, solar instrumentation, machine learning, forecasting theory and remote sensing in its quest to better predictive skills, a number of promising approaches have been developed in the past few years, and the incipent research field of solar meteorology for renewable generation has grown considerably. This work
presents an overview of the forecasting methods for solar resourcing and solar power generation, as well as the theoretical basis for the most promising methods, and a discussion on their effectiveness for operational use [1]. For as long as significant amounts of these renewable energy resources have been connected to the electric grid the forecasting of power generated by variable energy resources such as wind and solar has been the focus of academic and industrial research and development. The progress of forecasting capabilities has largely followed the penetration of the respective resources, with wind forecasting having achieved a more mature state-of-the-art compared to its solar equivalent. Still, in the last 5 years, there has been substantial and material progress in the state-of-the-art of solar forecasting. Numerical Weather Prediction (NWP) models became more sophisticated in assessing cloud interactions with aerosols; infrared satellite imagery allowed discovery of pre-sunrise cloud formations; advanced data processing methods such as deep machine learning became increasingly accessible; probabilistic forecasts began replacing deterministic ones; and, in balancing areas with high PV penetration, solar forecasts are now used operationally.

The problem of high volatility of PV power plants can also be mitigated by using energy storage techniques e.g. batteries to store and replace energy production from PV power plants in the event of cloud interference. However, large, system-sized battery storage facilities, now, are predominantly in the test-phase mainly due to economic reasons.

II. PHOTOVOLTAIC FORECASTING AND ITS LINK TO SOLAR FORECASTING

Different uses of PV forecasts require different types of forecasts. Forecasts may apply to the aggregation of large numbers of systems spread over an extended geographic area or refer to a single PV system. Forecasts may focus on the output power of systems or on its rate of change (also known as the ramp rate). Accordingly, different forecasting methods are used. Data from weather stations and satellites, PV system data and outputs from numerical weather prediction (NWP) models are some of the tools and information which forecasting methods depend on. Forecasting methods can be broadly characterized as physical or statistical. The physical approach uses solar and PV models to generate PV forecasts, whereas the statistical approach relies primarily on past data to “train” models, with little or no reliance on solar and PV models [2], [3].

III. THE IMPORTANCE AND SOURCE OF SOLAR FORECASTING

The solar industry has started paying attention to solar forecasting as an answer to increasing number of installed utility-scale PV plants and a growing need for predictable energy generation. The reasons behind this are:

- Solar generation is variable in nature.
- Being able to predict solar output will make the electric grid work better under variable conditions.

Essentially, solar forecasting provides a way for grid operators to predict and balance energy generation and consumption. If the grid operator has access to a mix of generating assets at their disposal, reliable solar forecasting lets said operator best optimize the way they dispatch their controllable units. The applications of a solar forecast largely remain the same even though capabilities vary from grid to grid. The first component which makes up solar forecasting tools is the weather model. As already mentioned, solar generation is variable by nature. Cloud cover causes this variability by impeding sunlight from hitting the solar panels. If one can predict the weather with a great amount of certainty, he is already one step ahead. The second factor in a solar forecast is the model which uses weather model to predict utility plant power output. In predicting the performance of a PV plant under environmental conditions like irradiance, wind speed, temperature and relative humidity the solar industry uses these “PV simulation” models. PV simulation models also incorporate important plant behavior such as tracking, which can predict the orientation of the PV panels mounted on single or dual-axis tracking hardware.

Using mechanisms like imbalance/penalty charges and reliability curtailment to pass on the costs of grid imbalance to the market has become a common practice for grid operators. In the former example, imbalance charges are assigned to deviations from forecasted production to allow the market to replace missing energy. These types of penalties have existed with controllable generation to assure reliable power delivery to the grid operator but are now becoming an option for renewable plant operators that see economic value in using forecasts to schedule power. Accurate forecasting is definitely required to take on that type of additional risk. The operator can step down solar production to the forecasted amount to force grid balance. If a plant owner relies on poor solar forecasts stepping down solar production can be costly [4].

IV. FORECASTING METHODS

In general, forecasting methods fall into two categories. Physical methods input weather data (e.g., temperature, pressure, surface roughness, and obstacles) into numerical weather prediction (NWP) models to create terrain-specific weather conditions, which can after be converted to energy production. Statistical methods use historic and real-time
generation data to statistically correct results derived from NWP models. Persistence forecasting is a simple statistical method that assumes current generation levels will remain unchanged in the very near future. To evaluate more advanced methods, persistence forecasts are often used as a benchmark or reference model [5], [6].

Short-term solar forecasting methods can also be classified into four groups. The first group uses a statistical approach which is based on data-driven formulation using historical measured data. The second group relies on artificial intelligence (AI) which utilizes advanced AI techniques (e.g. artificial neural networks) to construct solar forecast. However, some authors classify AI approaches into the first group i.e. into statistical approach. Physical models, which are based on numerical weather prediction or satellite images, are classified as the third group and finally, the hybrid approach, that combines the three methods represents the fourth group.

Gathering data for the forecasting can be achieved through different methods, which in turn results in different data types being collected. Looking at the satellite images as an example, it is observed that because of their low resolution they are used to forecast production on a larger geographical area, e.g. an entire region. That data is used to forecast production a few hours in advance. Data collected on the solar panel location by a camera (Whole sky imagery) is used to forecast production on a much smaller area, but results in substantially higher precision and reliability of the forecast. A downside of forecasting solar production on a smaller area is that such forecasting is valid for a short time span which means that overshadowing of panels can be forecasted 10 minutes in advance at best. The numerical analysis uses a mix of data collected by Geostationary satellite imagery and sensors set up on the geographical area for which we are creating a forecast. Numerical analysis is mostly used to forecast one day ahead of time or for a larger time span.

Different solar forecasting techniques and their characteristics are shown in table 1.

<table>
<thead>
<tr>
<th>Technique</th>
<th>Spatial resolution</th>
<th>Spatial extent</th>
<th>Suitable forecast horizon</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Whole sky imagery</td>
<td>10 to 100 meters</td>
<td>0 – 10 km radius</td>
<td>1 - 10 min ahead</td>
<td>ramps, regulation</td>
</tr>
<tr>
<td>Geostationary satellite imagery</td>
<td>1 km</td>
<td>Region</td>
<td>4 – 6 hours ahead</td>
<td>load following</td>
</tr>
<tr>
<td>Numerical weather prediction</td>
<td>2 to 50 km</td>
<td>Worldwide</td>
<td>one day ahead and further</td>
<td>unit commitment, regional power prediction</td>
</tr>
</tbody>
</table>

An overview of the most important aspects of methods used for solar forecasting and the most influential factors for the correct choice among them is shown in table 2.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Whole sky imagery</td>
<td>Used to forecast from real time (nowcast) up to 1-10 minutes ahead by applying image processing and cloud tracking techniques to sky photographs. The highest spatial resolution is achieved, which is the reason why this technique is most precise, but it can not be used for long-term forecasts.</td>
</tr>
<tr>
<td>Geostationary satellite imagery</td>
<td>Satellite imagery is used to predict near-term cloud motion from geostationary satellites. Satellite forecasts are dominant in the short-term, typically up to 4-6 hours ahead, and are the best method to detect small clouds.</td>
</tr>
<tr>
<td>Numerical weather prediction (NWP)</td>
<td>Physical relationships are used to predict large-scale atmospheric trends. NWP models are good for longer (one day ahead and further) forecast horizons but they have a limited capability to predict smaller clouds.</td>
</tr>
</tbody>
</table>

V. ARTIFICIAL INTELLIGENCE MODELS

Theoretically, multilayered feedforward neural networks (NNs) can be universal approximators with any degree of accuracy and have tremendous capability to approximate any nonlinear mapping [7].

![Fig. 2. Typical structure of a feed-forward neural network.](https://source.unsplash.com/random/300x200)

As an alternative to conventional approaches, artificial neural networks (ANNs), shown in the figure 2, have been successfully applied to solar forecasting [8]. A short-term solar irradiance forecasting model has been built based on a back-propagation (BP) neural network and time series that avoids over-fitting and is able to reach accurate solar irradiance prediction [9]. Multilayer Perceptron (MLP) is utilized to predict the solar irradiance on the basis of 24 h realistic data from Trieste, Italy [10]. The proposed MLP-model provides references to grid connected photovoltaic plants (GCPV) and enhances the control algorithms of charge controllers. Considering the aerosol index as an additional input parameter to forecast the next 24-h PV power outputs, a PV [11] power forecasting model based on BP NN is proposed. Experimental results demonstrate that the proposed approach performs better than traditional ANN methods that consider temperature, humidity, and wind speed. In [12], a large-scale PV plant located in southern Italy, three distinct ANNs are established to fit three typical types of days (sunny, partly cloudy, and overcast) for short-term forecasting of the power generated in said plant. ANN is applied to small solar panel to determine the highest representative of solar
prediction horizon for small scale solar power system applications [13]. Bayesian neural network (BNN) is proposed for estimating the daily global solar irradiation with the input parameters of air temperature, sunshine duration, relative humidity, and extraterrestrial irradiation, which has superior performance comparing with classical NN and empirical models [14]. Wavelet based ANN approach is proposed to forecast solar irradiance in Shanghai, indicating that more precise forecasts can be produced due to the application of wavelet [15].

For the making of the AI model the open source software library called TensorFlow is being used. TensorFlow is used for its high performance numerical computation and its flexible architecture allows easy deployment across a variety of platforms. TensorFlow is originally developed by researchers and engineers from the Google Brain team within Google’s AI organization, it comes with strong support for machine learning and deep learning and the flexible numerical computation core is used across many other scientific domains.

VI. DESIGN OF THE ARTIFICIAL NETWORK

A. Data collection

Testing grounds (shown in the figure 3) utilize security camera which continuously record the sky above it and send the data to the computer for the analysis. Testing grounds also contain pyranometer which records solar radiation flux density (W/m²) from the hemisphere above. Recorded parameters are used as input data for the model which uses said data to predict cloud movement as well as their shadows which impact the solar panel production. For solar panel production forecasting model to work, training of an Artificial neural network is required. In classic programing, source code is created, in the case of AI source code does not exist. There exists only data which is used for training and settings which we define the neural network. Accuracy of a neural network depends highly on input data which the network is trained with and upon settings which are setup during the network creation. For a more successful training of a neural network, large quantities of neural network input data from the pyranometer output are needed. Because recording of atmospheric changes in a single day can be recorded only in limited time span throughout the day, an absurd amount of time would be needed to collect sufficient input data. That is why a relative Sun movement simulation over the hemisphere and realistic cloud movement simulation are needed. In such simulation, relatively short time is needed to create sufficient input data which neural network uses for training. When solar panel production forecast using the simulation input data reaches 95% accuracy, said network can be used in real life situations [16].

B. Preparing input data

To achieve the most efficient operation of the neural network, it is necessary to prepare the input data in such a way that the information becomes more simple and compressed. AI can train faster if its input data is simpler. First, we need to turn the video from the camera into a series of photos. It is necessary to select the factor with which we will speed up the recording and reduce the number of images being processed. Real-time cloud motion photography would consist of too much unnecessary data and would be too big for quick processing. We need a recording of the cloud that consists of a picture that is being taken every ten seconds to one minute. This recording contains much less data than a real-time recording and still contains a lot of unnecessary data. Pictures that are contained in the video need to be converted into the simplest image format. Each pixel represents only one bit if the pixel is black or white. In this way, the amount of information processed is greatly reduced. In addition, the security camera we use to capture the video records at a resolution of 1920x1080 pixels which is too high for our needs. Video resolution can be drastically reduced, yet holding high enough resolution to predict cloud motion. Figure 4 shows the quality reduction process of a single video frame. In the photo marked with a) the image of the original quality is visible, in b) the same image with reduced resolution is given, while in c) the result of applying black-and-white two-tone transformation is visible. The picture shows that the sun has an effect on the image, in fact, the image does not clearly show the position of the sun in the relation to the other clouds [17].

![Fig. 3. Testing grounds](image)

![Fig. 4. The quality reduction process of a single video frame.](image)
C. Relative motion of cloud and Sun

From the footage of the sky, it is easily observable the clouds moving above the place where the camera is set. In order to know the position of the Sun in the sky, we need information on the geographical position of the measuring equipment. For accurate solar forecasting, we do not need information on the height of the clouds, only the time for this cloud to reach the point between the place where the measuring equipment and the Sun are located. Thus, the system does not need the absolute speed and movement direction of each cloud, but only the angular velocity of the clouds in relation to the position we measure. Clouds at higher altitudes must move faster to move at the same angle as low-altitude clouds moving slower.

It is necessary to predict the motion vector of each cloud and ignore all the clouds whose motion vector does not go in the direction of the current position of the Sun. Then the clouds that could make the shadow at the measuring site determine the time it will make that shadow.

VII. CONCLUSION

Artificial neural network (ANN) modeling offers improved nonlinear approximator performance and provides an alternative approach to physical modeling for irradiance data when enough data is available. ANNs are generic non-linear approximators that deliver compact solutions for several non-linear, stochastic and multivariate problems. Like regressive methods, ANNs perform well in both data-rich/poor environments and are not typically temporally limited. These techniques have successfully modeled irradiance on intra-hour to yearly time horizons. By using artificial neural network and relatively cheap security cameras, solar forecasting becomes significantly simpler. Afore said permits usage in a greater number of systems and easier renewable resources integration into the existing power grid. Solar forecasting assists grid operators significantly to predict and balance energy generation and consumption. With increased integration of renewable resources in the power systems and with increasing prices of traditional energy sources needed for peaking power plants to work, solar panel production forecasting data becomes more valuable.

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