SEVENTH FRAMEWORK PROGRAMME

GreenDataNet

D3.5 – Summary of PV Production Forecasting Tool Design and Implementation

Final Version - Public

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REVISION SHEET

Revision Number	Date	Brief summary of changes
Rev 0.1	18/07/2015	First draft document
Rev 0.2	27/07/2015	Second draft document
Rev 1.0	28/07/2015	Final document

KEY REFERENCES AND SUPPORTING DOCUMENTATIONS

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1. INTRODUCTION

In WP3 of GreenDataNet project, the work is focused on developing an energy management tool of a data center (DC) in order to maximize the self-consumption rate and self-production rate of photovoltaic (PV) production. That's why the PV forecasting tool is needed to estimate the available PV resources for the day after which is named as D+1 PV production forecasting. In this context, a forecasting tool to predict the photovoltaic production of the Data Centre PV plant has been developed (Task 3.1.3).

The developed solution uses weather forecasts supplied by specialized providers (data from NOAA – US National Oceanic and Atmospheric Administration – are proposed). The aim of this tool is to predict in a given day D (typically at end of the afternoon) the pattern of production of the PV plant for day D+1 from 0h to 24h (with a time-step of 1-minute or more).

1.1 DOCUMENT PURPOSE

As explained here above, the aim of the PV forecasting tool is to provide PV production forecast for the SEMS (Smart Energy Management System) of the DC that is developed in Task 3.2 (Deliverable 3.7).

The PV production forecasting tool, as well as the electricity consumption forecasting tool (Task 3.1.2 and Deliverables 3.2 and 3.3) and the analytical model of thermal behaviour of the DC (Task 3.1.1 and Deliverable 3.1), will be used as an input by the SEMS in order to define the most adapted predictive control. This control aims to satisfy DC targets in terms of self-consumption / self-production but also services for the electrical grid.

This document is a summary of the more detailed Deliverable *D3.4 PV forecasting tool design and implementation*.

An overview of different approaches detailed in literature for PV production forecast is presented in Section 2. The developed PV forecasting tool for GreenDataNet and its evaluation are detailed in Section 3.

2. PHOTOVOLTAIC PRODUCTION FORECASTING IN LITERATURE

The approaches used to forecast photovoltaic production are partly similar to other forecast techniques, for example to the ones used for wind power. It is indeed noteworthy that academic research teams and companies who developed a forecasting wind power generation [1] activity often tend to expand their business to the prediction of PV production. In this context, it can be noted that, in many cases, the proposed approach of these actors is biased by keeping the basic structure of their initial systems and to adapt it to the characteristics of photovoltaics.

From a meteorological point of view, the critical point is the accuracy of the prediction of the irradiance, followed by the temperature and wind speed. The sensitivity of the power produced to the last two parameters could be relatively small. Some forecast models are directly sensitive to the irradiance (power received by a unit area), while others prefer to consider the cloud (or cloud cover, i.e. the fraction of the sky covered by clouds).

Four method classes are generally defined and will be detailed after in Parts 2.2, 2.3, 0 and 2.5:

- Approaches based on statistics relying exclusively on past measurements. They are generally grouped under the name of "time series based methods".
- Approaches based on weather forecasts provided by a specialized service. They are generally gathered under the name "NWP based methods" ("NWP" for "Numerical Weather Prediction").
- Approaches based on satellite images of the Earth that were the first to be used. They are generally grouped under the name of "satellite imagery based methods".
- Approaches based on observations of cloud cover from the ground at the plant site. They are generally gathered under the name of "sky image based methods".

Several works have been published in order to « Review » the different approaches regarding the PV production forecast [2], [3], [4], [5], [6].

2.1 PROPERTIES

The four different approaches shares common framework and properties explained in the following sub-parts.

2.1.1 TIME HORIZON OF PREDICTION

The Energy meteorology team of Oldenburg University in Germany has studied the requirements in terms of time horizon and spatial resolution of PV production prediction to comply different customers' needs or application cases [7].

Depending on the application covered by the PV or solar plant, the required time horizon is not similar. For instance a solar thermal power plant and a hybrid PV-Diesel power plant need a small time horizon (some minutes) in order for example to adapt its control for not interrupting reliable power supply or for not impacting electrical grid frequency. On the other side grid utilities or grid connected power plant operator are interested in long term PV previsions (24h to several days) to plan grid balance or to offer grid services. However, as soon as larger time horizon is used the spatial resolution must be decreased.

For operating a system or a building from an energy point of view, for instance through Energy Management System, a time horizon between 1h to 24h is generally needed; lower is the time horizon better the correlation between PV production and local loads could be set.

2.1.2 GOLD STANDARD FOR COMPARISON

In order to evaluate the performances of a PV forecasting tool, the results are usually compared with what can be achieved with a simple reference method. The commonly used reference is persistence due to its simplicity; an advanced PV forecasting tool should at least be better. The persistence method assumes that the production is repeated from one day to next one or from D-1 to D+1.

Another method for providing a reference is based on seasonal values. With this method an average production is calculated on a given period for data (for example, the average production for the same month considering all available data). The drawback of this solution is the need of a large amount of data prior to the study. For this reason, this type of reference is less often used than persistence, despite the fact that it seems a bit more efficient.

2.1.3 EVALUATION OF METHODS

It is difficult to find in the literature a deep and complete evaluation of different methods (the four presented previously) on a sufficiently large number of stations, facing various weather conditions and for a long period. The authors of publications and work results on PV prediction often present their new algorithm, and then they compare it to old ones and / or persistence method considering 1 to 2 years of data and for only one or few plants.

Furthermore the locations where the four different methods have been evaluated are mainly concentrated in Europe and North America and have not been faced to south hemisphere characteristics (see Figure 1). As it lacks an objective method and a wide-shared evaluation method, results claiming an improvement of the PV forecast due to a new algorithm or a new method should always be considered carefully.

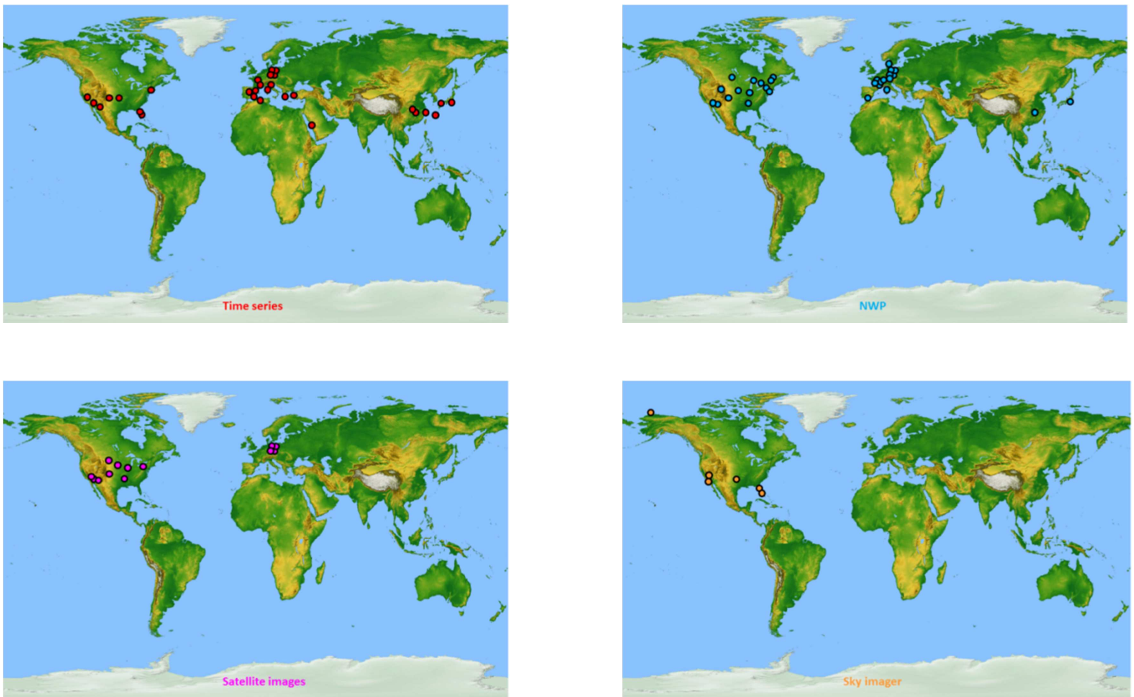


Figure 1 : The overview of the places which have been carried out by the different publications on PV prediction. Inset top left: Methods "time series" top right inset: "NWP", bottom left inset: Methods "satellite images" at the bottom right inset: Methods "sky vision"

2.2 TIME-SERIES BASED METHODS

Methods based on "time series" rests on past measurements monitored on the site. An algorithm uses this historical data (or a subset generally consists of the most recent data) to predict the irradiance (global, direct, diffuse) and / or other weather-related variables in the near future.

The time horizon is usually set up to 24h, but could be decreased to 1h and down to several minutes.

These methods have the great advantage of not requiring exogenous data (as opposed to data required by NWP forecasts or satellite images).

The main drawback of such time series based methods is that they require reliable historical measures. Depending on the complexity of the method, the historical data need to be monitored for a quite long time. This is possible with adapted sensors and monitoring system, but in practice the PV plant operator often wishes to benefit from forecast before having important volume of historical measurements.

2.3 NUMERICAL WEATHER PREDICTION BASED METHODS

Forecasting methods based on NWP operate on the following schedule:

- weather forecasts are provided by a specialized meteorological service
- forecasts (one or several) are post-processed depending on the know-how of the forecasting provider. This post-process step aims to produce various kinds of irradiation forecasts or directly forecasts of PV plant or a set of it.

The time horizon which is claimed to have accurate performances for PV prevision methods based on NWP are expected starting from 6 hours [8], [9] to 24h [10], [11]. Sometimes it can go up to one week.

Of course, the results obtained with these approaches are highly dependent on the quality of weather forecasts. Some studies have evaluated forecast providers, comparing their ability to predict the global horizontal irradiance, and have been published recently [12] and [13]. Several techniques are also commonly used in the hope of improving the results obtained from the weather forecast models; Model Output Statistics and Downscaling methods are part of them.

The main advantage of such methods based on NWP is the efficiency. In fact, it allows benefiting from the expertise and tremendous computing capabilities of organizations specialized in weather forecast.

The main drawback of this kind of system is probably the lack of responsiveness to new events. Indeed, the updating of forecasts by meteorological agencies is quite slow (typically every six hours). Hence when unforeseen circumstances happen, it may only be taken into account six hours later.

2.4 METHODS OF FORECASTING BASED ON SATELLITE IMAGES

The PV forecasting based on the satellite images could be updated faster than the one based on NWP and it is one of the main advantages of this method.

Basically, satellites can transmit images of large portions of the Earth regularly refreshed (typically every quarter of an hour). Such images can estimate cloud cover at the time of shooting. It is easy to figure that the analysis of the evolution of cloud cover around an area of interest (for example, around a PV system) can lead to forecasts of future movements of the clouds, and thus make a forecast of PV production (of a plant or a set of PV plant) for the coming minutes and hours (in fact, these methods are generally deemed to achieve good performance in a relatively short horizon).

However, in the case of satellite images, the raw data is quite difficult to use immediately due to the associated large amount of information for each high resolution picture focused on a large area. For this reason, a pre-treatment has to be applied for extracting useful information (in particular the irradiance on the ground and / or local average cover). Used pre-treatment methods are rarely mentioned but it can be assumed that in at least almost all cases, the methods "Heliosat-1", "Heliosat-2" or "Heliosat-3" [14] have been implemented.

Time horizons for which these methods have been found effective range from 30 minutes to several hours [7], but such satellite image based forecasting methods are generally designed for a 1h time horizon [15].

2.5 METHODS OF FORECASTING BASED ON SKY VISION

Satellite images give access to pictures, each pixel corresponds to an area whose size is of the order of kilometers - the exact size depends on the position of the land area in relation to the satellite position and the picture resolution. The knowledge of the local situation of the sky is rather vague and the precise shapes, characteristics and positions of clouds are not available by this approach. For this reason, estimating the coming path of the clouds (speed and direction) is also difficult. In addition, the breaks in the clouds are undetectable from satellite images. Due to these drawbacks, the predictions based on satellite images are not efficient for time horizon inferior to 30 minutes and/or for small spatial scale. In that case, PV forecasting methods based on sky vision should be implemented if an accurate and efficient prevision is required with short-term horizon.

Such systems for sky vision for PV prevision seem to be very powerful to anticipate sudden decrease of PV production due to clouds and is then useful to permit PV plant power smoothing through other energy sources (for having constant production or for avoiding grid disturbances especially for large PV plant and weak electrical grid), to avoid any power outage for stand-alone system.

Nevertheless, such methods require the installation of a sky vision system dedicated to the PV plant. Another limitation of sky vision based PV prevision methods is the staked vision range of the camera; the time horizon of such methods runs generally from 5 minutes to 30 minutes and it has to be coupled with another method, through a hybrid system, for PV forecast with longer time horizon.

3. PV FORECASTING TOOL DESIGN

In this section, the PV forecasting tool design developed for the WP3 of GreenDataNet project is presented.

First it is important to define what the objectives of the PV forecasting tool are for GreenDataNet project.

The results of the PV forecasting tool together with the storage status and the DC power consumption forecast are used as input data by the Smart Energy Management System (SEMS) tool. The main goal of this SW is to maximize the self-production of the Data Centre from its proper PV plant for having a lower environmental impact (and save money by decreasing power consumption from the grid) and also to maximize the self-consumption of the DC for avoiding a large power injection into the grid from the PV plant.

Further, thanks to the energy storage system, the SEMS could provide services with medium-long discharge duration (1h to several) and quite low time response requirement as peak shaving, electric energy time shift and load levelling to help the grid from technical point of view or to gain money in case of variable electricity prices.

Finally the Aggregated Energy Management System (AEMS) for a smart grid interaction of network of DC (Task 3.3) will permit to dispatch the IT loads from one DC with too low renewables power or too expensive electricity to one DC with available renewable (or also low cost) power (PV real production, high PV prevision, high State-Of-Charge - SOC - within energy storage system). As it is easily foreseeable to detect low SOC and to correlate it with accurate consumption and PV previsions, the critical answer time should not be much faster than 30min or 1h.

The time horizon of the PV forecast required by the SEMS is of several hours (1h to ten of hours), as it is a good trade-off for managing PV, energy storage system, cooling loads and IT loads. It has to be extended to 24h if supplying services as electric energy time shift and peak shaving are wanted.

Based on this first specification of SEMS design (that will be detailed in Task 3.2), a PV production forecasting tool with 24h time horizon and 30min-1h time step is completely adapted but it should be updated a couple of times a day.

Regarding this specification and following the explanations of part 2, the selected approach for GreenDataNet PV forecasting tool is to mix the Numerical Weather Prediction approach with the time-series based method.

A simplified scheme of the PV forecasting tool architecture that will be used for GreenDataNet DC is presented in Figure 2. The combination of the two methods permits to get different advantages.

From the NWP method the PV forecasting tool for GreenDataNet benefits the expertise and computing capabilities of strong and world-recognized organizations specializing in weather forecasting (yellow ellipse in Figure 2). The weather forecasting will be updated a couple of times a day (down to every 6h).

The time-series based method used for the GreenDataNet PV forecasting tool (blue ellipse in Figure 2) helps to have a better knowledge of the impact on PV plant production of the PV plant specificities for a given time and a given location without having a well detailed model of PV plant for simulation. The time-series based approach selected works on the evaluation of the difference between the PV prevision and the real production the day before (D-1). It permits, among other benefits, to limit seasonal effect and it uses a learning module; this aspect is explained further in part 3.2.

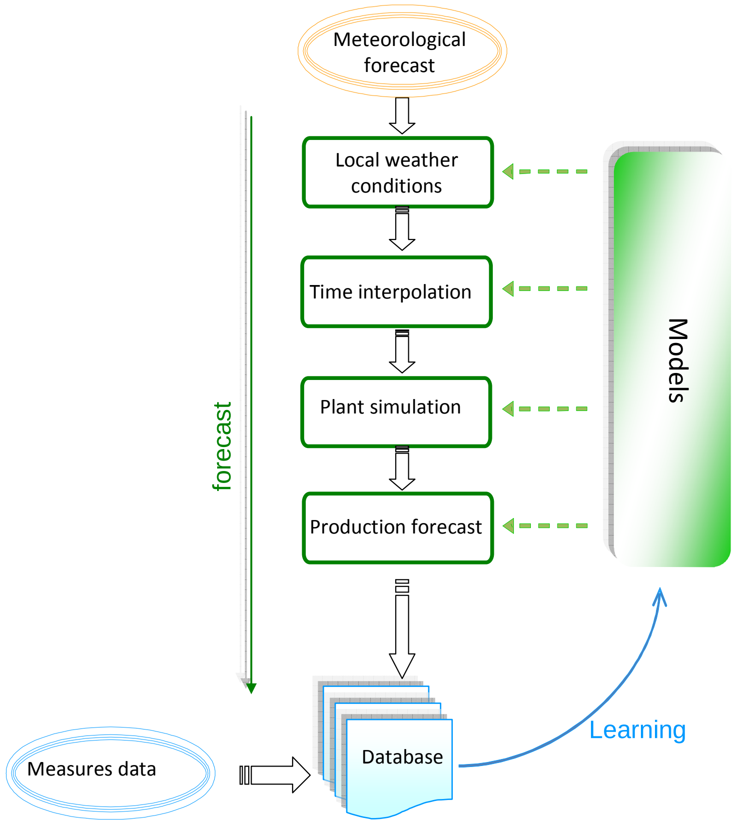


Figure 2: Overview of PV production forecasting tool design. The green arrow is used for the forecasting mode and the blue one is for the learning mode

This forecasting tool has two types of operating modules:

- forecasting module where the next day production is predicted (in green in Figure 2)
- the training mode based on the difference between what has really been produced the day before and what was expected with PV prevision (in blue in Figure 2).

3.1 FORECASTING MODULE

The website, on which the weather forecast is downloaded (eg NOAA website, National Oceanic and Atmospheric Administration), is queried regularly by the forecasting module of the PV forecasting tool. When new forecasts are available, they are uploaded and processed by the proper algorithms (not developed in the framework of GreenDataNet project) of the forecasting module of the PV forecasting tool. Thus, it is able to generate PV production forecasts for the PV plant (from temperature and irradiation forecasts) by using either models from previous learning if they exist or default configurations if they do not exist.

When the prediction is calculated for the PV plant of the DC the forecasting data are stored in a database, to ease the evaluation of forecasting and learning process; it permits to be used as part of learning to update the models, and to assess the effectiveness of the system in the long term.

3.2 LEARNING MODULE

Every day the measurement file ridges of the PV plant site (if any) are uploaded (irradiation, temperature, production… measured at day D-1) and then processed. The methodology of this data process step permits to provide data verification and correction, and consists in two stages: censoring or correcting (as applicable) of any outliers, then interpolating the PV production data to fill potential "holes" (within one hour). Indeed it is usual to encounter outliers, missing data … if working with real monitored data. Finally, the model is modified by automatic learning.

The PV plant model and its sub-models are refined every day on the basis of this measured and processed data. The new models generated by the learning module will be used to adapt the next forecasts of the PV plant. For the DC PV production forecasting tool, it creates an artificial intelligence behaviour that, thanks to the experience gained day by day on the PV plant, will consider particular characteristics of the plant regarding spatial and time conditions.

3.3 PV FORECASTING TOOL INTERACTIONS WITH SEMS

Beyond the prevision of the PV production, it is important for GreenDataNet project that the value of the PV prevision is easily available for the SEMS. In order to be as modular as possible and easy to implement, it has been chosen that the data exchange between PV forecasting tool and SEMS would be done through a web service.

The web service collects the production data from the PV plant through the SEMS (and its monitoring capabilities) for the time-series based approach, collects the weather forecasts for the NWP approach, and supplies the PV prevision data to the SEMS of the DC. Then a dedicated PV forecasting tool could be implemented physically in each DC with the SEMS and has exterior communication only for getting the weather forecasts. Otherwise the PV forecasting tool could be used as a common tool for several DC, i.e. several SEMS; it is not hosted in the DC, gets the data of former PV production (D-1) from several SEMS and allows these SEMS to have access to the PV prevision data at D+1 (see Figure 3). This architecture offers a flexible service for PV previsions and has been developed for GreenDataNet.

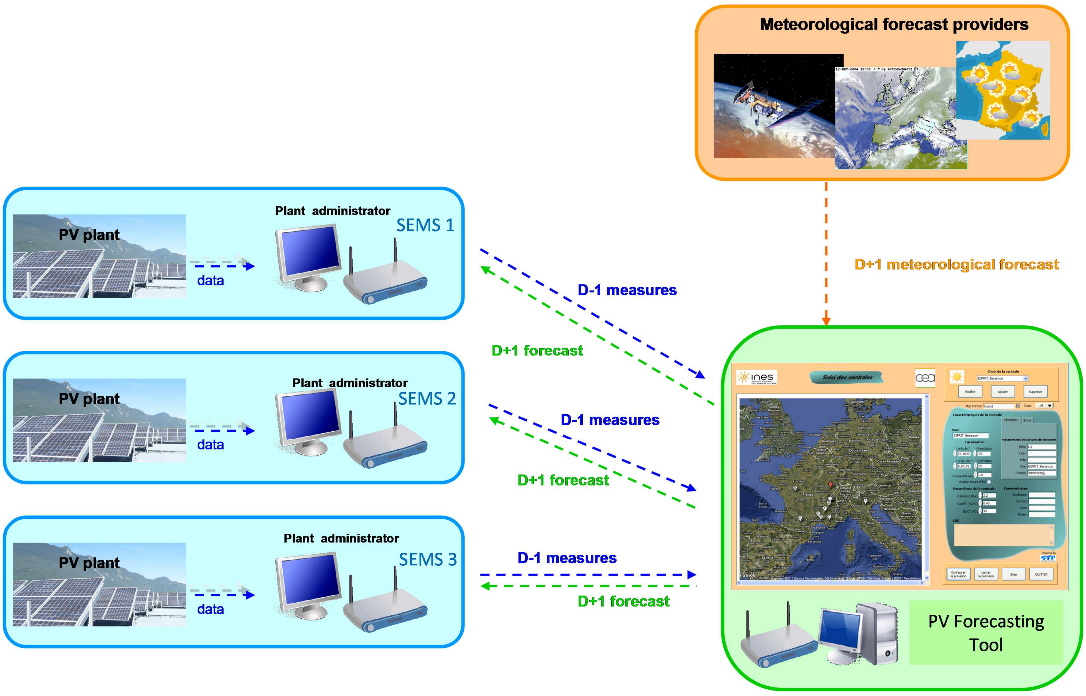


Figure 3*: PV forecasting tool implementation as a web service and data exchanged with weather forecast and SEMS*

As illustrated by the Figure 3, the PV forecasting tool receives from the SEMS the previous PV production data (in blue) and from the NOAA the weather forecast (in yellow). After the running of the forecasting and learning modules the PV prevision data for the next day is available for the SEMS.

It has been decided that the D-1 measurements (in blue) should be a text file or csv file with four columns: the first one reports the date using “YYYY-MM-DD:hh-mm-ss” format (UTC time), the second column is the PV power production in kW, the third column corresponds to the temperature measurement as temperature impacts PV production, and the fourth one consists in the irradiance measurement. This file contains the measurement of D-1 (yesterday) from mid-night to mid-night. Then this data file has to be updated only one time per day using ftp protocol to the server of the PV forecasting tool. Basically, the SEMS sends every day before mid-night the data.

The format of the PV production forecasting (in green) is also a text file and has two columns. In the first one the date of prevision (UTC time) is reported whereas the forecasting of PV power production forecasting at D+1 from sunrise to sunset is given in the second one. The filename is defined to “YYYYMMDD_Prev_Horiz.txt”.

It is better that this 1 day PV prevision file is available for the SEMS several hours (for instance 5 to 7 hours) before the beginning of the PV production especially if the PV plant of the DC could supply grid services or should follow a production plan. However this PV production file of one day could also be updated several times during a day. This update aims at improving the accuracy of PV forecasting according to the requirements of SEMS; the period of PV prevision’s updating could be as low as 3 to 6h (normally new NOAA weather forecasts are available every 6 hours).

On the other hand the SEMS can pick the PV prevision file up on the server with its own frequency; the new file replaces the old one. Thanks to this design, SEMS of the DC and the PV forecasting tool can work at different dynamic independently.

3.4 EVALUATION OF THE PV FORECASTING ON DEMONSTRATION SITE AT CEA INES

Due to Meteorology uncertainty principle, forecasts of photovoltaic power are imperfect. It can be at best hoped that the PV previsions match the average trend of production and an evaluation of the accuracy and quality of the prediction is useful.

Some precautions should also be taken regarding the interpretation of the claimed performances. It is obvious that when the forecasting methods are running, an assessment procedure must be associated. But so far, it was not possible to define an objective method for evaluating such results as many parameters must be set arbitrarily and numerous evaluation functions exist. In fact, almost each developed forecasting method for PV or irradiance has its associated evaluation method resulting in a non-objective approach!

The amount of advanced information provided to the tested forecasting system must also be questioned. In practice, one can observe that this amount can range from "none" to "several years." It goes without saying that it makes a significant difference and some methods are unable to work even without prior knowledge.

Ideally, if it is wished to perform an objective assessment of the various methods discussed in the literature, a similar approach of the following dedicated process should:

1) define a common assessment methodology;
2) assess the systems on data from a relatively large number of stations located in different climates with different types of plants and different types of monitoring; These plants should also have never been used in the various teams that product forecasting tools included in the test;
3) have necessarily a similar distribution of data between learning and test for all, if it is chosen to set up basic training data.

Otherwise, the comparison between two given methods is of course unfair. Due to the lack of such comparison framework, too precise comparisons should be considered with caution.

3.4.1 MAE EVALUATION METHOD

The proposed calculation for assessment is based on the "mean absolute error" (MAE). This choice is not the most traditional one for the assessment of wind or photovoltaic prediction. The RMSE (root-mean-square error) estimator is mainly used due to its very interesting statistical properties. Here, the MAE has been selected as both methods are close [16] and MAE is a comprehensive amount for anyone, as it is "the average level of error" of the forecast tool. But it is not claimed that it is always the best method to estimate the quality of a forecast system; its value is impacted by several parameters such as the geographic location of the plant, the climate, the season, the defined peak power to declare and so on.

A MAE value is calculated for each forecast time step and is normalized according to the defined maximum power of the PV plant to ease the comparison of forecast performances with other PV plants. Only diurnal period is considered and based on all these values of MAE, a daily MAE is calculated. Then a value of MAE is calculated for the whole evaluation period.

Finally the obtained MAE is compared to a baseline forecast based on persistence method (PV production of D-1 is used as D+1 forecast). Hence the following index is proposed here for evaluating the improvement of GreenDataNet PV forecasting tool:

$$improvement = \left(1 - \frac{MAE}{MAE_{persistence}}\right)$$

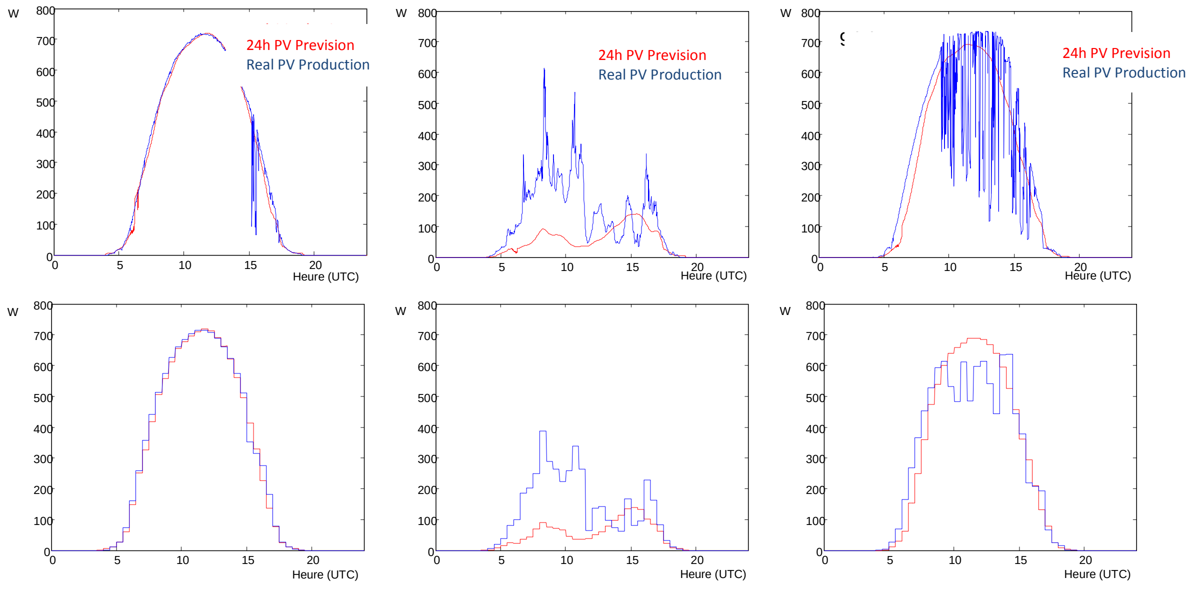
If the index of improvement is negative, it means that persistence is more effective than the forecast system considered. If the index is 0, the two systems are equal.

3.4.2 TIME RESOLUTION FOR PV FORECASTING TOOL

The PV forecasting tool designed for GreenDataNet could provide a PV power prevision for each minute. However, forecasting curves are always smoother than measurements because the forecasted power is ground on meteorological forecast with a time resolution equals to 3 and up to 6 hours. Hence using a larger time resolution is necessary; 1 hour is a common choice in the literature [17]. As far as GreenDataNet objectives are defined, it is rather proposed half an hour for time resolution because the SEMS should not provide real time control but only an energy management. The 30 minutes time-step fits also the French and many national rules in Europe for energy market. Of course, any value between half an hour and 1 or 2 hours could be chosen instead if the GreenDataNet needs will be re-evaluated.

3.4.3 RESULTS OF PV FORECASTING TOOL EVALUATION

Figure 4 : Three 24h PV power prevision (red curves) regarding real PV production (blue curves) on 1kWp PV plant at INES and for three specific days (sunny - left, cloudy - middle, sunny with numerous cloud passages – right). The graphs show the power (Watts, Y-axis) regarding the day time (UTC, X-axis).Figure 4 illustrates the quality and the limitations of 24h forecasting PV production obtained by the developed PV forecasting tool. It represents the results for 3 different typical days on a 1kW PV plant installed at CEA Le Bourget-du-Lac (France) and also illustrates the forecasting time step (discussed in section 3.4.2) impact.



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The graphs of the first line correspond to the achievement with a time step of one minute. The bottom line shows the same data, but considering a time step of 30 minutes.

3 days were selected because they are representative of 3 different conditions:

- The first day (first column), is a day with sunny weather.

- The next day (second column), the weather is very cloudy.
- The last day (last column) fast variations of the power produced (variable sky) can be observed due to numerous passages of clouds.

It can be observed in Figure 4 that the forecasted powers averaged per half hour (bottom graphs) fit with a pretty good sharpness the general behavior, erasing rapid variations, which confirm the choice of the time resolution of 30 min (see previous section 3.4.2). It will be the task of the reactive layer of the SEMS to be able to face as well as possible the difference between PV prevision and real PV production.

Figure 5 : PV plant 10kW peak power for green Data Net Project for PV tool forecasting tool implementation in INES

For the GreenDataNet demonstrator in CEA-INES, a PV plant with 10kW peak power using polycrystalline modules on CEA-INES PRISME platform is setup (Figure 1Figure 5). Some results obtained on this PV plant are described in Figure 6 and in Figure 7.

The PV prevision data provided by the PV forecasting tool for this 10kW PV plant have been evaluated for different days (several days in summer and several days in winter). It can be observed that the performances of PV prevision provided by the tool are very good as soon as clear weather conditions occur. It is more complex to evaluate the performance in winter and with variable sky conditions; the PV forecasting is sometimes more optimistic than the real production and sometimes gives an average value of the fast PV production variations. Based on CEA experience, the provided forecasts often predicts the general trend of the PV production during a day or half-a-day but always fails to predict the several minutes to several hours' variability.

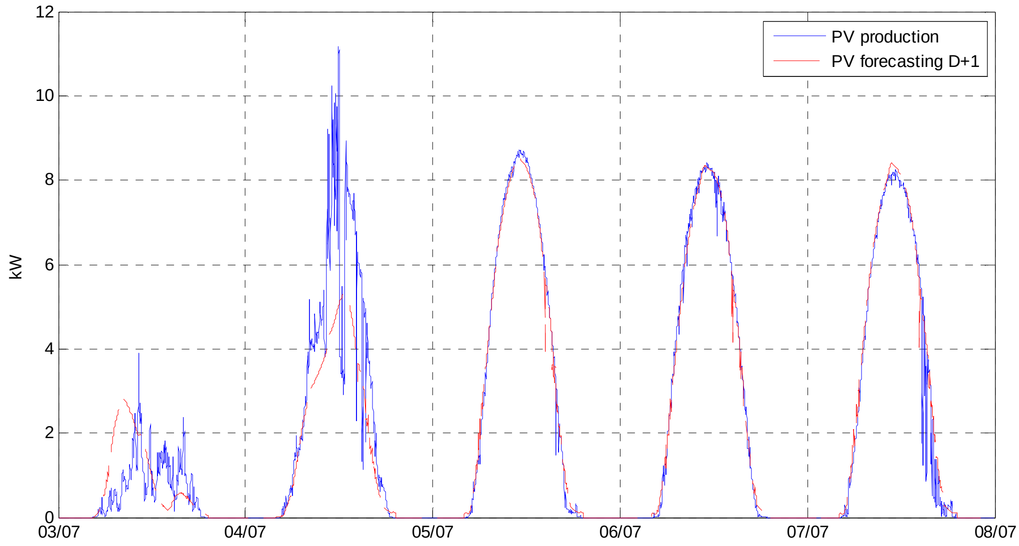

Figure 6 : PV real production recorded at INES during summer days for 10kW PV plant [blue] vs the 24 hours before PV production forecasting provided by the developed PV forecasting tool [red]

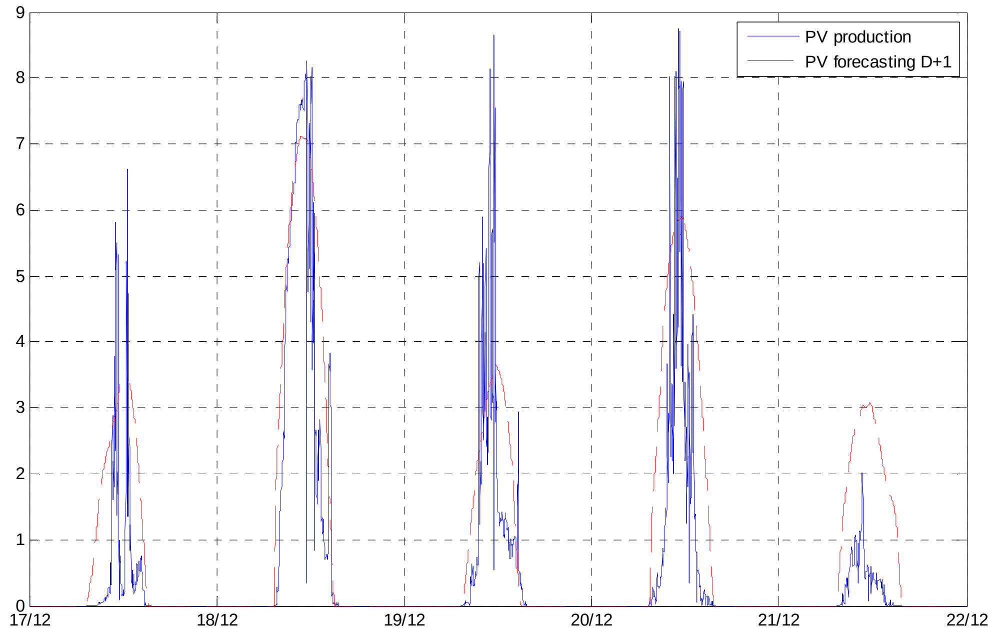

Figure 7 : PV real production observed at INES during winter days for 10kW PV plant [blue] vs the 24 hours before PV production forecasting provided by the developed PV forecasting tool [red]

4. CONCLUSION

This deliverable is a summary of Deliverable 3.4 and provides an introduction of the existing methods and current research about the PV forecasting and explains how the PV forecasting tool has been designed and implemented for GreenDataNet project.

The PV forecasting tool is based on Numerical Weather Prediction method combined with a time-series based method. This hybrid approach is used through two main modules: forecasting module that have for inputs data from large meteorological service, and learning module that allows to take into consideration specific characteristics (type of PV modules, shading effects, seasonal effects, ageing,…) of the PV plant installed for the DC.

The PV forecasting tool will be integrated in a higher level Data Centre management tool called SEMS (Smart Energy Management System) whose goals are to increase self-production of the DC with local PV production, to increase self-consumption of the DC to restrict grid perturbations due to PV production, and to make the DC behave as a "Prosumer" by supplying possible services to the grid (Active demand, peak shaving, electric energy time shift, load levelling …).