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Data-driven upscaling methods for regional photovoltaic power estimation and forecast using satellite and numerical weather prediction data

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ABSTRACT

The growing photovoltaic generation results in a stochastic variability of the electric demand that could compromise the stability of the grid, increase the amount of energy reserve and the energy imbalance cost. On regional scale, the estimation of the solar power generation from the real time environmental conditions and the solar power forecast is essential for Distribution System Operators, Transmission System Operator, energy traders, and Aggregators.

In this context, a new upscaling method was developed and used for estimation and forecast of the photovoltaic distributed generation in a small area of Italy with high photovoltaic penetration. It was based on spatial clustering of the PV fleet and neural networks models that input satellite or numerical weather prediction data (centered on cluster centroids) to estimate or predict the regional solar generation. Two different approaches were investigated. The simplest and more accurate approach requires a low computational effort and very few input information should be provided by users. The power estimation model provided a RMSE of 3% of installed capacity. Intra-day forecast (from 1 to 4 h) obtained a RMSE of 5%–7% and a skill score with respect to the smart persistence from −8% to 33.6%. The one and two days ahead forecast achieved a RMSE of 7% and 7.5% and a skill score of 39.2% and 45.7%. The smoothing effect on cluster scale was also studied. It reduces the RMSE of power estimation of 33% and the RMSE of day-ahead forecast of 12% with respect to the mean single cluster value.

Furthermore, a method to estimate the forecast error was also developed. It was based on an ensemble neural network model coupled with a probabilistic correction. It can provide a highly reliable computation of the prediction intervals.

1. Introduction

Large share of photovoltaic (PV) power brings new challenges for the stability of the electrical grid, both at the local and national level, since it introduces into the electric load a stochastic variability dependent on meteorological conditions. Indeed, the electricity demand (residual load) that should be fitted by not intermittent generation results from the difference between the electric consumption and the distributed PV production.

Thus, in case of high PV generation higher secondary reserves and ready supply are needed to ensure electrical balancing and overcome the unpredictability and variability of the residual load. Moreover it implies an increase in costs related to transactions on the day-ahead and intra-day energy market and dispatching operations on the real-time energy market.

To sustain the growing PV distributed production, the use of modern power electronics, distributed control together with ancillary services like PV generation forecast is becoming essential for many European countries. Indeed, in Europe the PV penetration is now around 3% with Italy leading at 7.9% and International Energy Agency (IEA) scenarios predict for 2030 a PV generation of 10%–25% of the UE27 electric demand (IEA, 2014a,b).

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Nomenclature

Acronym	Meaning
DSO	Distribution System Operator
TSO	Transmission System Operator
NWP	Numerical Weather Prediction
WRF	Weather Research and Forecasting model
MOS	Model Output Statistic
ANNsE	Ensemble of Artificial Neural Networks
GNN and 6GNN	ANNsE models for power output estimation based on irradiance inputs (G)
RHNN and PCARHNN	ANNsE models for power output day-ahead forecast based on relative humidity inputs (RH)
PM and KPM	simple and smart persistence models

Variables	Meaning
GHI, GHIcs, RH and Tair	global horizontal irradiance, clear sky global horizontal irradiance, relative humidity and air temperature at ground level
PPK_{cs}	Pseudo clear sky performance index
PO^{obs},PO^{PM},PO^{KPM},PO^{for}	PV power output observed and predicted by the simple and smart persistence, forecast models
$P_n(dd)$	daily plant capacity

On a regional scale, PV power estimation and forecast are relevant for Distribution System Operators (DSO), Transmission System Operator (TSO), energy traders, and Aggregators. In particular the estimation of regional PV power generation from the real time environmental conditions is needed since in Italy the actual energy meters used by DSO do not allow a real time power monitoring of the distributed photovoltaic production. Thus, power estimation can be used for PV power supervision, real time control of residual load and energy reserve activation in case of deviation. PV power forecast can be employed by users for transmission scheduling to reduce energy imbalance and related cost of penalties, residual load tracking, energy trading optimization, secondary energy reserve assessment.

An overview on benefit of PV power forecast in solving problems related to the grid integration of intermittent solar energy production can be found in Emmanuel and Rayudu (2017), Shivashankar et al. (2016), Alet (2015), Alet et al. (2016), Zhang et al. (2015).

For power estimation and intra-day forecast the use of ground measurements or satellite data is essential as for day-ahead forecasts Numerical Weather Prediction (NWP) data should be employed to obtain an acceptable accuracy level. The NWP data are generated by global or mesoscale simulation models able to provide the numerical integration of the coupled differential equations describing the dynamics of the atmosphere and radiation transport mechanisms (Lorenz et al., 2016).

Moreover, these data are usually corrected by post-processing algorithms (Model Output Statistics) that use past ground measurements to partially remove systematic errors of NWP (Pierro et al., 2015; Lorenz et al., 2009a,b).

Then PV power estimation or forecast can be achieved through deterministic i.e. (Pelland et al., 2011; Lorenz et al., 2011) or data-driven models based on machine learning or probabilistic approaches i.e. (Zamo et al., 2014a,b). For the deterministic models detailed information on the PV plant set up (geographic position, modules technologies, etc.) are needed. On the contrary for the data-driven models past power measurements are essential for training, validation and test while none or very few system information are required (Pierro et al., 2016a).

The starting point for Regional PV power estimation and forecast is the so-called bottom-up strategy. It consists in the estimation or forecast of all the distributed PV plants in the considered area. Nevertheless, it requires a large computational and data handling effort. Indeed, models should be implemented for each plant (even if the distance between two plants is lower than the spatial resolution of the irradiance or NWP data) and then the models should run for all the distributed systems. Moreover, when there are not enough historical data to train machine learning algorithms, a deterministic approach must be adopted. Nevertheless, it often happens that some system information needed for the model set up (such as orientation and tilt or module characteristic) are unknown. For these reasons, ongoing research is focused on upscaling methods that allow the estimation and forecast of distributed power of aggregates of PV plants through simplified approaches that reduce the computational effort and require less information on the PV fleet. For example, Fonseca et al. (2015) proposed four different upscaling method that can be used according to different plant information and data availability scenarios. Zamo et al. (2014a) developed a data-driven model for regional PV power forecast that only requires the whole installed capacity and the historical PV generation in the controlled area for model's training.

Upscaling methods are mainly based on the selection of a subsets of PV plants with a power output that can be considered representative of the regional photovoltaic production. Then the forecast of the subsets power output is rescaled taking into account the subsets capacity and total capacity to obtain the regional prediction.

Several strategies have been developed in order to select the representative subsets. In Lorenz et al. (2008) two different random selections were tested. In the first the spatial distribution of the selected subsets should reflect the regional distribution while in the second just a uniform distribution of selected systems was chosen. In Lorenz et al. (2011, 2012) a subsets selection was proposed so that their distribution with respect to the location, installed capacity and system characteristics (plane orientation and technology) reflects the distribution of the whole ensemble. In Fonseca et al. (2015) for the selection of representative subsets a stratified sampling method according to installed capacity and PV system location was developed.

Another upscaling method considered the PV generation in the controlled area as it was produced by a virtual PV plant. Then, the power output of this virtual plant is directly forecast by machine learning algorithms as reported in Zamo et al. (2014a).

Only recently, a hybrid upscaling strategy between the two above mentioned approaches has been tested. Instead of sampling strategy, clustering methods were used for spatial grouping of PV plants and then the power output of each cluster is considered produced by a virtual PV plant and directly predicted by deterministic or machine learning models (Wolff et al., 2016).

Moreover, the accuracy of regional forecast is greatly improved with respect to single site forecast due to the "ensemble smoothing effect". This effect is related to the forecasting errors correlation, the PV capacity distribution and the number of systems in the controlled area. The errors correlation between sites decreases with the distance (or with the size of the area) thus the regional forecast accuracy can be improved even by 50% with respect to the accuracy of single plant power prediction. For this reason, the performance of each site forecast only slightly affects the performance of regional prediction so that up-scaling methods can achieve similar accuracy of the bottom-up approach.

The smoothing effect in irradiance and PV power forecasting of ensemble of plants has been studied in Perez et al. (2011), Perez and Hoff (2013), Hoff and Perez (2012), Lorenz et al. (2008, 2009b) and Fonseca et al. (2014) while in Saint-Drenan et al. (2016) the smoothing effect was analyzed related to the spatial interpolation of the power yield produced by a random subsample of reference PV plants. The same smoothing effect can be observed in regional PV power estimation.

Another problem in the regional operative power estimation or

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