The Renewable Energy Sources (RES) power production has been significantly increasing world-wide thanks to technological advancements, cost reduction and government policies. Therefore, the power generation sector is facing significant challenges in the reliability and control of the power transmission system. Furthermore, the “day-ahead electricity market” is a market for wholesale electricity trading where prices and exchanged quantities are defined for the following day, hour by hour. This work compares different methods for PV plant output power forecasts of the next 24 hourly samples on the basis of the available weather forecasts (this approach is called “day-ahead forecast”) [1], [2].

The existing approaches of forecasting models can be classified into the following three categories: physical, statistical and hybrid. Physical models describe the conversion processes, and we adopted them to predict the daily generated power by using the expected weather conditions in a given day. On the contrary, statistical methods are based on the concept of persistence, or stochastic time series, and they are typically relying on machine learning. Artificial Neural Networks (ANN) have been successfully applied for the forecasts of fluctuating energy supply [3], [4]. Any combination of two or more previously described physical/statistical methods leads to hybrid models, with the idea to overcome the single negative performance and finally improve the forecast [5].

The aim of this study is to compare the PV output power day-ahead forecasts performed by different methods by providing the same weather forecasts [6]:

- deterministic (3 and 5 parameters PV models, with NOCT PV cells thermal model);
- hybrid (PHANN – Physical Hybrid Artificial Neural Network).

Furthermore, deterministic models are employable from the beginning, while the hybrid method requires historical data to be trained. A goal of this study is to find out, on average, the most effective forecasting model starting from the first day of the PV plant operation. For this reason, the most performing features, in terms of accuracy provided by different approaches in the training set composition as a function of the increasing training set size has been studied.

This comparison and analysis was realized on experimental data recorded from a PV module at SolarTechLab located in Milano.

By comparing the mean NMAE% calculated considering all the available days forecasted with different methods, the three-parameter model performs slightly better than the five-parameter one (8.5% vs. 9.0% respectively), on the other hand PHANN always shows higher accuracy in the range of 6%, as shown in Figure 1.
Concerning the PHANN, the training based on hourly samples randomly taken by the whole dataset (Method B) has scored better results starting from datasets of 50 days or more, while the use of a moving window with limited random hourly samples (Method A) better performed with shortest training set. Furthermore, by increasing the training set size with any approach, forecasting errors are generally lowered, due to the capability of the hybrid method to learn both the weather forecasts inaccuracy and PV plant peculiarities.

In conclusion, this study shows that the day-ahead output power forecast should be first performed with the three-parameter model. After few days of operation (from 10 to 50 days) an accurate forecast can be performed by the PHANN model, trained with Method A. Starting from the 50th day on, the PV output power forecast could be reached by adopting Method B.

BIBLIOGRAPHY