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Online 3-h forecasting of the power output from a BIPV system using satellite observations and ANN

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ABSTRACT

Photovoltaic (PV) systems are the reference technology in the solar-based electricity generation market. Rapid changes in solar radiation can alter PV power output; for this reason, knowledge of future atmospheric scenarios helps system operators to control the PV production in advance, reducing the instabilities that the electrical grid may suffer in electricity integration, and managing the auto consumption power output. With this is mind, we present a model to forecast (up to 3 h ahead) the building integrated photovoltaic (BIPV) system's power output, which is installed on the roof of the Solar Energy Research Center (CIESOL), Almería, Spain. The satellite images have been combined with Artificial Neural Networks (ANN) primarily to predict power output using the lowest number of input variables. The results, which can be considered highly satisfactory, demonstrate the ANN's prediction accuracy with an normalized root mean square error for all sky conditions of less than 26%, and with practically no deviation. We demonstrate how beneficial matching of two already proven techniques can bring about spectacular results in energy generation prediction for the BIPV system.

1. Introduction

The growing human population is causing an ever-increasing demand for conventional energy resources, which results in environmental pollution issues. Renewable energies offer a viable and potent solution to counter the effects of this problem since they are pollution-free, inexhaustible and affordable. Amongst the renewable energy resources available today, PV is the one favoured by most utility companies. The advantages of such technology encourage the development of micro-grid PV systems. Micro-grids involve supplying electrical power from local renewable energy resources such as a BIPV system. If the power generated exceeds consumption, the surplus energy can be transmitted to other areas in order to avoid using power from traditional sources.

Most grid-connected PV systems employ maximum power point tracking (MPPT) control systems to ensure that the PV panels operate at a point that produces maximum power generation. This operation point is known as the maximum power point (MPP). Nonetheless, maintaining a PV array near its MPP is a difficult feat when atmospheric conditions lead to variations in temperature and solar irradiance. Rapid changes in solar irradiance can confuse MPPT trackers and can potentially cause a PV array to operate at voltages outside the inverter's DC operating range if the PV system has not properly designed. Some strategies to avoid this are related to the optimization of the whole system [1–3] or starting from the single components of the plant [4–6]. When solar irradiance increases rapidly because of clouds that quickly appear and disappear (cloud transients), the MPPT control system continues to decrease the PV array operating voltage according to the previous low radiation values. In some cases MPPT controllers drop PV operating voltages below the inverter's DC voltage operating range, causing the inverter to shut down and stop supplying power to the power system. As a result of such a scenario, large step changes in PV output power can take place due to simultaneous inverter tripping. These inverter-tripping-induced PV power changes often exceed the size and severity of any cloud-induced PV power fluctuations [7].

In BIPV systems, rapid solar irradiance changes have a significant impact, becoming more serious when the PV system penetration is high since the control system has to deal with sudden surpluses or drops in power production [8]. One way to address this problem is to forecast the BIPV system's power production. Consequently, eventual drops or surpluses in power production can be predicted and compensated for by, for example, balancing PV use with other kinds of energy systems. PV system power production can be directly or indirectly forecast. When indirectly forecast, a variable related to the PV system's power production, such as the incident radiation, is first forecast and then, using appropriate models, the power production itself is calculated.

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Regardless of the approach and application, currently developed state-of-the-art incident radiation forecast methods are still unable to provide high accuracy radiation forecasts for a wide range of weather patterns. As a consequence, forecasting PV system power production based on radiation forecasting is directly affected, as it incorporates the errors of the latter [9]. Therefore, further method improvements are urgently required to obtain high accuracy forecasts.

Satellite images have been used in this way to estimate the solar resource for different locations; this is done by quantifying the amount of solar radiation reaching the ground. Global horizontal irradiance (GHI) were estimated using hourly ground measurements over a year period for a location in the USA [10], for which the relative root mean square error values were 21.5% for global irradiance, and the relative mean bias error values were −4.9%. One of the most important models for estimating solar radiation under clear sky conditions is the Heliosat-2 method, developed as part of the European Solar Radiation Atlas [11].

Current state-of-the-art techniques for predicting PV power output mainly include a large-scale PV plant [12], where they are used to understand and characterize PV variability from the system operators' and planners' perspective to manage variability at different levels of PV penetration. Utility operators require a ten-minute warning to bring spinning reserves on-line. Besides ramp rate issues, an accurate forecast within a solar-aware smart grid can also help to prevent keeping industrial-scale loads such as water pumps on when not needed [13]. Accordingly, based on temporal series, PV distribution was predicted using complex-valued neural networks where only similar days were used for the results [14]. Under all sky conditions, the BIPV was estimated using a statistical model to obtain GHI, and block-object parameters [15]. A daily PV prediction was also developed for two different locations: for the first emplacement, in south-western United States, the methodology achieved a forecast ability of 13–23% over a persistence model (such as a temporal series) [16]; whereas the second model was developed for a plant located in Spain, where the authors combined non-parametric models and several meteorological variable forecasts from a Numerical Weather Forecast model [17]. Furthermore, hourly PV values were estimated using weather observations for the purpose of electricity purchases from the PV plants [18]. Similarly, numerical weather predictions and multi-linear regressions were employed to obtain the PV power output of a PV plant in Germany [19]; in this work, the authors asked for more PV forecast studies using meteorological variables.

Machine-learning techniques are another group of supporting methodologies related to solar radiation estimation. In these, ANNs are a consolidating tool able to learn key information patterns within multidimensional information domains. Over the last few decades, ANNs have attracted particular attention from system modellers. Recently, a lot of effort has gone into developing and testing different direct and indirect methods of PV power output forecasting. A number of researchers have already demonstrated ANN application in PV power output [20,21]. Because of abstraction neural network capability, PV prediction systems are including this technique, and obtaining highly successful results. Some authors state the importance of having future predictive radiation and cloud control for PV systems. As seen, artificial intelligence is playing an important role in the PV forecasting [22]. One of the relevant tasks in the application of machine learning techniques is to identify the optimal inputs of the method [23]. In that sense, 5 U.S. locations were considered for predicting the hourly PV output, obtaining that global irradiance and ambient temperature were the most important variables in these areas [24]. In other study, ambient temperature, dew point, humidity and wind speed served as input of temporal series to predict the PV generation for identifying better the optimal periods where purchasing electricity [25]. In the PV prediction field, the most widespread forecasting is carried out for one day-ahead. Three PV plants were studied in the northern part of Italy, to obtain the optimal representative number of variables to model the PV production and the hidden layers of a neural network. In that sense, the results shown that normalized Mean Absolute Error (nMAE) value was of about 12% in the cases studied [26]. 32 PV plants were analyzed in Italy and Sicily to choose the best machine learning algorithm from a total of six (grey-box model, neural network, quantile random forest, k-nearest neighbours, support vector regressions and ensemble averaging) [27]. The results manifested that there were not significant differences between models. Deterministic and stochastic methods together with ANN, determined the daily-PV output of an PV plant, where the input characteristic vector was composed by a clear sky solar radiation algorithm, ambient temperature, global irradiance, plane of total solar irradiance array, wind speed and direction, pressure, precipitation, cloud cover and cloud type. In that case, the nMBE was 9% for 216 days analyzed. Using five different models, the PV plant output was predicted two days ahead in two Egyptian places [28]. The root mean square error (RMSE) presented significant differences between Cairo and Aswan plants, reaching percentage differences higher than 40%. Daily ahead PV output predictions have been obtained in a similar way for several emplacements. In one case, through historical data combined with ANN and meteorological variables, the output of a PV plant placed in Portugal was calculated for one day ahead, obtaining an nRMSE value lower than 8% in all cases [29]. Other study was performed in an Italian PV plant, where ensemble methods combined with solar radiation forecasting determined the daily PV output with a normalized RMSE value of about 7% [30]. Also, extreme learning machines predicted, under all skies, the output of three PV-systems grid-connected. In the predictions from one hour to one day, the nRMSE values varied from 18% to 35%. Furthermore, few reports exist, to our knowledge, regarding the BIPV system, which is a promising technology in sustainable building design and is the essential element of the micro-grid scheme [31]. Likewise, there are few studies dealing with PV system power output forecast techniques that apply satellite observations (which have been shown to yield useful information regarding the direction and speed of approaching clouds [32]) and ANN techniques in tandem. It is therefore evident that more developments are required on this issue.

In the present work, the BIPV power output has been predicted with horizon up to 3 h ahead, using ANN and satellite observation techniques. With such BIPV forecasting, PV plant planners and controllers can predict important problematic situations because they need to know what sort of variability and uncertainty are associated with PV plants. This knowledge will allow them to improve the operation of a PV-connected power grid as they will be able to determine the speed at which solar irradiance changes over time, providing useful information to better understand how quickly PV power would drop when exposed to solar irradiance fluctuations.

2. Experimental data

In this work we used measurements of global (I_{glo}), direct (I_{dir}) and diffuse (I_{dif}) incident radiation intensity. The instrumental uncertainty for that was 5% for global and diffuse radiation, whereas for direct radiation the error in the measure was ± 3%. Also, the ambient air temperature (T_{amb}) where the precision was ± 0.2 °C, relative humidity (H) with an error lower than 2%, speed and wind direction (precision ± 0.2%), CO_2 (with an uncertainty of ± 2%, an where the device works with a laser pulse in different wavelengths, obtaining the concentration of a gas in a particular wavelength that is compared with a reference value to calculate the final absorption in the correspondent spectral point), atmospheric pressure (where the precision was ± 0.15 hPa) as well the BIPV system's power output registered in the CIESOL building (University of Almería, Spain) with a precision of ± 3%.