INTERNATIONAL JOURNAL OF
ENERGY AND ENVIRONMENT

Volume 8, Issue 2, 2017 pp.195-208

Journal homepage: www.IJEE.IEEFoundation.org

Forecasting of photovoltaic power at hourly intervals with artificial neural networks under fluctuating weather conditions

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Received 5 Oct. 2016; Received in revised form 1 Dec. 2016; Accepted 17 Dec. 2016; Available online 1 March 2017

Abstract
The requirement of the in advance knowledge of the future photovoltaic (PV) production in the domestic field for a better allocation of the on-site PV generation to the local load demand and the available storage facilities is more and more emerging. In this study two different methods were applied so as to forecast the next hour PV power using artificial neural networks (ANN). In the first case the weather parameters of solar irradiance and ambient temperature were predicted, the output was fed to the developed model of the PV installation and the next hour PV power was computed. In the second case it was attempted to predict directly the PV power. The performance of the applied ANNs was compared with the respective outcomes from the persistence models. In each case the applied ANN outperforms the persistence model. In addition, during the evaluation phase the extracted annual energy results were compared with the respective registered data from the installed meters. Again in both cases the results approximated the reality, though in the first case the difficulty in identification and representation of malfunctions in operation of the PV plants due to snow accumulation on the panels caused minor deviations.

Keywords: Ambient temperature; Artificial neural network; Forecast; Photovoltaic; Power; Solar irradiance.

1. Introduction

In an era when more and more households install photovoltaic (PV) panels and attempts to succeed self-autarky are increasing, the necessity for the in advance knowledge of the daily or hourly renewable energy production from PV installations is rising. Especially in cases where also stationary storage systems are available, the prospect of storing surplus of locally produced energy at times when the weather conditions are favorable and feed it back to the house when domestic loads are significantly increased during the day, necessitates the beforehand assessment of future PV energy production.
In this context several studies have already been implemented dealing with the prognosis of PV energy production. The clustering of all these studies in generalized categories depends on the respective

selected parameter. That can be the forecast variable, the method used or the forecast horizon. After a thorough analysis of the recent studies, it was detected that most of them, which deal with the subject "PV energy forecasting" focus on predicting the solar radiation, since this is the most significant parameter influencing the output of a PV plant [1-13]. Others though prefer to predict the PV output itself avoiding intermittent steps of weather parameters forecast and then calculation of the future production [14-24].

The most prominent solar forecasting methods were grouped and included in various reviews for solar forecasting methods. Indicatively in Innman's et al. [25] systematic review, the forecasting methods have been separated into the following categories: regressive methods, artificial intelligence techniques, remote sensing models, numerical weather prediction (NWP), local sensing and hybrid systems. A similar classification has been also adopted from Wan et al. [26]. In the IEA report [27] the classification is conducted according to the forecasting horizon. Intra-day (from 0 to 6 hours ahead) and mesoscale forecasts (from 6 hours to days ahead) constitute the two timescales selected to be examined. Finally, Diagne et al. [28] adopt an own classification in three subcategories, namely the statistical models, the cloud imagery and satellite based models, and the NWP and the hybrid models.

What can be concluded from all these reviews is that there is not an optimal method or model for all forecast categories. Depending on the timescale, the site, the available input variables different techniques are applied for best results. Furthermore, calculated metrics for evaluation of the various models are not identical, so a comparison among them is not feasible.

Indicatively in Table 1 a collection of various recent forecast studies is summarized. Developed forecast models show the diversity in this field and the weakness in identifying the most suitable model for every case. ANN, regression methods and hybrid models with their principal attributes are listed below.

In the current study, algorithms based on artificial intelligence tools, were developed in order to estimate renewable energy production in a hypothetical dwelling, in order to increase its autarky and self-energy consumption and so as to efficiently manage domestic produced energy during a day. The assumed residence is located in Wolfenbüttel, a central north city of Germany, and has two PV installations, of 5.1kW and 1.02kW. The referred plants are real facilities of the Laboratory for Electrical Engineering and Renewable Energy Systems at the Faculty of Supply Engineering in the Ostfalia University of Applied Sciences in Wolfenbüttel (Figure 1) and power data obtained from installed meters are utilised for validating and verifying the simulation results.

The 1st Plant with installed power of 5.1 kW is consisting of two strings of 30 modules each. Each string consists also of two times of 15 modules in series and then in parallel connected. The solar panels are south oriented with a fixed angle to the ground of 30^{o}. The plant is connected to the grid via 2 sting inverters Sunny Boy 2000 from the SMA company. The 2nd plant with installed power of 1.02 kW is composed of one string of 12 modules, it is also south oriented but its angle is adjustable and for every month in the year new determined, so as to benefit from the increase of the tilt angle during the winter and in summer coming to a more flat position. In this case the on-site produced energy is fed into the public grid via the Inverter Sunny Boy 1200 from the SMA [29]. The coordinates of the installed solar panels are 52°10'32.4"N, 10°32'52.0"E.

The climate of North Germany can be addressed to the category Cfb according to Koeppen's climate classification [30]. This type of climate is dominated all year round by the polar front, leading to changeable, often overcast weather. Summers are cool due to cool ocean currents, but winters are milder than other climates in similar latitudes, but usually very cloudy [31]. Great solar irradiance fluctuations are dominant all year around leading to unstable PV energy production during the day. These abrupt ramps are difficult to forecast, thus introducing an additional challenge to the addressed problematic when the appropriate and most reliable technique or method to forecast solar irradiance in such a place is to be detected.

The requirement for a more adaptive model to forecast PV power in regions with often overcast skies appears to be emerging after the systematic analysis of the reviewed literature, where most of the models are validated with data stemming from areas where the solar irradiance is not fluctuating abruptly or they have high annual direct normal irradiance. As Cornaro et al. state in [32], although the short term forecasting could be achieved by developing artificial neural network (ANN) models with simple algorithms that make use of local weather measurements as well as statistical parameters, the forecast is not that successful when it refers to places with unstable weather conditions. Countries such as Turkey, Spain, Australia or Italy are extensively mentioned in such studies, while places with more cloudy conditions, such as Germany are rare or appear not at all in the literature.

Table 1. Synopsis of publications on solar radiation forecast.

Authors	Forecast Variable	Method	Input Variables	Site	Forecast Horizon	Error Metrics
Melit et al. [1]	Solar Irradiance	ANN (Multilayer Perceptron MLP)	Mean Daily Solar Irradiance and Air Temperature	Italy	24-h	K-fold cross-validation
Hocaoglu F. A. et al. [2]	Solar Irradiance	ANN	Day, Hour, Solar Irradiance	Turkey	1-hour	RMSE, R2
Melit et al. [3]	Global, Diffuse And Direct Solar Irradiance	Adaptive a-Model	Sunshine Duration, Air Temperature and Relative Humidity	Saudi Arabia	1-hour	R2, MBE
Marquez R. et al. [4]	Global Horizontal Irradiance, Direct Normal Irradiance	ANN	Predicted Meteorological Variables from the US National Weather Service's (NWS)	California, USA	Up to 6 days	MBE, RMSE, R2
Huang J. et al. [5]	Solar Irradiance	Combination of an autoregressive (AR) model with a dynamical system model	Solar Irradiance	Australia	1-hour	MeAPE
Yang, D. et al. [6]	Solar Irradiance Including Cloud Cover Effects	ARIMA	Global Horizontal Irradiance (GHI), Diffuse Horizontal Irradiance (DHI), Direct Normal Irradiance (DNI) and Cloud Cover	Miami and Orlando, USA	1-hour	MBE, RMSE
Martin L. et al. [7]	Global Solar Irradiance	Autoregressive, Neural Networks and Fuzzy Logic	Global Solar Irradiance	Spain	3 days	rRMSD
Cao J. et al. [8]	Global Solar Irradiance	Recurrent Neural Network (RNN) with Wavelet Neural Network (WNN)	Global Irradiance, Cloud Cover and Related Temperature	China	1-hour to 1-day	RMSE, R2
Chatziagorakis P. et al. [9]	Solar Irradiance	Recurrent Neural Network (RNN)	Solar Irradiance	Greece	1-hour	MSE
Wang F. et al. [12]	Solar Irradiance	ANN	Irradiance Gsavg (n), Third-Order Derivative (TODmax(n)) and Normalized Discrete Difference (NDD(n)) of Solar Irradiance, Ambient Temperature Tavg(n) & Date Sequence Number n	China	24-hour	MAPE, RMSE, MABE
Azimi R. et al. [13]	Solar Irradiance	Hybrid Method, based on a clustering technique and an MLP ANN	Solar Irradiance	Iowa, USA	1-hour	RMSE, nRMSE, Forecast Skill
Ding M. et al. [14]	PV Power	ANN	Power Output, Temperature	Oregon, USA	24-hour	MAPE
Lonij V.P.A. et al. [15]	PV Power	Calculation of clearness index K based on Cloud Velocity	Plane of Array (POA) Irradiance, Cloud Velocity	Arizona, USA	15 min to 90 min	MBE, RMSE
Izgi E. et al. [16]	PV Power	ANN	Solar Power	Turkey	0-300min	RMSE

Table 1. Continued.

Authors	Forecast Variable	Method	Input Variables	Site	Forecast Horizon	Error Metrics
Fernandez-Jimenez A. et al. [17]	PV Production	NWP with ANN	Inputs from NWPs, Hourly Electrical Energy Generation		1 to 39 h	RMSE, MAE, ME
Bessa R.J. [18]	PV Power	AR, ARX	Solar Power	Portugal	1-hour	RMSE
Sumaili J. et al. [19]	PV Generation	Electrical based Model	NWP inputs	South of Europe	72-hour	NMAE, NRMSE
Dolara A. et al. [20]	PV Power	Hybrid Method, based on an Artificial Neural Network (ANN) and PV plant clear sky curves	Weather Forecasts provided by the Meteo Service	Italy	24, 48 or 72-hour	NMAE, WMAE, nRMSE
Chaouachi A. et al. [21]	PV Production	ANNs	Vapor pressure, humidity, cloud coverage, sunshine duration, temperature, irradiation and the SPG (solar power generation) output	Japan	24-hour	MAD, MAPE
Monteiro C. et al. [22]	PV Power	MLP NN and analytical PV power forecasting Model (APVF)	Data from NWP and PV power Generation	Spain	1-hour	RMSE
De Giorgi M.G. et al. [23]	PV Power	ANN	PV Power, Ambient Temperature, Module Temperature, Irradiance on Plain 3° and Irradiance on Plain 15°	Italy	1-hour	nMAPE
Almonacid F. et al. [24]	PV Power	ANN	Global Irradiance, Temperature	Spain	1-hour	RE

(a) (b)

Figure 1. The installed PV Power plants of (a) 5.1kWp Plant with 60 modules; (b) 1.02kWp Plant with 12 modules.

Conducting a trivial but reliable forecast without relying on exogenous sources, such as websites or tools with weather data prognosis, is another differentiation of this study from the existing ones. Moreover, the need for a parsimonious model that is well generalized in pertinent cases was also considered of great importance during the development phase.

In the frame of this study a comparison of two different methods of forecasting the PV power output is conducted. First the ambient temperature and the global solar irradiance of the site where the PV plants

are installed were forecast, since the PV energy production is promptly associated with these two parameters [33]. Consequently the temperature and solar radiation forecast values were transmitted to the already developed PV model for the two installations [34], from which the future solar PV power and energy for the two PV plants were calculated. The second method includes the direct PV power output forecast without the intermittent steps of forecasting weather parameters and then estimating the respective PV generation. The forecast results were compared with the outcomes from respective persistence models as well as with the measured values and conclusions on both techniques were drawn.
In the next sections the applied methodology is described as well as all the intermittent steps for extracting the required results and then a comparison of the two methods with the real registered data and outcomes from the persistence models is conducted.

2. Data retrieval and methodology

For forecasting the on-site PV generation two criteria were the most significant: First, the acquisition of reliable data and second the application of suitable techniques which would provide trustworthy forecasts. In the following sections the source of the utilized data as well as the methodology of the employed techniques are analyzed.

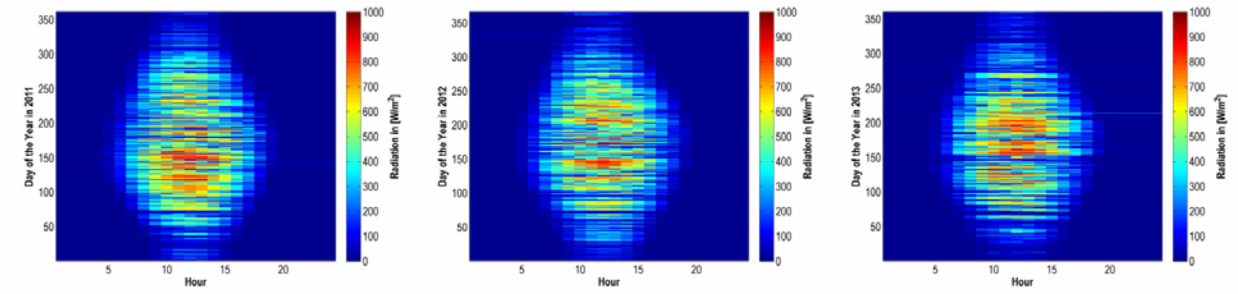
2.1 Data retrieval

The scientific methodology followed for the forecasting part was based on time-series data, which are collected with fixed time-step of one second by a weather station from the Thies Clima company located on the roof top of the Faculty of Supply Engineering at the Ostfalia University of Applied Sciences in Wolfenbüttel, Germany. The Clima Sensor 2000 measures among others the temperature with a standard platinum-resistant-thermometer Pt100 (acc. to DIN IEC 751) of long-term stability and high accuracy [35]. Moreover, a net radiometer, which ideally absorbs solar radiation of all wavelengths directed downward toward the earth's surface and upward away from it [36] and subsequently measures the difference between them, is used to measure the intensity of solar radiation. Both devices are displayed in Figure 2. In addition, the installed meters U1281 from the Gossen Metrawatt company for each PV plant transmit several network variables. The device has a digital counter for the display of the energy production and internal counters for the metering the power import and export and the active and reactive components of them. In addition, instantaneous current, voltage and power factor values are also accessible. The transmission of measured values, the recording and provision, as well as the storage of them are possible through a Local Operating Network (LON) bus system, the Open Platform Communications (OPC) technology and the database system MySQL [29].

(a) (b)

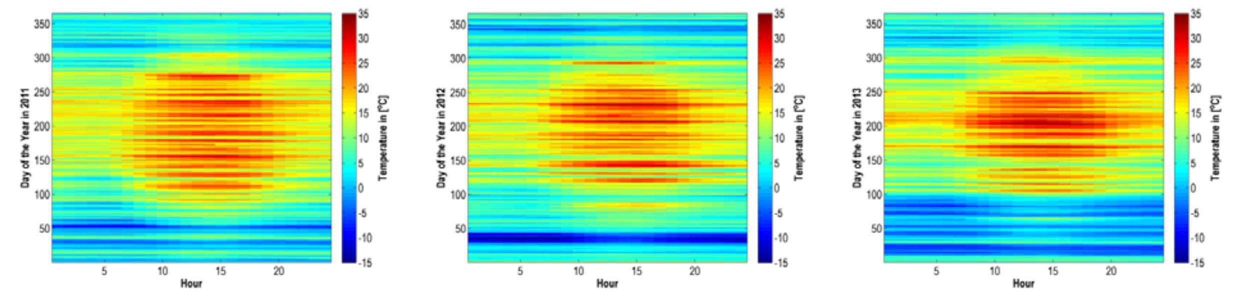
Figure 2. (a) Weather station Clima sensor 2000 (Thies Clima); (b) Net radiometer.

The used data derive from three consecutive years, namely 2011, 2012 and 2013. Figures 3a, 3b and 3c show the distribution of solar irradiance during a time interval of one year. The intensity of radiation during the days is characterized from higher values and longer periods of sunshine in summer. Dark blue areas in the graph show zero values in the night and low intensity in winter days.
The ambient temperature trend for the same years is also rendered in the Figure 4. Warmer colors state higher values achieved in summer days while colder colors are depicting the cooler days in winter.



(a) (b) (c)

Figure 3. (a) Solar radiation [W/m^2] in 2011; (b) Solar radiation [W/m^2] in 2012; (c) Solar radiation [W/m^2] in 2013.



(a) (b) (c)

Figure 4. (a) Ambient temperature [^{o}C] in 2011; (b) Ambient temperature [^{o}C] in 2012; (c) Ambient temperature [^{o}C] in 2013.

2.2 Methodology

So as to estimate the next one hour values of the global solar irradiance, the ambient temperature as well as of the direct PV power, three different ANNs for each time series were applied.

In the following chapter the models are described and explained analytically and the details of each one are presented through equations and schemas.

2.2.1 Artificial neural network

Temperature, radiation and power forecast models were formed based on ANNs. The ANNs are preferred for estimations of non-linear parameters and their architecture is mostly organised in layers. The ANNs can be classified into two big categories: the Feedforward (FF) and the Recurrent NNs. The first do not include any acyclic graphs while the latter distinguishes itself because it has feedback loops. Moreover, the if the ANN includes just an input and output layer then we refer to it as Single-Layer Perceptron Network (SLP). Otherwise, if also one or more hidden layers intervene between input and output units, the ANN is designated as Multilayer Perceptron (MLP). In each hidden layer multiple neurons are addressed. The process of calculating the output value of the NN includes the multiplication of the input value x_{ij} with a weight w_{ij} amplified with a threshold (or bias value) ϑ_{ij} by applying the activation function *f*. In Figure 5 a graphical representation of the general structure of a MLP feed forward neural network is depicted.

Architectures of Nonlinear Autoregressive (NAR) and Nonlinear Autoregressive with Exogenous input (NARX) were applied in this study for forecasting the three different variables. These two types of ANNs are classified also into the MLP FF architecture. It should be stated here that NAR and NARX approaches do not contain internal feedback and they are purely feedforward as it is mentioned in e g [37-39]. These two categories of ANNs are defined respectively from the equations (1) and (2) that follow:

$$y(t)=f(y(t-1),y(t-2),\ldots,y(t-d)) \quad (1)$$

$$y(t)=f(y(t-1),y(t-2),\ldots,y(t-d),x(t-1),x(t-2),\ldots,x(t-d)) \quad (2)$$

where d is the delay parameter in the model.
For activation function a Sigmoid Symmetric Transfer Function f_k was applied and is calculated according to the following equation:

$$f_k = \frac{1}{1+e^{-u_k}} \tag{3}$$

where u_k is the sum of all the inputs and bias values .

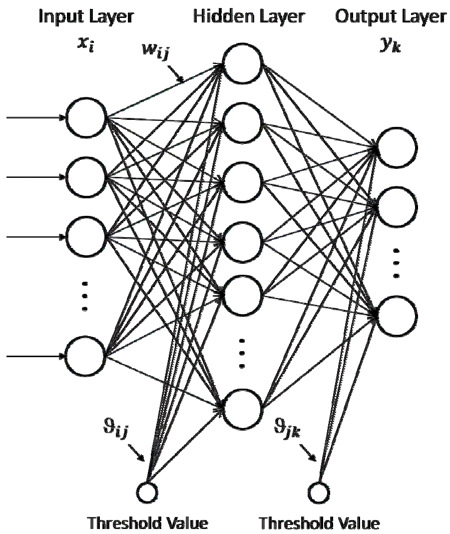


Figure 5. Graphical depiction of a MLP FF Neural Network Architecture

The training phase that followed was meant to adjust the weights with regards to minimising a specific statistical metric between the target and the output value. In this case the data division was randomly selected and the performance was evaluated from the Mean Squared Error (MSE). Finally, the Levenberg-Marquardt optimisation technique is used as a back propagation algorithm of the NN during the training process since it converges faster, while the learning dataset was divided in three subsets, namely 70%, 15% and 15% for the training, validation and testing phase. The networks were trained in open loop form avoiding so the intrusion of divergent output into the design process. The extracted function in each case is used to forecast the next hour values and the model are actually a one-step-ahead predictor. It should be stressed out that although data with time resolution of one second were available, for the sake of computational speed a time resolution of 24 samples per day (mean value per hour) was considered adequate for the training phase; consequently the processing time is reduced without losing in accuracy. The proposed process was designed and computed on the Neural Time Series Tool of Matlab.

2.2.2 Extraterrestrial radiation

For the calculation of the forecast values of the global irradiance and the direct PV power output the extraterrestrial radiation $B_o(0)$ is required as input to the applied NARX model. Its computation on a horizontal surface for the years 2011, 2012 and 2013 is based on the following equation [40]:

$$B_o(0) = B_o \times \varepsilon_o \times \cos\theta_{zs} \tag{4}$$

where B_o is the solar constant (1367 W/m^2), ε_o is the eccentricity correction factor, ϑ_{zs} is the solar zenith angle.
The eccentricity correction factor ε_o, which describes the deviation of the Earth elliptic orbit from the circular [40], is given by:

$$\varepsilon_o = 1 + 0.033 + \cos J' \tag{5}$$

where J' is a parameter which is defined by the equation (6):

$$J` = 360^o \times \frac{DayoftheYear}{TotalNumberofDay\sin aYear} \tag{6}$$

and the solar zenith angle ϑ_{zs} is the complementary angle of the sun altitude γ_s:

$$\vartheta_{zs} = 90^o - \gamma_s \tag{7}$$

For the calculation of the sun altitude γ_s the adopted computation method was based on the DIN 5034 Norm [41]. According to it several parameters have to be computed in advance before calculating the needed sun altitude γ_s. In particular the solar declination $\delta(J')$ and the time equation Teq are calculated as follows:

$$\begin{aligned}\delta(J') = \{&0.3948 - 23.2559 \times \cos(J'+9.1^o) - \\ &0.3915 \times \cos(2 \times J'+5.4^o) - 0.1764 \times \cos(3 \times J'+26^o)\}^o\end{aligned} \tag{8}$$

$$\begin{aligned}T_{eq}(J') = \{&0.0066 - 7.3525 \times \cos(J'+85.9^o) + \\ &9.9359 \times \cos(2 \times J'+108.9^o) + 0.3387 \times \cos(3 \times J'+105.2^o)\}\min\end{aligned} \tag{9}$$

From the local time LT the time zone and the longitude of the region the local mean time LMT is extracted as given below:

$$LMT = LT - TimeZone + 4 \times Longitude \times \min/^o \tag{10}$$

Then the local apparent time LAT and the time angle ω are calculated before completing with the calculation of the sun altitude γ_s [42]:

$$LAT = LMT + T_{eq}(J') \tag{11}$$

$$\omega = (12.00h - LAT) \times 15^o / h \tag{12}$$

$$\gamma_s = \arcsin(\cos\omega \times \cos\phi \times \cos\delta + \sin\phi \times \sin\delta) \tag{13}$$

where φ is the local Latitude.

2.2.3 Simulation of PV installation

The transformation of the forecast radiation and temperature data to DC power values delivered from a solar module considering the characteristics of the PV installations is conducted based on the mathematical analytical study of Perpiñan, Lorenzo and Castro [33]. According to it the DC output power P_{DC} of one module is related to the following parameters as described below:

$$P_{DC} = n_{eff}\left\{P_{peak} \times \left(\frac{G_{eff}}{G^*}\right) \times \left[1 - \beta \times \left(T_c - T_c^*\right)\right]\right\} \tag{14}$$

where n_{eff} is a correction factor for losses from modules mismatching, diodes and dirt (91%), P_{peak} is the rated power of one module (W), G_{eff} is the effective global radiation (W/m^2), G^* is the radiation in standard conditions (1000W/m^2), β is the temperature losses coefficient (0.005/°C), T_C is the operation cell temperature, T^*_C is the standard operation cell temperature (25°C).

The operation temperature Tc is calculated as follows:

$$T_c = T_{amb} + (NOCT - T_{NOCT,std}) \times \left(\frac{G_{eff}}{G_{NOCT}}\right) \tag{15}$$

where T_{amb} is the ambient temperature (°C), *NOCT* is the nominal operation cell temperature (47°C), $T_{NOCT,std}$ is the ambient temperature at *NOCT* conditions (20°C), G_{NOCT} is the radiation at *NOCT* conditions (800W/m^2).

The above mathematical calculation is represented from a Matlab/ Simulink model with input variables the global solar irradiance and the ambient temperature. So as to calculate the AC output of the plants the inverters were also modeled as Lookup Tables in Matlab/ Simulink based on the characteristic curve of the manufacturer SMA.

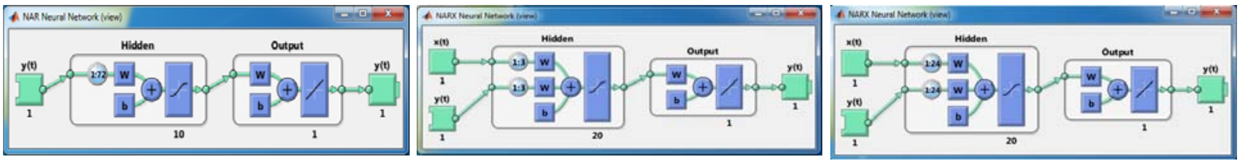
3. Results and discussion

3.1 Forecast results

So as to identify the optimal network in each forecast case, different architectures were tested in order to identify the number of neurons and the respective time delay to apply. Specifically, for the ambient temperature forecast needed to predict the PV energy production a Feed Forward ANN with the Nonlinear Autoregressive (NAR) architecture was selected. For the applied architecture an open loop network, with 1 hidden layer with 10 artificial neurons and a time delay of 72 samples was selected.

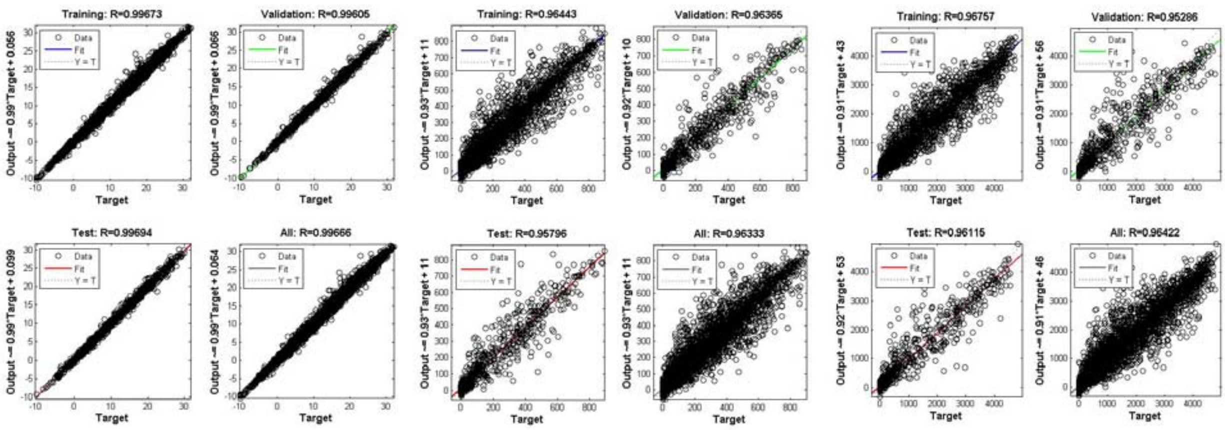
In the case of the global radiation forecast a Nonlinear Autoregressive with exogenous input (NARX) network was preferred. The external input parameters were the hour of the day as well as the calculated extraterrestrial radiation according to the method described in Chapter 2.2.2 and in this case the applied architecture included an open loop network, with 1 hidden layer with 20 artificial neurons and a time delay of 3 samples.

The architecture of the neural network for the direct PV power forecast was almost identical to the one applied for the radiation forecast. It was namely a NARX network with the same external input variables and the same number of hidden layers (1) and artificial neurons (20) but with a differentiation in time delay steps. 24 samples were essential for assuring an adequate training process. The schematic diagram for each case study is illustrated in Figure 6. The ANNs were trained always with time series data from 2011. The regression analysis from the training, validation and testing phase for all three forecast cases is presented in Figure 7.



(a) (b) (c)

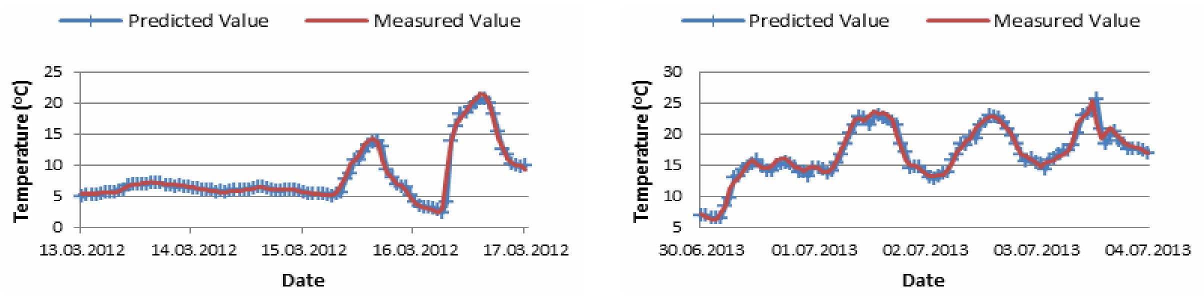
Figure 6. Graphical diagram of the (a) NAR for temperature forecast; (b) NARX for radiation forecast; (c) NARX for PV power forecast.



(a) (b) (c)

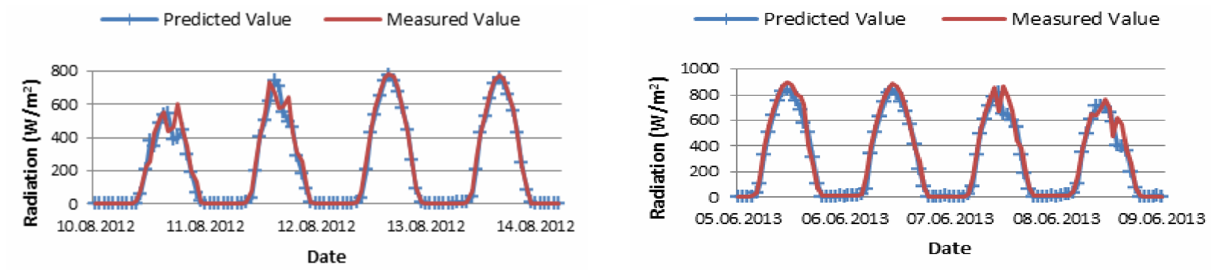
Figure 7. Regression analysis of the training, validation and testing phase between measured and forecast values for (a) Temperature; (b) Radiation; (c) PV power.

Finally the trained neural networks were applied for forecasting the next step ahead values of the respective parameter (forecast horizon of one hour) for a period of one year. It should be noted here that the trained networks were Figures 8-10 show during indicative time periods the match of predicted and measured values for the years 2012 and 2013 respectively.



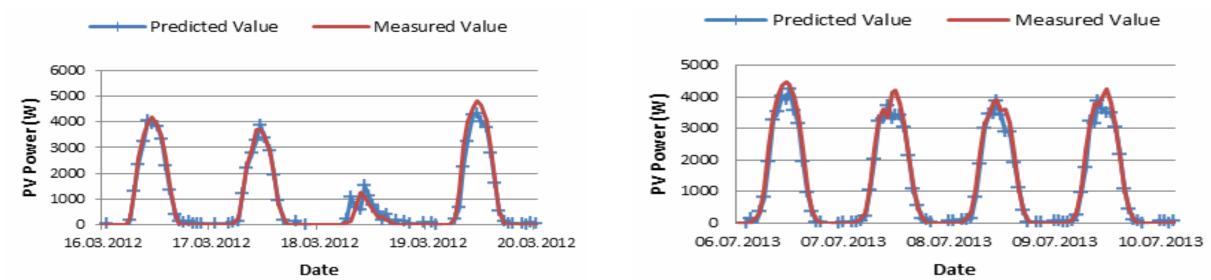
(a) (b)

Figure 8. (a) Comparison of measured and forecast temperature in 2012; (b) Comparison of measured and forecast temperature in 2013.



(a) (b)

Figure 9. (a) Comparison of measured and forecast solar radiation in 2012; (b) Comparison of measured and forecast solar radiation in 2013.



(a) (b)

Figure 10. (a) Comparison of measured and forecast PV Power in 2012; (b) Comparison of measured and forecast PV Power in 2013.

From the graphical depiction of the measured and forecast data it is obvious that the respective values match each other during many time steps. Rumps and abrupt fluctuations are not always foreseen but great mismatch and deviations from the actual values are not noticed, apart from some exceptions during the year. So as to estimate the success and adequateness of the applied methods two statistical error indicators are introduced namely the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE), which are calculated according to equations 16 and 17. In the Table 2 the total MAE and RMSE between the actual and forecast values for the years 2012 and 2013 are presented. The results are low enough to consider the forecast as reliable.

$$MAE = \frac{1}{n}\sum_{1}^{n}\left|\left(Y_{i,pred} - Y_{i,meas}\right)\right| \tag{16}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}\left(Y_{i,pred} - Y_{i,meas}\right)^2} \tag{17}$$

where $Y_{i,pred}$ is the predicted value, $Y_{i,meas}$ the measured one and n the sample size.

Table 2. Errors between forecast and measured values.

	Temperature		Solar Radiation		PV Power	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
Year 2012	0.44 °C	0.64 °C	26.7 W/m^2	55 W/m^2	200 W	362 W
Year 2013	0.41 °C	0.59 °C	26.9 W/m^2	53 W/m^2	184 W	334 W

3.2 Evaluation of results

So as to examine how satisfying the followed methods are and subsequently the finesse of the extracted results a benchmark reference model has been selected to compare the outcomes. For each case a persistence model was chosen. According to its definition, the model assumes that the output value of the time series remains the same for the time step *(t+1)h* as it was at time step *t*. Although its calculation is considered trivial, it is in fact quite difficult to produce a forecast model which outperforms the persistence one and therefore it is chosen in most cases as a reference benchmark model to evaluate the newly designed forecast techniques [26].

In Table 3 the total errors RMSE and MAE for the year 2013 are indicatively presented. These errors were calculated every time between the predicted value for the time step *(t+1)h* and the measured one at the same time step.

Table 3. Errors of the measured values from the reference persistence model and the NN model.

	Temperature		Solar Radiation		PV Power	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
Persistence Model	0.63 °C	0.92 °C	37.5 W/m^2	73 W/m^2	554 W	1173 W
ANN Model	0.41 °C	0.59 °C	26.9 W/m^2	53 W/m^2	184 W	334 W

As it is inferred from the results, the developed models have a better performance from the persistence one for forecast horizon of one hour, since they deliver smaller errors. The ANNs achieve significantly closer outputs to the reality in comparison to the reference models, and the forecast models applied to predict the next hour values of the parameters outperform the persistence ones.

Finally by feeding the forecast values of ambient temperature and solar irradiance to the Simulink model of the PV plants, which is described in section 2.2.3 and also presented in Dimopoulou et al. [34], the predicted PV power per hour is calculated. Consequently, the yearly on-site renewable energy was calculated and the same variable was also estimated from the direct forecast PV power output. The results are presented in Table 4. In particular the first column includes the energy as it was measured from the installed meters, the second one is the energy extracted from the Simulink model when the real registered global radiation and the ambient temperature data were given as input values. The third column is the computed energy from the Simulink model when the input parameters were the forecast values of radiation and temperature and the last one includes the energy extracted from the direct PV power forecast values.

Table 4. Errors of the forecast power values from measured and simulated ones.

	Measured energy	Energy from Simulink model	Energy from forecast radiation & temperature	Energy from forecasting PV power
Year 2012	5.37 MWh	5.44 MWh	5.47 MWh	5.38 MWh
Year 2013	4.86 MWh	5.23 MWh	5.27 MWh	4.90 MWh

Great deviations are not observed though in 2013 it is detected that the measured energy differs noticeably from the one stemming from the Simulink model. This mismatch is not caused by an inadequate model or unreliable input data. It is occurring due to the particularly heavy winter, when large quantities of snow were covering the PV panels, thus causing a reduced renewable energy sources (RES) production, given the available solar radiation and temperature. Since the model is not considering the snow accumulation it was not possible to foresee such a reduced production. It is therefore expected that the energy from the direct PV power forecast approaches the measured one (since the modelling process does not intervene) whereas the forecast energy computed based on the forecast values of the radiation and the temperature verges on the energy extracted from the simulation of the real weather values. To summarise, both methods of forecasting the next hour PV power are delivering reliable outputs though the direct forecast of PV power is producing data closer to the measured actual values.

4. Conclusions

In this paper it was studied the adequateness of the direct PV power forecasting instead of forecasting the weather variables of global radiation and ambient temperature and subsequently calculating the next hour PV power output for the two installed plants. The ANN method was applied in each case and the 'future' value was computed. In the first case the next hour temperature and radiation values were fed in the Simulink model and then the PV power and the annual energy were extracted while in the second case from the direct forecast of the PV power the annual energy production was calculated. No great deviations were noticed though the direct PV power forecast approximated more the measured values whereas the forecast energy derived from the predicted weather parameters of global radiation and temperature approached the annual energy extracted from the Simulink model with input the real weather values.

Acknowledgements

This research was funded by the Cooperative PhD Program Electromobility (Kooperatives Promotionsprogramm Elektromobilität).

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